Louvain School of Management

Investigating the Influence of Cultural Attributes on Entrepreneurs' Risk Disclosures in Reward-Based Crowdfunding

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List of Abbreviations

RCF: Reward Based Crowdfunding

RC: Risk and Challenges

RIQ: Risk Information Quality

SPSS: Statistical Product and Services Solution

UA: Uncerstainty Score

USD: United States Dollar

1. Introduction

As nations evolve to meet innovation needs, crowdfunding presents itself as an alternate financial intermediary facilitating the growth of new ventures. Characterized by a less strenuous regulatory environment, crowdfunding helps shift and spread the financial burden of an entrepreneur's venture onto the public and presents little-to tangible rewards in return to the funders of said project. This presented a unique setting for researchers to study predictors of project success versus failure. In a traditional setting, institutional mediators such as banks and other private professional entities carried the responsibility of profiling and assessing the feasibility of entrepreneurial projects and imposed strict conditions on applicants. In a crowdfunding setting, this responsibility is shifted to funders who need to rely on the information communicated by the entrepreneur in order to make their investment decision; hence the considerable risk of dishonesty and fraud through misappropriation of funds (Mollick, 2014).

Furthermore, existing literature sought to examine the decision-making process from a backer's point of view, and particularly the reason some projects were perceived as lacking transparency and legitimacy from backers' perspective; some sources evaluated preparedness cues as a measure of quality (Chen et al., 2009; N. Wang et al., n.d.), others examined the influence of funder related signals such as updates (Song et al., 2020), experience (N. Wang et al., n.d.) and endorsement as a measure of trust (Li et al., 2018), some also examined culture's impact on contribution motivation (Galuszka & Bystrov, 2012). This aligns with psychometric perspectives on risk perception that extensively highlight the influence of trust, values, perceived benefit affect, knowledge and culture on risk perception (Raue et al., 2018).

Special attention was also devoted to assessing the impact of risk disclosures on reward-based crowdfunding (RCF) success as they became mandatory on prominent RCF platforms such as Kickstarter. Existing sources mainly highlighted the impact of risk disclosures' attributes on backers' contributions (Hopp et al., 2025), such as content and length (Madsen & McMullin, 2018; Shrestha et al., 2023), textual cognitive load (W. Wang et al., 2025), tones (Kim et al., 2022). However, fewer studies have explored the influence of fundraisers' risk perception on risk disclosure content. Tao Wand and collaborators made one attempt to understand the impact of perceived financial risk and plagiarism risk on fundraisers' "*willingness to disclose*" project information (T. Wang et al., 2018). To complement this line of questioning, the intention behind this paper is to explore the impact of cultural attributes on fundraisers' risk disclosures in the RCF process, as many scholars have proven culture has a strong influence on risk perception which in turn impacts risk communication (Shannon & Weaver, 1964).

As most fundraisers resort to RCF to gain exposure and financial support, they also carry the responsibility to minimize the risk of non-delivery. In this report, risk is regarded as "*the possibility that human actions or events will lead to consequences that damage aspects of things that people value*" (Klinke & Renn, 2002); as Boholm suggests, perceiving an event as risky is not without prior uncertainty surrounding that event (Boholm, 2003). Communicating information about risks is hence presenting information about aspects that are essentially uncertain. Sources have argued that cultural differences exist in the process of dealing with uncertainty (Wright & Philips, 1980).

As culture is not an easy term to define, in this paper it refers to the "collective programming of the mind that distinguishes members from one category of people from those of another" as defined by Hofstede (Hofstede, 1991); for the purpose of this study, only country-level cultural attributes are considered. The popular and earliest references on national cultural analysis are Hofstede's publications on cultural dimensions (Hofstede, 1998). Uncertainty Avoidance (UA) is the relevant cultural attribute in this context, because UA is presented as the extent that a country's citizens exhibit anxiety in the face of an uncertain future (Hofstede, 2011).

Ultimately, this research aims to add to the crowdfunding information disclosure literature, namely voluntary information disclosure (T. Wang et al., 2018) by shifting the focus onto fundraisers' approach toward risk communication. As such, this paper aims to first identify the risk disclosure attributes contributing to crowdfunding success, then assess how high and low UA cultures approach risk communication. Accordingly, it attempts to operationalize these findings by using Large Language Modeling (LLM) to assign a Risk Information Quality (RIQ) score between 0 and 2 to each fundraiser's Risks and Challenges (RC) disclosure on Kickstarter, the largest RCF platform. The findings from the quantitative analysis will eventually help understand if the RIQ score has an impact on success, and if the RIQ score varies according to the cultural attribute UA, in other words if crowfunding success is influenced by culture through risk communication.

The study's structure starts with an introduction as a first section. The second section will consist of the literary review and theoretical frameworks used to develop the presented hypotheses. Particularly, crowdfunding literature will be examined to shed light on general crowdfunding mechanisms, the specificity of RCF and campaign success factors. Also, literature on the influence of culture on risk perception and its implications on risk communication and risk management will be presented. After presenting the hypotheses development, the fourth chapter will tackle the methodology by presenting the sample selection method, sample population specificity, data variables, data presentation and collection techniques and analysis methods. The fifth chapter will present the results followed by a discussion and conclusion on the overall contribution and future research avenues.

Resources provided through the Universite Catholique de Louvain's (UCL) online libraries are used for the purpose of building the theoretical standpoint of this study. Online libraries include scientific articles, journal publications, conference proceedings, books and academic publications of which all will be peer-reviewed and assessed for reliability through reference examination; UCL online libraries are linked with platforms such as ABI/INFORM, DIAL, and SAGE. Other external online libraries will also be utilized such as Google Scholar and online databases of other regional research institutes. Empirical data used to answer the research question and draw discussion points will be of quantitative nature and sourced from a crowdfunding database. Finally, ChatGPT is utilized to generate the system prompt used to assign a RIQ score for each individual RC sample unit.

2. Literature review

2.1. Risk disclosure and crowdfunding success

2.1.1. Entrepreneurial financing

Access to financing for a sole proprietor, or small business, was previously confined to the approval of formal legal institutions such as commercial banks, or private backers. Previous studies have shown the important link between pace of economic growth and developped financial systems; whereby developped financial systems refer to ones that effectively mitigate factors preventing economic activity from taking place such as high transactional cost and lack of information (Peachey & Roe, 2004). The three key functions of financing are threefold: mobilization of savings, resource allocation and risk mitigation (Peachey & Roe, 2004). While venture capitalists mainly favor projects with more lucrative opportunities, microfinancing then emerged as an alternative to grant small ventures access to funding through informal loans by not-for-profit organizations, especially for poorer underserved communities (Robinson, 2001). The forms in which microfinance emerged differ from one institutional context to another; while it has emerged in institutional environments with varying legislative constraints, it has evolved to utilize digital tools and online platforms to bridge opportunities and investors (Bruton et al., 2015).

The internet and the rise of the digital era have accelerated and facilitated the diffusion of yet other financial alternatives such as crowdfunding and peer to peer lending. Although not a new phenomenon (Hoque, 2024), crowdfunding is a term that encapsulates the new dynamics of such financing enabled by digital platforms, and does falls under the general categories of microfinancing, as fundraisers seeking financing are individuals or a small team (Gutiérrez-Urtiaga & Sáez-Lacave, 2018). Crowdfunding platforms incorporate elements of crowdsourcing in the sense that they centralize the sourcing of funds, as well as sourcing for insights through a two-way conversation between fundraisers and donors. Before elaborating on the latter, types of crowdfunding must be differentiated. Crowdfunding, in exchange for a type of gain, typically takes three forms, equity, debt or reward based. As per Miglo, entrepreneurs choose to raise funds through equity crowdfunding when they aim to sustain and scale an available demand for a service or product, access a large pool of potential donors and not be bound to a strict due diligence process typical of venture capital firms (Miglo & Miglo, 2016). In debt crowdfunding, funders provide loans and receive interest on payback installments. The difference between the previous two forms and reward based is rewards are non-monetary; funders invest what could span from a minimal contribution up to couple of thousands USDs to receive the said product, service promised, or simply an ackowledgement (Ferreira & Pereira, 2018).

Although any investor who considers crowdfunding has a higher risk appetite by default, RCF is the most innovative form as it does not secure any sort of financial return, and can be described as a "no- penalty contract" since no clear legal action can be sought against the creator in case of project failure (Gutiérrez-Urtiaga & Sáez-Lacave, 2018). Taking Kickstarter as an example, renowned RCF platform, every donor backing a project must do his or her own due diligence before pledging, as no refunds are permitted once a creator's campaign has reached its funding goal (Kickstarter, 2025a). On Kickstarter creators use various communication cues to promote their project as well as interact with existing or potential backers to bridge any information asymmetry; the platform operates with an "All or Nothing" concept, as such it secures refunds of all pledges if a project's goal was not met; it also monitors complaints for suspected intellectual property or copyright violation and provides comprehensive guidelines to manage expectations. Despite the relaxed regulations in the RCF process, Kickstarter alone has recorded approximately 497 million USD total annual backer investment since its inception in 2009 (Kickstarter, 2025b).

RCF crowdfunding has enabled an early stage, two-way conversation between "user" and "producer", thus enabling creators to update and adjust their offering as the interaction grows to meet user expectations (Testa et al., 2018). In order to entice the backer to support his project, a creator must build a and cultivate a "trust relationship" with the backers (Zheng et al., 2016). Communication management is evidently at the heart of the process, which involves handling a complex mix of cues both available and external to the RCF platforms (Kraus et al., 2016). Moreover, the success and diffusion of crowdfunding as a form of alternative finance received heightened attention from scholars and business practitioners to understand key drivers of campaign success and explore social, institutional and legislative implications on the future of entrepreneurship. In the next section, studies around the evaluation of communication cues related to risk information will be presented.

2.1.2. Risk disclosures and investment impact in RCF

In traditional financial markets, regulatory bodies have increased oversight and requirements for qualitative and "meaningful" risk disclosures following the financial crisis in 2008, to ultimately further enhance investor protection (European Commission, 2014). The RC section introduced by Kickstarter became a compulsory part of campaigns as of September 2012 (Strickler et al., 2012), as a measure to improve information asymmetry and to alleviate backers' perception of the platform as a store for established or mature products (Kim et al., 2022). However, unlike traditional financial markets where risk information is audited and analyzed by professional third parties, alternative financing platforms such as Kickstarter do not inspect or monitor the risk information content for veracity or other related quality indicators.

Consequently, studies in crowdfunding literature sought to explore the impact of RC disclosures on project success, adding to the already challenging endeavor for fundraisers to effectively portray authenticity (Wood et al., 2022). The specificity of risk disclosures is the cognitive cost they add in the decision making process; accordingly, some studies have found that the presence of risk information decreased the average contribution amount (D'Arcangelo et al., 2023); others found that risk disclosures negatively impacted campaign success specially for projects deemed "high-risk" (Kim et al., 2022). However these conclusions were complimented with the potential of carefully prepared risk information in mitigating backer resistance (Kim et al., 2022). Further developing on the latter, a research conducted by Madsen and McMullin suggests the positive impact of longer RC disclosures on backer funding (Madsen & McMullin, 2018), and noted observable changes to non-risk disclosures, as well as campaign financing structure (goal size, discounts, delivery times) to decrease risks associated with information asymmetry (Madsen & McMullin, 2018). This adds to the specificity of RC disclosures' concern with systematic risks typically associated with uncontrollable and macroeconomic events (Campbell et al., 2010).

Further evidence provided that a positive curvilinear relationship between quantity of risk information and successful attainment of campaign funding (Shrestha et al., 2023);

this means that beyond an optimal point, too much risk information deters backers from investing. On a content standpoint, many studies mention the importance of language and emphasize the negative impact of overly positive tones in risk disclosures (Huo et al., 2024; Kim et al., 2022). In addition, other studies show empirical evidence that risk disclosures addressing project-relevant uncontrollable risk events have a higher likelihood of funding success due to their perceived value in enhancing quality assurance (W. Wang et al., 2025). On that note, a separate study suggests that perception of quality exist when authenticity has been established, and posits that positive language used in a manner to demonstrate risk mitigation efforts is an effective risk disclosure strategy in crowdfunding (Bolinger et al., 2024).

Finally, existing literature extensively studies the impact of risk disclosures' textual and linguistic attributes on backers' risk perception and campaign funding outcomes. This brings our attention to understanding the antecedents of risk disclosure attributes, therefore focusing on a fundraiser rather than a funder perspective on risk.

2.2. Impact of culture on risk communication

2.2.1. Influence of culture on risk perception

In the early years, risk theory was a research field characterized with treatment of risk as an objective phenomenon, resulting in a focus on probabilistic theory and related technical and scientific foundations to decision making. However, since the 20th century, psychologist Ward Edwards released a publication on the psychological issues underlying economic theories and sparked the emergence of behavioral economics (Raue et al., 2018). In addition, studies in the 1970s have shown the absence of correlation between expert risk calculations and public perceptions of risk, as public risk perception was rather correlated with qualitative factors such as trust and equity among others (Healy, 2004). This in turn introduced the psychometric paradigm as a research approach centered around explaining nonexperts' risk perception, and invited researchers across disciplines to reflect on the complex intersection of human behavior, external influences and decision-making management (Siegrist, 2010).

Risk perception theory hence emerged as a body of knowledge that includes foundational inter-disciplinary theories that complement scientific approaches to risk and account for psychological, political, sociological and economic perspectives. In other words, it specifically revolves around studies that depict people's characterization of an activity as risky, the meaning they attach to the activity concerned and the constructs that underlie such judgements (Slovic, 1987). Among the potential constructs, Wildavsky and Dake highlighted the strong influence of cultural biases on risk perception (Wildavsky & Dake, 1990) as depicted by Douglas' work on the cultural theory of risk (Douglas, 1992). As societies and cultures evolved, one's response to risk or threat went from basic strategies such as "fight" or "flight", to take on cultural patterns (Raue et al., 2018).

Mary Douglas received credit for being the originator of cultural theory; she took an institutional approach to highlight the strong relationship between institutions and shared thought categories to propose a classification mechanism that allows for sociological comparison at an aggregate level (Douglas, 1982). When applied to risk perception cultural theory posits that each classification or "worldview" serves as an "orienting mechanism"; each worldview will have his own mechanism of navigating dangers and uncertainties by attributing selective importance to risks and by coping with uncertainty according to its set of biases or norms of its social environment (Douglas & Wildavsky, 1982).

Furthermore, major milestones gained from psycological studies on risk perception concern the identification of qualitative elements that characterized and predicted the magnitude of perceived risk, being "catastrophic potential" and "dread" among others (Renn & Rohrmann, 2000). Studies by Slovic et al. not only highlighted the validity of the mentioned characteristics in predicting risk perception (Slovic et al., 1985), but also provided insights regarding cross-cultural differences in the cognifitve or mental routes underlying these characteristics (Slovic, 2009). Thus, this sparked further questions in cross-cultural research on the antecedents that shape these mental models and whether they are culture specific (Galotti, 2017). For example, among others, one study found that "analytical" information processing was exhibited by Western cultures, versus "holistic" information processing by Eastern Asian cultures (Ji et al., 2000). Although not all findings point towards a specific direction, culture can't be dismissed as an antecedent to risk perception and was recognized as one of the contextual precedents to risk perception is Renn's and Rohrman's framework (Renn & Rohrmann, 2000).

Finally, risk perception is just one facet of one's subjective evaluation of risk, where a complex mix of factors come in play to influence risk appraisal, acceptability and behavior (Rohrmann, 2008). The previous and ongoing research that provide empirical support to the different theoretical contributions on risk perception have a substantial impact on other areas of academic research, as well as professional disciplines; these studies contribute to the development of public policies, healthcare services, marketing and risk communication practices among others.

2.2.2. Uncertainty avoidance and implication on risk communication

Cultural nuances in risk perception have been at the center of communication research, given the needed cultural understanding in navigating today's globalized commercial environment. In general terms, risk communication involves providing information about a risk issue with the intention to raise awareness or impact attitudes and behavior. Risk communication in particular, as ascerted by Renn, serves as the bridging element between risk perception and risk management (Renn, 1989). Taking Shannon and Weaver's (1964) risk communication framework as a reference, the implication of risk communication in an RCF context, concerns both the fundraiser's perception of risk and intention.

In a RCF setting, the risks that entrepreneurs are exposed to are the risk of idea replication and the risk of delays in delivery caused by operational difficulties; operational difficulties can be brought on by unforeseen circumstances or an entrepreneur's miscalculated decisions (Hoque, 2024; M. Alshater et al., 2024). A fundraiser can be torn between opportunism or self-promotion by downplaying risks on the one hand, and authenticity by choosing transparency to gain legitimacy (Fisher et al., 2017; Jones & Pittmand, 1982) on the other hand. This suggests different ways an entrepreneur copes and reacts to the uncertainties surrounding risks. As mentioned earlier, among the many factors that characterize one's perception of a given risk is the feeling of "dread" that he/she associates with that risk (Renn, 1989). Dread refers to exhibiting anxiety and uneasiness. Hofstede's cultural dimensions theory is among the known cultural frameworks that brought forth explicit measures that differentiate between national cultures' display of dread and uneasiness towards uncertaity, among other distinguishable attributes (Hofstede, 2001).

Accordingly, Hofstede's "Uncertainty Avoidance" (UA) index quantifies the likelihood of experiencing uneasiness in uncertain situations according to a given national cultural setting (Hofstede, 2001). On the one hand, cultures characterized as highly uncertainty avoidant strive to minimize uncertainty surrounding future events and cope by seeking clarity and structure; on the other hand, cultures who are less uncertainty avoidant exhibit openness to change and unfamiliar risks (Hofstede, 1980). In addition, literature has shown the relevance of Hofstede's UA dimension in assessing cultural influences on risk disclosure attributes (Wong, 2012). In addition, Hofstede's model of cultural dimensions presents a suitable framework whereby dimensions are statistically distinct, and country scores allow for large-scale quantitative data analysis (Greene, 2024).

In a risk communication context, existing studies have found a positive association between uncertainty avoidance index and level of risk disclosures (Dobler et al., 2016); authors Micheal Dobler and associates suggest that cultures associated with high UA exhibit a higher level of disclosure on risk sources, risk types and risk management. Furthermore, a recent study by Bolinger sought to evaluate the effectiveness of early-stage entrepreneurs' risk disclosures on Kickstarter; the study results indicate the effectiveness of disclosures using a "compensation" mechanism, in which risks and challenges are transparently conveyed and coupled with existing buffers and/or planned efforts to attenuate risks (Bolinger et al., 2024).

3. Hypotheses development

Previous studies have pointed out that risk disclosures in RCF is an effective tool to bridge and foster trust between fundraisers and backers (Hopp et al., 2025; Yang et al., 2021). Others have explored which risk disclosure attributes have an impact on campaign success and among these attributes are the disclosure length, amount of risks mentioned, presence of affect, and more; the findings majorly support the fact that risk disclosures have a considerable impact when they are balanced in a way to include information without going beyond a threshold, where the added weight of risks can become unsettling (Hopp et al., 2025; Shrestha et al., 2023).

Furthermore, research findings of Bolinger et al. (2024) and Wang et al. (2025) also confirms that introducing cognitive load does not have a negative impact on RCF risk statements as long as clear mitigation measures are presented against mentioned risks.

This study makes an attempt to operationalize the presence of risks along with their mitigation approach in RC statements, by allocating a Risk Information Quality (RIQ) score using machine learning. Aligning with the previous studies mentioned, the first hypothesis is as follows:

H1: RCF campaigns whose risk disclosures contain risk information coupled with risk mitigation efforts, hence a high RIQ score, have a higher likelihood of success

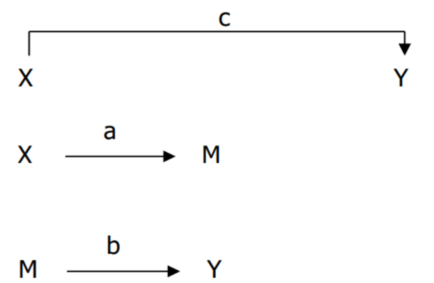
Second, findings by Dobler et al. (2016) revealed that comprehensive risk dislcoures addressing risk types and their respective management are found to be practiced by cultures scoring higher on Hofstede's UA index. Hence, the study first seeks to establish if high UA cultures have a higher likelihood of success. Then, since culture has an impact on risk perception, and ultimately risk communication, this study will explore if high UA cultures achieve success through their RIQ. Accordingly, high UA cultures should theoretically exhibit a higher RIQ score. The second hypothesis is therefore as follows:

H2: The level of UA positively influences success likelihood through RIQ. As such, the RIQ score mediates the relationship between fundraiser's level of UA and campaign success

- **H2a**: National UA score significantly influences project success
- **H2b**: UA score has a significant impact on RIQ score

Following the mediation approach introduced by Baron and Kenny (Baron & Kenny, 1986), the result of regressions in paths *a*, *b* and *c* as shown in figure 1 below have to all be statistically significant. Path *b* represents the outcome of H1, path *c* the outcome of H2a and path *a* the outcome of H2b. Since this approach applies for continuous variables, we will support the findings with the ouput of a mediation analysis using Haye's methodology (Hayes, 2022), made available by the PROCESS macro utility on SPSS when testing mediation with the binary funding outcome variable.

Figure 1 – Mediation testing through step by step regressions



4. Methodology

4.1. Data collection

For the purpose of this study, the sample is limited to publicly available data on project campaigns launched on Kickstarter. Kickstarter, launched in April 2009, is the most popular and largest RCF platform. Kickstarter has alone recorded approximately 497 million USD total annual backer investment since its inception in 2009 (Kickstarter, 2025b); it gathers entrepreneurial projects launched from nearly 100 countries, which makes it a good setting for exploring the impact of cultural nuances in risk communication. Project categories span across 15 different categories, consequently offering a fair representation of the wider industry and market (Shrestha et al., 2023).

Li's Kickstarter Structured Relational Database (LI, 2019) facilitated the extraction of 9,950 campaigns launched between January 2015 up to January 2019, long after the announcement of the required RC disclosure in 2012 (Strickler et al., 2012). The list of variables captured per project are outlined in Appendix 1. Since many previous publications have used Kickstarter as a ground for research, comparison of findings is adequately enhanced.

4.2. Data preparation and variables

To start, all labels other than English under "campaign language" were excluded. Accordingly, 487 exclusions were made out of 9,950 individual entries. In addition, only the RC sections of each sample's project description were kept. Among these, RC disclosures with more than 1 detected language were located and adjusted by manually removing foreign language translations. To ensure no other RC disclosures contained foreign languages, RC disclosures of countries other than (US, United Kingdom, New Zealand or Australia) were manually inspected and adjusted. Finally, when samples returned a "#NAME?" value for RC disclosures, the section was manually copied from the respective ".txt" file to ensure data was not lost. The resulting sample to population ratio is 95% (9,445/9,950).

4.2.1. Dependent variables

The dependent variable for this study is *funded* which represents the funding outcome of "1" for success and "0" for failure, and therefore a binary variable. In order to add robustness to our results, we will also explore results using *funding level* as a dependent variable. *Funding level* represents the total amount pledged over the original campaign goal set. *Funding level* will be logged (log(x+1)) to enhance the variable's normal distribution.

4.2.2. Independent variables

Risk Information Quality Score (RIQ)

In order to produce the *RIQ score* variable and systematically evaluate the risks identified in Kickstarter campaigns, this study employs Large Language Models (LLMs), which are advanced AI systems built on transformer architectures (Vaswani et al., 2023). The architecture is based on an encoder-decoder structure. The encoder maps an input sequence in the form of a vector that holds all the learned information. The latter is transferred to the decoder to construct an output sequence based on the information while also being fed by the previous output. Both the encoder and decoder contain a multi-head attention subcomponent that drives the self-attention mechanism which is based on three vector representations: query, key & value. The latter captures the closeness or context information for each word in the vector space.

Furthermore, studies showed how prompting (Brown et al., 2020; Liu et al., 2021) LLMs can perform many tasks. Prompting is simply designing a well-structured input (prompt) to the LLM to provide guidance on how it should respond. It's about choosing the right wording, structure, and context to get the output you want from it. The study conducted by Brown et al. (Brown et al., 2020) introduced GPT-3 (175B parameters) and showed that a frozen language model can perform many tasks by simply conditioning a system prompt with a few examples. GPT-3 was evaluated across tasks (translation, QA, commonsense, arithmetic, etc.) without any fine-tuning, relying simply on prompts. They found that larger model scale dramatically improves few-shot performance, often reaching or exceeding fine-tuned baselines.

Another study by Liu et al. (2021) provides a comprehensive survey of prompt-based learning. By simply defining a new prompting function the model is able to perform few-shot or even zero-shot learning, adapting to new scenarios with few or no labeled data. This framework is powerful and attractive for a number of reasons. First, it allows one to utilise an LLM pre-trained on substantial amounts of text. Second, with no labeling data required, the model can generate satisfactory responses. Whereas in traditional deep learning and machine learning models, it is required to train the models on labeled data which is time consuming. Finally, the main difference between zero-shot and few-shot learning is that in zero-shot learning, the user does not provide an example of how the LLM should respond. By adding few-shot examples – such as stating clearly that the LLM needs to structure the output by using bullet points for each main point– the LLM can yield to adequate results.

To further enhance the results, chain of thought (CoT) prompting was a step added to mitigate limitations of few-shot examples in reasoning capability. As previously demonstrated by Wei et al. (2023) and Ranaldi et al. (2024), CoT prompting yields significantly better results by allowing the integration of intermediate steps to support a refined reasoning outcome, proving higher efficiency in arithmetic, symbolic and common sense reasoning.

A full breakdown of the setup and prompt development is outlined in Appendix 2. The prompt was developed individually by manually screening 70 samples to effectively capture the assigned score level; the research study by Bolinger et al. was used as a reference for effective risk disclosures, whereby fundraisers who coupled their project-related risks with respective buffers and plans taken to avoid the occurrence and magnitude of such risks were more successful in attaining their project goal (Bolinger et al., 2024).

To illustrate the output of the LLM, the below RC section was assigned a score of 1, and the LLM justified this choice by pointing out that the sample "*identifies challenges but describes them vaguely without concrete mitigation or actionable steps; it simply states a goal and acknowledges a difficulty*". The entry is as follows:

"*There are virtually no risks to our project because we have been able to self fund up until this point. Our biggest challenge going forward will be the marketing and distribution of the books. We intend to meet this challenge on a two-fold front: first, with the assistance of my marketing team, a national company which distributes its products worldwide, and second, using today's social media outlets we want to create a ground-swell movement that so goes with the VW bus attitude.* "

By contrast, below is a RC entry that was assigned a score of 2, and for which the LLM judged it to "*acknowledge a potential delay in reward fulfillment due to funding limitations and outlines a plan to provide regular updates to backers in case of setbacks, demonstrating actionable steps to address the challenge".* The entry is as follows:

"One challenge that I may face after the project is successfully funded is getting the rewards sent in time. This is only because I am not asking the full amount in the fundraiser goal. I plan on funding the remaining expensive independently as to not ask too much from others. This being said, if there are any setbacks, I will be giving updates on a regular bases to keep you updated so that you will know what is going on and when you can expect your rewards."

Finally, to demonstrate what an excerpt with an assigned score of 0 looks like, the below was rated as low because "*The text only describes positive attributes and intentions without mentioning any potential risks or challenges ".* The entry is as follows:

"I will ship your rewards in time for holiday gift giving 2016. My ingredients are all natural and sourced from socially responsible, small family owned businesses. My packaging is all reusable, recyclable, compostable and simply all kinds of modern apothecary fun."

Uncertainty Avoidance score

Finally, the country-specific Uncertainty Avoidance score was added to run tests for the second hypothesis and was retrieved from "Country comparison tool" on the Culture Factor Group's website (Culture Factor Group, 2025); the latter is an organization that provides a digital interactive tool to visualize national scores per cultural dimension, and based off of data operationalized according to Hofstede's cultural scales.

4.2.3. Control variables

Following the steps of previous studies, many control variables were set to isolate the impact of the studied independent variable. Control variables, with a significant impact on funding success are outlined in Appendix 3, as well as their operationalization; the choice of variables follows the findings of the literature review done by Deng et. Al (2024). The dummy variables for project category are a total of 14, with technology as the reference; although many product are initiated under the technology category, they are the least successful in reaching their funding goal (Lui et al., 2023). Furthermore, dummies were also added for *region* with North America as the reference, and for *year* with 2015 as the reference. After testing for multicolinearity, variables with a VIF higher than 5 were eliminated; as such the eliminated variables are: *competing campaigns*, *google trend. Pledge amount* will not be part of control variables in the regression models as it is considered an alternative campaign success measure and embedded in one of our dependent variables. *Backer count* is also considered an alternative campaign success measure; it is however not as accurate and robust as the dependent variables already defined and hence will be excluded in this study.

4.3. Analysis tools

4.3.1. Binary logistic regression

The data prepared was imported on SPSS, a statistical analysis software provided by IBM and widely used for statistical analysis. The dependent variable used under Model 1 is funding outcome (*Funded*), a binary variable that takes one of two outcomes for each sample. As such, to test how likely *RIQ score* predicts *Funded* outcome, a binary logistic regression (BLR) is used to for which the control variables listed in Appendix 3 are added. *RIQ score* in this equation is an ordinal variable with a value of 0, 1 or 2, respectively low, moderate or high; *RIQ score* is also set as "Categorical" before running the BLR as there are no antecedants that assume a linearity accross the levels. To reduce outliers and skewness when observed with continuous variables, some variables like *experience* and *goal amount* were winsorized, and some were log-transformed to achieve enhanced result interpretation. Please refer to Appendix 4 for the normal distribution test results, explaining the log-transformation of variables. Model 1 will specifically address the first hypothesis (H1).

Similarly, a BLR will be utilized to study the impact of *UA score* on *Funded* outcome. Hence, under Model 2, we will first test if *UA Score* predicts *Funded* outcome using the same parameters taken for the earlier logistic regression. Model 2 will therefore specifically address hypothesis 2a (H2a). All BLR models can be found under Panel A (Table 1).
When accounting for control variables, the formula is as follows:

$$\log\left(\frac{P}{1-p}\right) = \beta_0 + \beta_1 {*}\mathrm{X} + \beta_2 {*}\mathrm{Z}_1 + \ldots + \beta_k {*}\mathrm{Z}_k$$

Where:

P= probability of funding success (i.e. outcome "1")

$\frac{P}{1-p}$= odds of success

β_0= intercept

X= independent variable

B_k= coefficient of each respective predictor variable (independent and control variables)

Z_k= control variables

Table 1 –PANEL A (BLR)

PANEL A	Model 1 (H1)	Model 2 (H2a)
DV (Dependent Variable)	*Funded* (binary outcome of 0 or 1)	
IV (Independent Variable)	*RIQ score*	*UA score*
Regression	BLR	BLR
Control variables	Please refer to Appendix 3	Please refer to Appendix 3

4.3.2. Linear regression

A linear regression will be performed to assess the impact of *RIQ Score* on an alternate funding outcome measure being *funding level,* log transformed to log(*funding level* +1); the results will be summarized under Model 3a and will specifically address H1.
To be consistent with the steps taken for the BLRs, the impact of *UA score* on *funding level* will be presented as well, to specifically address H2a under Model 4.
Finally, in Model 5 a linear regression will be applied to assess if *UA Score* predicts *RIQ Score* and specifically addresses hypotheisis 2b (H2b). Linear regression models will fall under Panel B, and are summarized below:

Table 2 –PANEL B (OLS)

PANEL B	Model 3 (H1)	Model 4 (H2a)	Model 5 (H2b)
DV (Dependent Variable)	log(*funding level* +1)		*RIQ score*
IV (Independent Variable)	*RIQ score*	*UA score*	*UA score*
Regression	OLS	OLS	OLS
Control variables	Appendix 3	Appendix 3	Appendix 3

When accounting for control variables, the formula for Model 3 and 4 is as follows:

$$\log(Y + 1) = \beta_0 + \beta_1 * X + \beta_2 * Z_1 + \dots + \beta_i * Z_k + \varepsilon_i$$

Where:

$\log(Y + 1)$ = dependent variable

Y= funding level

X= independent variable

β_0= intercept

β_i= coefficient of independent and control variables

Z_k= control variables

ε_i = is the error term

Whereas, when accounting for control variables for Model 5, the formula is as follows:

$$Y = \beta_0 + \beta_1 * X + \beta_2 * Z_1 + \dots + \beta_i * Z_k + \varepsilon_i$$

Where:

Y= RIQ score

β_0= intercept

β_i= coefficient of independent and control variables

X= *UA score*

Z_k= control variables

ε_i = error term

5. Results

As shown in Table 3 below, in Model 1, *RIQ score*'s Wald-test displays a significant p-value of 0.008, therefore *RIQ score* presents a significant overall impact on the probability of success. The effect is spread across score levels; with the reference category being *RIQ score* equal to *0*, there is no one *RIQ score* level whose impact significantly differs from the reference. In Model 2, *UA score*'s p-value of 0.004 presents a significant impact on the dependent outcome. In Model 1 and 2, the pseudo R^2 value amounts to 48%, and amounts higher than 40% assume the regression model is of considerable predictive ability.

As for the control variables, results align with previous findings on the significant impact of *goal amount, experience, endorsement, video, website* and *number of rewards, campaign duration* and *delivery duration* (Deng et al., 2024).. As for project categories, the categories of *crafts*, *design*, *music* and *theater* seem to have a higher likelihood to be funded compared to *technology.*

Table 3 – Beta coefficients for Panel A

PANEL A (N=9443)	**Model 1**	**Model 2**
-2 Log likelihood	8551.287	8555.964
Cox & Snell R Square	0.359	0.358
Nagelkerke R Square	0.484	0.484
Constant	*0.59659	*0.6672
UA Score		**-0.0072
RIQ score		
RIQ score(1)	**-0.203	
RIQ score(2)	**-0.027	
log_win_goal	***-0.59224	***-0.5861
log_num_rewards	***1.14868	***1.1546
log_word_count	***0.20033	***0.2188
Log1_win_exp	***0.81635	***0.8293
campaign_duration	***-0.02118	***-0.0214
delivery_duration	**-0.00051	**-0.0005
video	***0.87901	***0.8835
Website	***0.58602	***0.5861
Social_media	-0.122	*-0.1273
endorsement	***2.23787	2.239
readability_score	*0.01789	*0.018
D_EAPAC	0.000	-0.002
D_EurCA	-0.085	-0.060
D_LATAM	-0.133	0.110
D_MENA	0.716	0.986
D_SAsia	0.705	0.660
D_SubSAF	0.743	0.819
D_art	*0.30554	*0.2825
D_comics	-0.062	-0.082
D_crafts	***-0.70094	***-0.707
D_dance	0.556	0.529
D_design	***0.4485	***0.4527
D_fashion	-0.239	-0.248
D_filmandvideo	0.198	0.169
D_food	-0.152	-0.174
D_games	0.163	0.170
D_journalism	-0.101	-0.114
D_music	***0.90228	***0.8707
D_photography	0.278	0.269
D_publishing	0.180	0.158

D_theater	***0.8313	***0.7829
D_2016	*0.18103	*0.1814
D_2017	***0.2944	***0.2947
D_2018	***0.67279	***0.6706
D_2019	2.211	2.274

*p value < 0.05
**p value < 0.01
***p value < 0.001
N = *number of observations*

In Table 4 below, *RIQ score* has a more significant impact on *funding level* than *UA Score; RIQ score* presented a p-value of 0.01 under Model 3, versus 0.20 for *UA score* under Model 4. Under Model 5, *UA Score* does not show a significant statistical impact on *RIQ Score,* with a p-value of 0.486, therefore validating the null hypothesis for H2. To support this conclusion, the outcome of a mediation analysis using Hayes's PROCESS macro on SPSS was added in Table 5, using the *funded* variable (binary) as the dependent variable, *RIQ score* as the mediator and *UA score* as the indepdendent variable. As shown in Table 5, the indirect effect is not significant since 0 falls between the lower and upper bounds of the confidence intervals.

Table 4 – Unstandardized coefficients for Panel B

PANEL B (N=9443)	Model 3	Model 4	Model 5
R Square	0.3794	0.3790	0.274
Adjusted R Square	0.3770	0.3767	0.271
Std. Error of the Estimate	0.5144	0.5145	0.466
Constant	***1.025	***1.048	***-0.215
UA score		-0.001	-0.0003
RIQ score	*0.02923		
log_win_goal	***-0.13362	***-0.13317	*0.00767
Log1_win_exp	***0.2793	***0.28152	***0.07496
log_num_rewards	***0.15994	***0.16051	0.0120
log_word_count	***0.02757	***0.0362	***0.3077
campaign_duration	***-0.0016	***-0.00161	*-0.0009
video	***0.10173	***0.10237	0.0143
delivery_duration	0.000	0.000	0.0000
Website	***0.08523	***0.08554	0.0234
Social_media	-0.013	-0.014	-0.0147
endorsement	***0.48903	***0.48979	0.0144
readability_score	*0.00331	*0.0036	***0.01128
D_EAPAC	0.007	0.008	0.0381

D_EurCA	-0.019	-0.018	*-0.026
D_LATAM	-0.071	-0.051	-0.0064
D_MENA	0.060	0.083	0.0643
D_SAsia	0.062	0.053	-0.2053
D_SubSAF	0.018	0.029	*0.24073
D_art	***-0.11956	***-0.12135	-0.0363
D_comics	***-0.15849	***-0.15995	-0.0078
D_crafts	***-0.25212	***-0.25309	0.0025
D_dance	**-0.21314	***-0.21689	-0.1089
D_design	***0.11253	***0.1131	0.0123
D_fashion	***-0.14883	***-0.14963	-0.0181
D_filmandvideo	***-0.17412	***-0.17682	***-0.068
D_food	***-0.1224	***-0.1242	-0.0114
D_games	0.042	0.043	0.0016
D_journalism	***-0.20322	***-0.20362	-0.0192
D_music	**-0.06972	**-0.07342	***-0.09889
D_photography	***-0.15807	***-0.15869	-0.0305
D_publishing	***-0.16912	***-0.1725	***-0.09038
D_theater	**-0.13236	***-0.13759	-0.0616
D_2016	**0.04011	**0.03991	-0.0099
D_2017	***0.05837	***0.05785	-0.0237
D_2018	***0.12205	***0.12204	0.0014
D_2019	**0.56299	**0.55716	-0.2665

*p value < 0.05
**p value < 0.01
***p value < 0.001
N = *number of observations*

Table 5 - Mediation Indirect effect results

Variables:

X: UA score (ordinal, set as multicategorical
Y: Funded (binary outcome)
M: RIQ score (Mediator)

Indirect effect(s) of X on Y:

	Effect	BootSE	*BootLLCI*	*BootULCI*
RIQ score	-0.0002	0.0002	*-0.0006*	*0.0002*

Level of confidence for all confidence intervals in output:
95.0000
Number of bootstrap samples for percentile bootstrap confidence intervals:
5000
NOTE: STAND/EFFSIZE options not available with dichotomous Y.
NOTE: Direct and indirect effects of X on Y are on a log-odds metric.

6. Discussion

Through this study, the author tried to leverage LLM through machine learning to operationalize risk disclosure quality and understand if a fundraiser's level of UA, designated by his or her cultural background, impacts funding success through risk disclosure efficiency. Machine learning yields a better RIQ score predictor as it goes beyond counting frequency of certain words and accounts for meaning and context. On the one hand, the results have shown evidence to support the first hypothesis since *RIQ score* had a statistically significant effect on *funding outcome* and *funding level*, two different campaign outcome measures. In addition, country-level *UA score* similarly had a statistically significant effect on *funding outcome* (success or failure) which validates H2a. The same conclusion couldn't be reached regarding the effect of *UA score* on *funding level*, as RIQ score showed higher predictive power.

On the other hand, due to the absence of a statistically significant impact of *UA score* on *RIQ score*, there is weak evidence to support H2b. This implies that *RIQ score* does not explain or mediate the relaionship between *UA score* and campaign outcome despite the different success measures tested. This could result from the limited accuracy regarding the national background of the entrepreneur, as the location from which a campaign was launched is not necessarily equivalent to the entrepreneur's national background; the entrepreneur can be of Indian background for example and living in the United States.

7. Contribution, limitations and future outlook

This study contributes to the existing body of litterature by confirming prior empirical evidence of the impact of the quality of risk information on funding success, and introducing a cultural dimension to evaluate whether an entrepreneur's cultural background impacts his or her risk information quality. As such this study seeked to establish a possible relation between entrepreneur-related attributes and risk communication that may suggest culture's impact on success through risk disclosure efficiency, instead of focusing on the impact of entrepreneurs' risk communications' standalone attributes on backer risk perception or investment outcome.

However, this study was first, the result of an individual effort bound by limited time and resources; as such there was no validation of the LLM prompt development by risk management experts, nor is there any inherent guarantee that the appropriate score has been consistently assigned to all samples. It is a process that gets better with every iteration, so more time granted means a higher possibility of refining by comparing multiple iterations. Second, although country-specific UA score had a significant impact on the funding outcome of success or failure, it was difficult to establish that one's level of UA predicts the quality of risk information. If time and budget weren't a limitation, accounting for the real national background of each fundraiser would bring an added value to the results; as slightly more than 60% of the projects in this study's sample were launched from the United States, it is surely possible than many have Latin American, Asian or Middle Eastern origins. Hence, adding this level of precision could be explored for future studies.

Finally, this study was limited to measuring one cultural attribute against a specific aspect of risk communication. In the future, other cultural attributes can be tested against other textual aspects of a full project description or assess cultural cues during the post-campaign launch phase, where fundraisers interact and answer backers' questions and feedback in the comments section. It would also be interesting to explore if the majority of backers of a certain project shared the same cultural background as the fundraiser to understand if culture impacts campaign outcome though other avenues.

Appendices

Appendix 1– Data available per sample

Project identifier	
Unique_id	Variable used to identify the .txt file that contains the crowdfunding pitch of a given observation.
Language	Language in which the pitch is composed in
Crowdfunding – project outcomes	
Url	Project crowdfunding pitch url
Funded	Takes the value of 1 if the project succeeded in reaching the set goal, and 0 otherwise
Pledge_USD	Total amount pledged in USD
Backers_count	Total number of backers pledging an amount.
Crowdfunding – project attributes:	
Goal_USD	The size of the goal in USD
Campaign Duration	Number of days for which the project accepted contributions
Number Of Reward	Number of reward options on the campaign outcome
Video	Takes the value of 1 if the pitch contains a Video, and 0 otherwise
Endorsement	Takes the value of 1 if the campaign was listed as staff pick on the crowdfunding platform, and 0 otherwise.
Experience	Number of Kickstarter prior campaigns launched by the founder
Competition	Number of other campaigns launched on Kickstart while the campaign is live (in thousands)
Google trend	Measure of popularity of Kickstarter based on monthly Google searches (available at https://trends.google.com/trends/)
DeliveryDuration	Number of days until the estimated reward delivery date from the campaign launch date
Website	Takes the value of 1 if the pitch contains a website mention, and 0 otherwise.
Social Media	Takes the value of 1 if the pitch provides a Social media link and 0 otherwise.
Country	Country location of the project
Launched_at	Date on which the crowdfunding was launched
Category	One of the 15 project categories classified by Kickstarter

Appendix 2 – LLM Methodology

The methodology comprises of three primary components: environment setup, prompt design and evaluation protocol.

Environment Setup

To be able to chat with a LLM, the library Ollama provides an easy way to download open-source models and run them locally. The chosen LLM is Gemma 3 with 12 billion parameters. This model is selected for its strong balance between performance and resource efficiency.

A local testing environment was established on a Windows-based laptop equipped with a 4090 NVIDIA RTX series capable of handling up to 16GB of VRAM. Furthermore, Python 3.10 was used alongside the Ollama library to manage and serve the selected LLM model. Before running the LLM in a Jupyter Notebook, the model was pulled first from the official registry using the Ollama Command Line Interface (CLI): ` ollama pull gemma:3:12b` (https://ollama.com/library/gemma3:12b).

Then, to be able to run a local instance of the model we must pass the LLM model through Ollama CLI: ` ollama run gemma:3:12b`
Then we can use the following function to be able to interact with Gemma 3 via Jupyter Notebook:

```
def query_llm(input_text):
        user_prompt = f"""
Score the following sentence: "{input_text}"
FORMAT
<score><space>-<space><explanation (max 1 sentence)>
"""
        response = ollama.chat(
        model='gemma3:12b',
        messages=[
{'role': 'system', 'content': system_prompt
{'role': 'user', 'content': user_prompt }]
        )
        return response['message']['content']
```

The input_text represents the description about the RC for each startup. The user_prompt gives a direct instruction to the LLM. Finally, the system_prompt instructs the LLM on how to think and reason.

The function query_llm will be applied to each observation in the Pandas dataframe by using the progress_apply() method, which is similar to the apply() method, except that it can output a progress bar.

Lastly, the response that Ollama returns is a dictionary format output. Hence, to be able to explicitly access the response that we are looking for, we must pass in the keys 'message' and 'content'.

Prompt Design

The prompt is supported by few-shot learnings, a rubric with a tie-break rule that would help in reducing falsely classified RC sections, and an explicit chain-of-thought (CoT) instruction, as shown below.

Furthermore, a list of wordings are exposed to the model that can be helpful to enhance the scoring accuracy. Finally, by adding CoT prompting, the model will think through the task step by step to make its classifications more accurate. Those steps are hidden so that the private reasoning doesn't get exposed to the data that is being collected.

SYSTEM_PROMPT:
"""
Your task: assign a single integer score (0-2) to the text.

RUBRIC
0 - No risks or challenges mentioned.
1 - Risks/challenges mentioned only vaguely (hedging, generic).
2 - Risks/challenges described specifically **and** actionably
(concrete mitigation, contingency, next step, metric, or evidence of prior success).

Tie-break → If unsure between two levels, pick the **lower** score.

Indicative wording that OFTEN signals a **2** (not exhaustive, but helpful):
"*to minimize; in order to avoid; to ensure; this is why; even if; by doing this; the next step; tight planning; taken good measure; successfully; if ... occur, we will; solution; able to overcome; to counter; risk mitigation; prevention plan; proven track record; able to assure; to address; comprehensive; preparing for unknown; this is my second campaign; this is my third/fourth/... campaign; we have done this before; we have produced (x) before; decades of experience; not my first campaign; not my first release; I have already successfully fulfilled; we plan to; in order to; to help with; we have established; we expect; By pledging you will allow; By pledging you will enable; That's why; I plan to; that being said; this means; we're aiming to; to fulfill; can be solved by; many times in the past; in the event that; your financial support means that*"

EXAMPLES

#1 “We hope the system will be stable.” → 1 - vague hope, no action.

#2 “If a network failure occurs, we will switch to the backup cluster within 5 minutes.” → 2 - concrete contingency & timing.

#3 “Costs may increase.” → 1 - vague risk, no plan.

#4 “The design is complete.” → 0 - no risk/challenge indicated.

THINK STEP-BY-STEP (hidden)
1. Does the text mention a risk/challenge?
2. If yes, is there concrete mitigation, contingency, plan, metric, or evidence?
3. Decide 0, 1, or 2 using the rubric + tie-break rule.
4. Draft a one-text explanation.
5. Output only: <score> - <explanation>"""

USER PROMPT:
The user prompt is a simple instruction to that will be applied for each R&C description.
The user prompt is as follows:

user_prompt = f"""
Score the following sentence: "{text}"

FORMAT
<score><space>-<space><explanation (max 1 sentence)>
"""

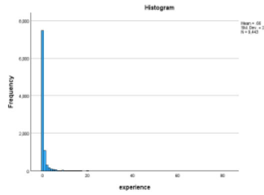
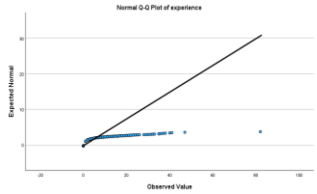
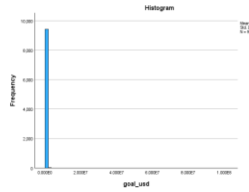
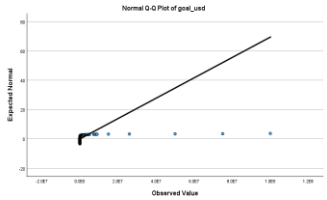
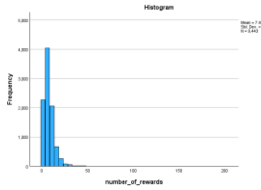
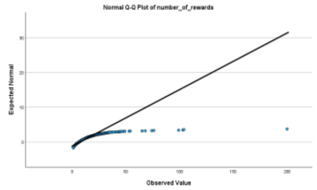
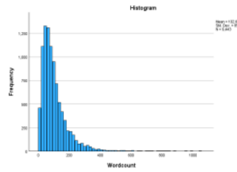
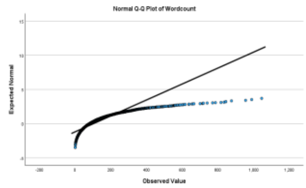
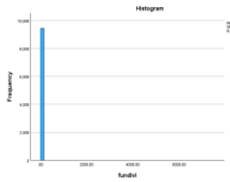
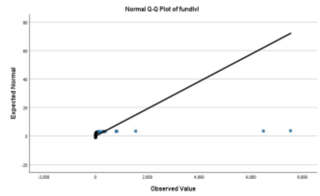
Evaluation protocol

Finally, a sample of the model’s responses were selected to evaluate the score assigned. The 30 sample entries inspected were fairly scored, highlighting the model’s proven robustness and accuracy.

Appendix 3 – Control variables

	Variables	Variable name	Operationalization
1	Goal amount (in USD)	Log_win_goal	Log(Win_Goal): Variable was winsorized and log-transformed
2	Campaign Duration	Campaign_duration	As outlined in Appendix 1
3	Number Of Rewards	Log_num_rewards	Log(WinRew): Variable was winsorized and logged
4	Video	Video	Binary (As outlined in Appendix 1)
5	Endorsement	Endorsement	Binary (As outlined in Appendix 1)
6	Experience	Log1_win_Exp	Log((Win_exp)+1): variable was winsorized and log transformed
7	Social Media	Socialmedia	Binary (As outlined in Appendix 1)
8	Delivery Duration	Delivery Duration	Continuous variable (As outlined in Appendix 1)
9	Website	Website	Binary (As outlined in Appendix 1)
10	Word count	Log_word_count	Log(WordCount): variable was log transformed
11	Readability score	Readability_score	Based on Flesch Kincaid grade level
12	Region	*North America* is the reference variable, grouping Canada and the United States, since it represents more than 60% of the total sample. D_EAPAC is *East Asia and Pacific* grouping Australia, Cambodia, China, Hong Kong, Indonesia, Japan, Malaysia, Micronesia, New Zealand, Philipines, Singapore, South Korea, Taiwan, Thailand, Vanuatu, Vietnam D_EurCA is *Europe and Central Asia*, grouping all European countries, plus Georgia, Armenia, United Kingdom, Russia, Iceland, Kyrgystan, Iceland, Ireland, Belarus, Cyprus, Turkey and Armenia D_LATAM is *Latin America and the Caribean,* grouping countries in the south American continent, plus Puerto Rico and US Virign Islands. D_MENA is Middle East and North Africa, grouping Israel, Jordan, Malta, Tunisia and United Arab Emirates. D_SAsia is *South Asia* grouping Bhutan, India, Nepal and Pakistan D_SubAF is Sub-Saharan Africa grouping Ghana, Kenya, Liberia, Malawi, Mauritious, Nigeria, Rwanda, South Africa, Tanzania, Uganda and Zimbabwe.	
13	Category	Dummy variables, total of 14 (with *technology* as a reference)	
14	Year (Launched_at)	*2015* is the reference variable *D_2016, D_2017, D_2018, D_2019* are the dummies created for projects launched in the remaining years	

Appendix 4 – Normal distributions before log transformations

Variable name	Histogram	Q-Q plot
Experience		
Goal amount		
Number of rewards		
Word count		
Funding level		

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