From human hands to machine minds: Financing AI-driven entrepreneurship in reward-based crowdfunding

Abstract

This study examines the effect of artificial intelligence (AI) adoption on financing performance in reward-based crowdfunding. Using Kickstarter data from U.S. projects, we find that AI projects raise less funding, receive fewer donations, and engage a smaller backer base. The negative effect is partly driven by abnormal narrative tone and moderated by information readability, geographic conditions, and backer sentiment. Additionally, subsample analysis shows that AI technology projects perform worst, while topic modeling indicates better outcomes when AI supports rather than replaces human creativity. Our findings highlight the critical role of public trust in financing innovation and entrepreneurship.

Keywords: artificial intelligence; reward-based crowdfunding; Kickstarter; AI ethics; deep learning

JEL classification: G11; G18; M13; M41; M48

1. Introduction

Artificial intelligence (AI), defined as the ability of machines to perform tasks involving reasoning, learning, and problem-solving (Slonim et al., 2021), is rapidly reshaping reward-based crowdfunding (RBC) by changing how projects are created, presented and perceived. This shift has sparked growing debate about the role of AI in creative and entrepreneurial work. In this study, we define AI adoption in RBC as either the development of AI technologies or the use of AI tools to support content creation or promotion. While prior studies have shown that AI can outperform human coders in evaluating project quality and creator credibility, and can serve as an external tool for predicting the success of RBC campaigns by analyzing text, images, and videos (e.g. Duan et al., 2020; Korzynski et al., 2021; Park et al., 2024), the implication of AI adoption within projects themselves remains underexplored. Bai et al. (2024b) offer insights by detecting AI-generated content using textual features, but their method focuses narrowly on promotional text and overlooks projects that integrate AI into their products or develop AI technologies. This study addresses these gaps by leveraging Kickstarter's recent policy[1] which mandates AI use disclosure by all creators, allowing a more comprehensive understanding of the implications of AI adoption in RBC.

Our study is motivated by two factors. First, AI adoption presents a complex trade-off. In corporate settings, while it improves operational efficiency (Sharma et al., 2022), manufacturing flexibility (Kinkel et al., 2022), and marketing personalization (Huang & Rust, 2018, 2021), and is linked to higher firm growth (Babina et al., 2024) and lower crash risks (Zhang et al., 2024), it also brings challenges such as algorithm aversion (Carabantes, 2020), copyright concerns (Quintais, 2025), and substantial upfront costs (Mikalef & Gupta, 2021). Moreover, the success of AI startup often depends more on investor networks than on technology itself (Siddik et al., 2024), suggesting that AI adoption can be as much about perception. Second, crowdfunding environment is fundamentally different. it is noisier, with weaker regulation, limited due diligence, and no third-

[1] For details on this policy, see: https://updates.kickstarter.com/introducing-our-new-ai-policy/.

party verification (Agrawal et al., 2014; Strausz, 2017). In RBC, backers are typically non-professionals who depend heavily on narratives and soft signals to form expectations under uncertainty (Mollick, 2014). This distinction makes AI adoption more psychologically and symbolically charged in RBC. While AI may signal innovation and technical strength, it may also raise concerns about trustworthiness. As a result, the effect of AI adoption in crowdfunding is not only uncertainty but may diverge from its effects in corporate settings. Building on these insights, we pose the following question: *Is AI adoption positively or negatively associated with the financing performance of Kickstarter projects?*

Using a dataset of 10,682 U.S.-based projects launched between 29 August 2023 and 29 August 2024, including 701 identified as AI-related, we find that AI adoption is negatively associated with financing performance. To examine the underlying mechanism, we test whether AI project creators engage in tone management. The results show that AI projects are more likely to adopt an abnormal tone, which erodes perceived authenticity and trust. We further investigate whether project readability and geographic context shape this relationship. Findings indicate that clearer and more structured narratives mitigate backer scepticism and improve performance, and that projects launched in states with higher AI literacy and more progressive political attitudes perform better. To assess the role of backer sentiment, we conduct BERT-based sentiment analysis and find that positive sentiment strengthens the performance of AI projects. Additional analyses show that technology-focused AI projects attract less funding, whereas these emphasizing human involvement receive more support. Finally, quantile regression analysis reveals that although negative effect of AI adoption persists across all funding levels, its magnitude diminishes at higher quantiles.

This study makes several key contributions to the literature. First, it extends the literature on the determinants of success in RBC. Prior research highlights the importance of various signals, such as project quality (Mollick, 2014), creator credibility (Butticè et al., 2017), social proof (Kunz et al., 2017), and rhetorical tone (Steigenberger & Wilhelm, 2018; Cumming et al., 2024). We extend this line of work by being among the first to identify AI adoption as a novel signal that shapes backer perceptions. Unlike Bai et al. (2024b), who infer AI-generated content using GPTZero, we rely on Kickstarter's mandated 'Use of AI' section, which offers a more transparent and consistent measure of AI adoption. This approach not only avoids classification errors but also captures how backers respond to openly disclosed AI use. Furthermore, we expand the scope to include both projects that use AI for content creation and those that develop AI technologies. We also explore the underlying causal mechanism and show that abnormal tone serves as a psychological channel through which AI disclosure affects financing performance.

Second, this study contributes to the literature on AI in entrepreneurial finance by underscoring the importance of AI ethics. While prior research has primarily discussed the costs and benefits of AI adoption in corporate contexts (e.g. Mikalef et al., 2022; Raisch & Krakowski, 2021; Babina et al., 2024; Zhang et al., 2024), we extend the discussion to RBC, where funding decisions depend more on project narratives than on standardized financial disclosures. Our findings uncover substantial public skepticism towards AI projects, particularly those emphasizing technical sophistication over human involvement. This reflects a deeper trust gap driven by concerns about reliability, authenticity, originally and feasibility. As a result, the potential benefits of AI can be overshadowed by ethical doubts. These findings suggest that technical innovation alone is not sufficient to gain public support; rather, backers place considerable weight on the ethical dimensions of AI use. Therefore, creators must pay greater attention to ensuring responsible AI practices.

Third, this study provides practical insights for the evolving regulation of AI on crowdfunding platforms. While prior studies have examined disclosure practices related to risk management (Kim et al., 2022; Madsen & McMullin, 2020); consumer protection (Cascino et al., 2019); staff picks (Cennamo et al., 2024); and environmental commitments (Bai et al., 2024a), the regulatory implications of AI adoption remain underexplored. This gap is particularly salient in the U.S., which leads global AI development yet lacks a unified AI disclosure policy in crowdfunding. Currently, RBC platforms mandate only basic transparency about AI usage, which remains insufficient for ensuring accountability and trust. Policymakers could take a more proactive role in promoting high-quality AI projects in RBC by leveraging platform features such as a 'Projects We Love' label to highlight credible initiatives. In parallel, platforms could invest in pre-launch verification processes to fact-check creators' AI-related disclosures. By balancing technological innovation with trust-building mechanisms, platforms can foster a more sustainable ecosystem for AI-driven entrepreneurship.

The remainder of this study is organized as follows. Section 2 reviews the literature and develops the hypotheses. Section 3 describes the data and research design. Section 4 presents the results. Section 5 presents the conclusion.

2. Literature Review and Hypotheses Development

2.1. Reward-based crowdfunding

Building on the framework outlined by Dinh et al. (2024), the RBC ecosystem operates across three levels: the institutional environment; the transaction dynamics; and the individual motivations. At the institutional level, broader regulatory and platform policies define the rules and expectations that shape crowdfunding activity. In crowdfunding, backers are typically small individual contributors who lack the analytical capacity and legal protections available to institutional investors. Moreover, crowdfunding platforms are not subject to the same stringent disclosure regulations as are capital markets (Agrawal et al., 2014). In addition, as highlighted by Strausz (2017), the absence of third-party monitoring makes crowdfunding particularly vulnerable to moral hazard because fundraisers may misuse funds or fail to deliver promised outcomes, and there is limited accountability for such failures. These institutional limitations contribute to a noisy funding environment where the risks of fraud, failure or overpromising are significantly heightened. In response to these challenges, RBC platforms such as Kickstarter have gradually introduced policies to strengthen transparency. In 2012, Kickstarter introduced a risk disclosure policy, requiring creators to outline potential risks and challenges associated with their projects. It has been found that detailed risk discussions can enhance the likelihood of securing funding (Madsen & McMullin, 2020) and promote innovation (Kim et al., 2022). In 2014, the Kickstarter platform updated its terms to strengthen creator obligations, requiring them to fulfil promises or refund backers. Cascino et al. (2019) find that this update made it easier for backers to take legal action against fraudulent practices on Kickstarter, which in turn improved trust in project disclosures. In 2018, Kickstarter implemented environmental disclosure policies, encouraging creators to provide details about the sustainability and environmental impact of their projects. Bai et al. (2024a) argue that more than 30% of creators adopt environmental commitment disclosure, leading to higher funding success and attracting environmentally conscious backers.

At the transactional level, success in RBC often hinges on how effectively creators engage with their backers. A key aspect of this engagement is signaling, which can bridge the information gap between project creators and potential supporters (Spence, 1973). Mollick (2014) finds that project quality signals (including the use of videos); detailed project descriptions; and creator credibility signals (e.g. the size of the founder's social network); significantly influence crowdfunding success. Similarly, Kunz et al. (2017) demonstrate that social media cues, such as the number of Facebook likes, serve as indicators of popularity and function as social proof, which backers interpret as a sign of the creator's influence and credibility. Butticè et al. (2017) further support the importance of credibility signaling by demonstrating that creators with prior crowdfunding experience accumulate internal social capital through past interactions with backers, which also strengthens backers' trust and increases the likelihood of future campaign success. Building on these traditional signals, Steigenberger and Wilhelm (2018) extend signaling theory by introducing rhetorical signals, including emotional appeals, credibility-building language and logical reasoning, which complement traditional cues by shaping how messages are interpreted by potential backers. They argue that in high-uncertainty environments such as RBC, not only *what* is communicated but also *how* it is communicated plays a critical role in influencing campaign success. In line with this argument, Cumming et al. (2024) emphasize that maintaining a tone that is both aspirational and realistic is crucial for building trust and securing funding from backers.

At the individual level, RBC centers on the motivations of backers and creators. According to self-determination theory (Deci & Ryan, 1985), individuals are motivated by a combination of intrinsic and extrinsic factors. For backers, intrinsic motivation includes the satisfaction of supporting innovation and being part of a community, while extrinsic motivations include receiving a unique product or gaining early access (Allison et al., 2015; Bento et al., 2019). This dual motivation explains why backers often fund projects that align with both their personal values and their expectations for tangible rewards. In addition to these driver, herding behavior is another important mechanism, where people tend to follow others' decisions when they are unsure (Kunz et al., 2017). Bao et al. (2022) find that inclinational comments, such as expressions of excitement or support from earlier backers, can trigger herding behavior and increase the likelihood that others will also contribute to the project. Similarly, creators are also influenced by mixed motivations. Drawing on interviews with Kickstarter participants, Gerber and Hui (2013) find that creators are driven by internal factors, such as the desire for creative expression and having a positive influence, alongside external factors such as securing funding and gaining exposure. These motivations not only drive the decision to launch a campaign but also shape how it is designed and communicated to potential backers.

2.2. AI adoption in RBC

AI enhances productivity and decision-making through two key mechanisms: automation and augmentation (Raisch & Krakowski, 2021). Through automation, creators can streamline campaign-related tasks and better align offerings with backer preferences. Similar to AI systems used in industries like fashion design (e.g. Stitch Fix), where algorithms generate personalized clothing options based on user data (Townsend & Hunt, 2019), crowdfunding creators may leverage AI to offer more tailored and appealing products. For instance, AI-enabled devices, such as smart coffee machines that can dynamically learn and adapt to individual tastes, exemplify how automation personalizes user experiences with minimal human input. By offloading routine and time-intensive tasks, creators can concentrate on strategic decisions and creative refinement. As a result, their products can be more useful, enjoyable, and attractive to backers, which lead to more support and funding.

Augmentation, on the other hand, empowers human decision-making by offering data-driven insights and recommendations. Beyond operational benefits, AI lowers entry barriers to launching and improving crowdfunding projects by empowering creators through enhancing their communication capabilities and content generation abilities. De Kok (2025) shows that AI tools such as ChatGPT can significantly enhance the clarity and communication, while visual generative tools such as Midjourney enable high-quality promotional content (Wahid et al., 2023). These features can be valuable for crowdfunding creators in crafting persuasive and transparent campaign stories. According to signaling theory, backers rely on observable cues to infer project quality. AI-assisted content can act as persuasive signals of professionalism. Bai et al. (2024b) find that AI-assisted narratives increase project success, particularly benefiting minority and first-time creators. Yet, they warn that such tools may also lead to overpromising, especially in contexts with weak institutional support.

By enhancing operational efficiency, enabling content personalization, and strengthening credibility signals, AI adoption may increase project appeal and increase the likelihood of fundraising success. Thus, we propose the following hypothesis:

H1a. *AI adoption is positively associated with the financing performance of Kickstarter projects*.

While AI adoption offers potential benefits for RBC, it also introduces concerns about reliability, authenticity, originality and feasibility that may negatively affect financing performance. First, concerns about the reliability of AI often underlie backers' hesitation to support AI projects. A key issue is algorithm aversion—people's tendency to distrust decisions made by statistical models, even when they outperform human judgement (Dietvorst et al., 2015; Prahl & Van Swol, 2017; Reich et al., 2023). This aversion is amplified when AI operates as a "black box", making decisions through opaque processes that are hard to interpret (Carabantes, 2020). In contexts like healthcare or personalized financial services, users often prefer human judgement, perceiving AI as less trustworthy (Castelo & Lehmann, 2019). In RBC, such skepticism is particularly acute for projects involving AI-driven personalization, such as career-matching or sleep-monitoring tools. Backers may question the reliability of outputs they cannot verify (Martin & Murphy, 2017).

Second, even tech-savvy backers may view AI-generated content as undermining authenticity and originality, which are core values on platforms like Kickstarter that emphasize personal passion and craftsmanship (Manning & Bejarano, 2017). When creators rely heavily on AI-generated content, particularly for storytelling about their project or for the artistic design of products such as games, illustrations, or fashion, backers may doubt the genuineness of their creative input, fearing that the product is simply a polished output of algorithms. Legal concerns about copyright infringement, especially when AI models are trained on protected data, further complicate perceptions of originality and ownership (Quintais, 2025). For instance, the 2025 'Ghiblification' trend, where OpenAI's new image tool mimicked Studio Ghibli's style, sparked backlash over unauthorized replication (ABC News, 2025). Such cases illustrate how even augmentative uses of AI can trigger skepticism when they blur the line between inspiration and imitation.

Third, AI projects may face feasibility concerns due to high upfront costs and market hype. Building AI solutions demands substantial investment in infrastructure, talent, and coordination (Mikalef & Gupta, 2021; Wamba et al., 2017), pressuring creators to secure funding early. Meanwhile, AI hype drives creators to signal innovation even when their idea remain conceptual (Logue and Grimes, 2022). This often results in exaggerated claims or vague, futuristic language aimed at attracting support. However, such strategies may backfire. Many solutions like virtual assistants are intangible and lack demonstrable prototype (Corrado et al., 2021), making them hard for backers to evaluate. This amplifies uncertainty and skepticism, especially when communication appears overstated or overly technical, ultimately reducing trust and support.

Taken together, concerns about algorithm aversion, diminishing authenticity and originally, and feasibility challenges associated with AI projects contribute to heightened skepticism and eroded trust among backers, ultimately undermining the financing performance of AI projects. Thus, we propose the following hypothesis:

H1b. *AI adoption is negatively associated with the financing performance of Kickstarter projects.*

3. Methodology

3.1. Data and sample

Following the approach of Cumming et al. (2024), this study utilizes Kickstarter project data sourced from Web Robots, covering the period between 29 August 2023 and 29 August 2024 (one year after the Use of AI section was introduced on Kickstarter). To collect additional project information, we use Python scripts to extract campaign descriptions, reward offerings, creator profiles and backer discussions directly from Kickstarter.com. Appendix A presents the sample selection process. We start with 18,535 U.S.-based projects downloaded from Web Robots. After excluding duplicate, live, and canceled projects, the final sample consists of 10,682 projects.

3.2. Measuring financing performance

The dependent variable (*FINANCING*) is measured using three proxies to capture different dimensions of financing performance. First, *LnPLEDGED* is employed to reflect the degree to which backers are willing to support a project. The total amount pledged in RBC serves not only as a measure of fundraising success but also as a powerful signal of backer interest and project legitimacy. Calic and Mosakowski (2016) argue that pledged amounts serve as a direct market signal, indicating how credible and appealing a project appears to the crowd. Similarly, Cascino et al. (2019) highlight that higher pledged amounts reflect increased confidence among backers about a project's viability. The total amount pledged provides a clear indication of the financial commitment and support from backers, with a higher amount reflecting greater financing performance. Second, *LnDONATION* represents backers' willingness to contribute to a project without expecting material rewards in return. Allison et al. (2015) argue that backers in crowdfunding are often driven by psychological fulfilment rather than by financial incentives. Consistent with the view of self-determination theory that individuals act based on both intrinsic and extrinsic goals (Deci & Ryan, 1985), such donations represent a non-transactional form of support, emotional connection or shared values with the creator. A higher donation amount may reflect stronger community trust and alignment with the project's purpose, indicating financing success that extends beyond typical reward-based exchanges. Third, *LnBACKERS* directly correlates with the amount of funding a project receives, as each backer contributes to the total pledged amount. Cascino et al. (2019) demonstrate that backer count signals trust and engagement, attracting further financial support. Even if individual contribution levels vary, a higher number of backers generally leads to greater appeal of and wider engagement with the project, serving as a clear indicator of financing success.

3.3. Measuring AI adoption

On 29 August 2023, Kickstarter introduced a new AI policy that mandates that 'projects utilizing AI tools for generating images, text or other outputs to disclose relevant details on their project pages'. Furthermore, 'projects developing AI technology, tools or software must disclose information about databases and data being used'. To enforce this policy, Kickstarter has integrated a new set of AI-related questions into the submission process. Failure to comply with the disclosure requirements during the submission process may result in project suspension. Once a project is approved, any AI-related components will be displayed in the newly introduced Use of AI section on its project page. The *D_AIPROJECT* variable is a binary indicator, coded as 1 if a project includes a dedicated Use of AI section on its Kickstarter page as mandated by Kickstarter's AI disclosure policy, and 0 otherwise.

3.4. Control variables

We select the control variables based on the following considerations. First, project characteristics significantly influence financing performance by shaping backers' perceptions of project quality and clarity (Calic & Mosakowski, 2016; Cascino et al., 2019). Accordingly, we control for the funding goal (*LnGOAL*); project duration (*LnDURATION*); video presence (*D_VIDEO*); external links (*D_FACEBOOK*, *D_WEBSITE*); staff-pick status (*D_STAFFPICK*); and campaign description length (*LnTOTOALWORDS*). Second, creator characteristics affect financing performance by signaling creators' credibility and competence (Bai et al., 2024a; Butticè et al., 2017). Thus, we control for the creator's previous crowdfunding experience (*LnPASTCREATED*); backing history (*LnPASTBACKED*); and engagement, indicated by the length of the 'About the Creator' section (*LnCREATORWORDS*). Third, macroeconomic conditions influence crowdfunding success through regional economic factors that affect backer willingness and ability to contribute (Peng & Zhang, 2024). We control for regional economic conditions using the natural log of gross domestic product (GDP; *LnGDP*). Additionally, we include year-month fixed effects (*Year_Month FE*); category fixed effects (*Category FE*); and US State fixed effects (*State FE*). Detailed variable definitions are provided in Appendix B.

3.5. Model specification

To test the association between AI adoption and financing performance, we use the following baseline model.

$$\begin{aligned} FINANCING = {} & \alpha + \beta_1 D\_AIPROJECT + \gamma Controls + Year\_Month\,FE \\ & + Category\,FE + State\,FE + \varepsilon \end{aligned} \tag{1}$$

where *FINANCING* captures the financing performance of Kickstarter projects, proxied by either *LnPLEDGED, LnDONATION,* or *LnBACKERS*. *Controls* refer to the set of control variables employed in the analyses. We also include the year-month, category, and state fixed effects in all the models.

4. Empirical Results

4.1. Summary statistics

Table 1 displays the descriptive statistics for the variables used in the empirical analysis. It reveals that the mean (median) values of *LnPLEDGED*, *LnDONATION* and *LnBACKERS* are 7.850 (8.249), 6.412 (6.929), and 3.907 (4.007), respectively, reflecting the financial commitment and the level of backer engagement across projects on Kickstarter. The mean value of *D_AIPROJECT* is 0.066, indicating that 6.6% of the projects in the sample are classified as AI projects.

Moreover, Pearson correlation metrics and variance inflation factor (VIF) tests are conducted to assess potential multicollinearity in the regression models. In untabulated results, all pairwise correlation coefficients are below the critical threshold of 0.80, and the highest VIF observed is below the commonly accepted cutoff of 10. These results suggest that multicollinearity is not significant concern and does not compromise the reliability of the regression estimates.

[Insert Table 1 Here]

4.2. Baseline results

We use Model (1) to test H1, and the results in Columns (1)–(3) of Table 2 reveal that the key variable of interest (*D_AIPROJECT*) is negative and statistically significant across all specifications $(\beta_1 = -1.111, p < 0.01;\ \beta_1 = -1.057, p < 0.01; \beta_1 = -0.670, p < 0.01)$. These results indicate that RBC projects that adopt AI have, on average, lower financing performance than those that do not adopt AI, supporting H1b. Specifically, AI projects raise 67.08% (=$e^{-1.111} - 1$) less funding than non-AI projects, implying that backers may question their authenticity, leading to hesitation in providing financial support. In addition, AI projects receive 65.25% (=$e^{-1.057} - 1$) fewer donations, suggesting that backers are less willing to contribute altruistically. This decrease indicates that AI projects may struggle to evoke the sense of purpose that typically motivates altruistic contributions. Furthermore, AI projects attract 48.83% (=$e^{-0.670} - 1$) fewer backers, suggesting that backers are more cautious toward such projects and less willing to engage. These findings highlight that, although AI-driven innovation offers new possibilities, backers may perceive it as less appealing or trustworthy.

[Insert Table 2 Here]

4.3. Endogeneity concerns

There are two potential endogeneity concerns in Model (1): sample selection bias and omitted variable bias. First, sample selection bias may arise if creators who adopt AI differ systematically from those who do not. Second, even with an extensive set of controls in the baseline model, there may be unobservable factors, such as creators' educational or cultural background, which could simultaneously affect the likelihood of AI adoption and financing performance. To test for these endogeneity concerns, we employ three methods: propensity score matching (PSM), entropy balancing and the instrumental variable (IV) approach.

4.3.1. Propensity score matching

To address sample selection bias, we employ PSM with 1:1 nearest-neighbor matching of treatment projects ($D\_AIPROJECT = 1$) to control projects ($D\_AIPROJECT = 0$) based on the control variables. In an untabulated analysis, covariate balance and common support are achieved postmatching, supporting the plausibility of the conditional independence assumption. Consistent with the baseline results, the PSM test results in Columns (1), (3) and (5) of Table 3 indicate a significant negative correlation between AI adoption and financing performance.

4.3.2. Entropy balancing

To further address sample selection bias, we adopt the entropy balancing approach, following recent studies such as Zhang et al. (2025). This method adjusts the weights of the treatment and control groups to achieve balance in the covariates without requiring a specific matching model. After entropy balancing, the means and variances of the control variables are nearly identical between groups, confirming the effectiveness of this approach. The regression results using the entropy-balanced sample continue to demonstrate a significant negative association between *D_AIPROJECT* and *FINANCING*. As reported in Columns (2), (4) and (6) of Table 3, the coefficient for *D_AIPROJECT* remains significant and negative ($\beta = -0.760, p < 0.01$; $\beta = -0.777, p < 0.01$; $\beta = -0.486, p < 0.01$). These consistent findings further reinforce the robustness of the results of a negative association between AI adoption and financing performance, even after controlling for sample selection bias using entropy balancing.

[Insert Table 3 Here]

4.3.3. Instrument variable

Although we include a comprehensive set of control variables and fixed effects in the baseline model to address omitted variable concerns, employing an instrumental variables (IV) approach remains necessary. Specifically, we use two IV approaches: industry averages as an external instrument and Lewbel's (2012) heteroscedasticity-based IV method.

The industry average is commonly used as an IV in accounting and financial research because it captures exogenous variation while mitigating firm-level endogeneity (e.g., Liu et al., 2014; Wang et al., 2022). This study uses the average proportion of AI projects within the same year-month, category and state as the IV. This IV influences AI adoption (relevance) but does not directly affect financing performance (exclusion). By isolating the variation in AI adoption unrelated to unobserved factors, the IV method provides a more credible causal inference. Panel A of Table 4 reports the two-stage least squares (2SLS) regression results. The first-stage regression results in Column (1) of Panel A demonstrate a significant positive correlation between IND_AI and $D\_AIPROJECT$ ($\beta = 0.991, p < 0.01$). The Cragg–Donald Wald F-statistic of 5364.140 far exceeds the Stock–Yogo 10% maximal IV size threshold of 16.38, indicating that the instruments are sufficiently strong. The second-stage regression results demonstrate that $Fit\_AIPROJECT$ is negatively associated with financing performance, suggesting that the regression outcomes remain robust to endogeneity concerns and further reinforce the findings of the baseline model.

To further strengthen identification, we apply the heteroscedasticity-based IV approach introduced by Lewbel (2012). Unlike traditional IV methods that require external instruments, Lewbel's approach leverages heteroscedasticity in the first-stage regression's error term to construct instruments from within the existing model. This method is particularly useful when strong external instruments are unavailable. Recent studies have applied this method successfully (e.g. Mavis et al., 2020; Hasan et al., 2021; Ouyang et al., 2024). To confirm the presence of heteroscedasticity, we regress *D_AIPROJECT* on the control variables included in the model and conduct a Breusch–Pagan test. The test rejects the null hypothesis of homoscedasticity ($\chi^2(1) = 4366.00, p < 0.01$). Panel B of Table 6 presents the results from the Lewbel IV estimation. Column (1) reports the first stage regression including Lewbel estimated instruments which are based on a subset of exogenous control variables in the model. The Cragg–Donald Wald F-statistic of 386.463 far exceeds the 10% threshold (24.58), indicating strong instruments. In Columns (2)–(4), the coefficient of *Fit_AIPROJECT* continues to be negatively and significantly associated with all three measures of financing performance ($\beta = -1.574, p < 0.01$; $\beta = -1.657, p < 0.01$; $\beta = -0.985, p < 0.01$). Importantly, the *p*-values of the Hansen-J test are large across all three regressions, indicating that the instruments are valid and uncorrelated with the error term.

[Insert Table 4 Here]

4.4. Mediation analysis

To explain why AI adoption may lead to lower financing performance, this study introduces abnormal tone as a psychological mediator that shapes backer perceptions. Abnormal tone refers to language that deviates from a firm's underlying fundamentals, often reflecting managerial tone management, particularly when incentives to influence stakeholder perceptions are strong (Huang et al., 2014; Allee & DeAngelis, 2015). Tone management involves deliberately highlighting firm strengths and downplaying weaknesses (e.g. Davis & Tama-Sweet, 2012; Riedl & Srinivasan, 2010). However, this strategy can backfire, that is, an abnormally positive tone can be perceived as misleading, and it has been linked to poor future firm performance and audit concerns (Huang et al., 2014; Hossain et al., 2020). In RBC, creators of AI projects face pressure to secure funding amid high costs and AI hype (Wamba et al., 2017; Logue & Grimes, 2022), prompting exaggerated claims. Yet, AI projects are harder to evaluate due to algorithm aversion and their intangible nature (Dietvorst et al., 2015; Corrado et al., 2021), making backers especially sensitive to overstatements. As a result, confident messaging may be interpreted as deception, undermining trust.

Following Huang et al. (2014), we assume that disclosure tone reflects both project fundamentals and strategic intent. Using VADER, we estimate a normal tone (*NTONE*) model based on project features like funding goal and duration. The residual, abnormal tone (*ABTONE*), captures tone not explained by fundamentals and thus more likely signals strategic embellishment. The estimation results of the tone model are reported in Appendix C. We find that *NTONE* is more positive in projects with higher funding goals and longer durations, as well as those that include video promotions. Conversely, *NTONE* is negatively associated with the presence of a website link, 'Projects We love' status and longer project descriptions. This suggests that project founders are less likely to use a positive tone when their projects are subject to website monitoring, receive platform endorsement or provide extensive project information.

To examine whether abnormal tone mediates the relationship between AI adoption and financing performance, we follow a mediation analysis based on the procedure outlined by Sobel (1982), as detailed below:

$$\begin{aligned} ABTONE = {} & \alpha_0 + \alpha_1 D\_AIPROJECT + \gamma Controls + Year\_Month\ FE \\ & + Category\ FE + State\ FE + \varepsilon \end{aligned} \tag{2a}$$

$$\begin{aligned} FINANCING = {} & \alpha_0 + \beta_1 D\_AIPROJECT + \beta_2 ABTONE + \gamma Controls \\ & + Year\_Month\ FE + Category\ FE + State\ FE + \varepsilon \end{aligned} \tag{2b}$$

where *Controls* denote the set of control variables present in Model (1). Detailed variable definitions can be found in Appendix B.

Table 5 presents the results of the mediation analysis. In Column (1), we examine the indirect effect by analyzing the pathway through abnormal tone (*ABTONE*). *D_AIPROJECT* is positively and significantly associated with *ABTONE* ($\alpha_1 = 0.002, p < 0.01$), indicating that AI projects tend to exhibit higher levels of abnormal tone in their disclosures. Furthermore, Column (2) reveals that *ABTONE* has a negative and significant effect on *LnPLEDGED* ($\beta_2 = -6.642, p < 0.01$). The indirect effect is approximately −0.013, calculated as the product of α_1 and β_2 from Models (2a) and (2b), respectively. Given that all key path coefficients are highly statistically significant, a Sobel test is not required. Columns (2) and (3) reinforce these findings using alternative model specifications. Across all specifications, abnormal tone is consistently found to be a significant mediator, helping to explain how AI adoption leads to reduced financing performance in RBC.

[Insert Table 5 Here]

4.5. Moderation analyses

The results presented above provide evidence of a negative and significant relationship between AI adoption and financing performance in RBC projects. However, the exact conditions under which this relationship varies remain unclear and require further investigation. Thus, moderation analyses are conducted to examine whether and how this effect is contingent on specific contextual factors. The study explores two potential channels: information readability and geographic conditions.

4.5.1. Information readability

Information asymmetry refers to situations where one party in a transaction has more or better information than the other. This imbalance can lead to inefficient outcomes such as adverse selection or moral hazard (Akerlof, 1970). Accounting and finance research consistently highlights the importance of information readability in reducing information asymmetry between firms and their stakeholders (e.g. Bonsall et al., 2017; Loughran & McDonald, 2014). Loughran and McDonald (2014) demonstrate that higher readability in financial disclosures enhances investor understanding and improves market reactions. Similarly, Bonsall et al. (2017) find that lower readability is linked to less favorable credit ratings and a higher cost of debt, underscoring the practical implications of clear and accessible information disclosure.

In RBC, where backers rely heavily on project narratives to make investment decisions, readability becomes even more important. AI adoption often introduces technical jargon and complex concepts that may increase perceived risk and erode trust. Readability moderates this relationship by ensuring that backers can clearly understand the benefits and implications of AI in relation to the project, thereby mitigating skepticism and enhancing the ability of backers to evaluate the project's potential. To test the influence of information readability on the relationship between AI adoption and financing performance, we construct the following regression model:

$$\begin{aligned} FINANCING = {} & \beta_0 + \beta_1 D\_AIPROJECT + \beta_2 D\_AIPROJECT \times READABILITY \\ & + \beta_3 READABILITY + \gamma Controls + Year\_Month\ FE + Category\ FE \\ & + State\ FE + \varepsilon \end{aligned} \quad (3a)$$

where *READABILITY* is measured using two widely adopted textual complexity metrics: SMOG index (*D_SMOG*) and The Flesch–Kincaid grade level (*D_FLESCHKINCAID*), following the approach of De Franco et al. (2015). *Controls* denote the set of control variables present in Model (1). Detailed variable definitions are provided in Appendix B.

The estimation results of regression Model (3a) are presented in Table 6. In Panel A, the interaction terms of $AIPROJECT \times D\_SMOG$ are negative and significant across all specifications ($\beta_2 = -0.705, p < 0.01$; $\beta_2 = -0.804, p < 0.01$; $\beta_2 = -0.444, p < 0.01$), highlighting the moderating role of readability. These results indicate that AI projects with lower readability (higher SMOG scores) have lower financing performance than do projects with higher readability. The results in Panel B further reinforce the findings using the Flesch–Kincaid grade level as a readability metric. The interaction terms of $AIPROJECT \times D\_FLESCHKINCAID$ are also consistently negative and significant across all models. These findings demonstrate that information readability significantly moderates the effect of AI adoption on financing performance. Given that AI adoption introduces technical complexity and abstract concepts, entrepreneurs may consider keeping project narratives clear and accessible to backers. A high level of readability bridges the gap between complex technological details and backers' understanding, ultimately improving backer engagement and funding success. By crafting narratives with lower complexity and higher clarity, entrepreneurs can maximize their chances of securing funding for AI projects.

[Insert Table 6 Here]

4.5.2. Geographic conditions

Geographic conditions, which capture the social, economic, and institutional characteristics of a location, is a key area of study in accounting and finance (e.g. Lin & Viswanathan. 2016;

Bonaparte et al., 2017; Jiang et al., 2022). We consider two proxies: (1) the level of AI literacy among residents; and (2) state-level political orientation.

Backers often display home bias in crowdfunding. Lin and Viswanathan (2016) find that 7% of investments occur within the same state, far exceeding the 2% expected by chance, highlighting geographic proximity influences online funding. Jiang et al. (2022) further show that this bias stems from information advantages rather than just emotional ties. In states with more computer science (CS) education and higher AI understanding, local backers may better evaluate AI projects, easing skepticism and improving funding outcomes. Political orientation also plays a role. Bonaparte et al. (2017) find Democrats are more open to risk and emerging technologies than Republicans. Claudy et al. (2024) show conservatives are more resistant to innovation like AI, often due to concerns over job loss and autonomy. Thus, projects based in Democratic-leaning states may benefits from a more innovation-friendly environment, signaling credibility and institutional support. By contrast, projects from Republican-leaning states may encounter more skepticism. To assess these effects, we construct the following regression model:

$$\begin{aligned} FINANCING = {} & \beta_0 + \beta_1 D\_AIPROJECT + \beta_2 D\_AIPROJECT \times GEOGRAHPY \\ & + \beta_3 GEOGRAHPY + \gamma Controls + Year\_Month\ FE \\ & + Category\ FE + State\ FE + \varepsilon \end{aligned} \tag{3b}$$

where *GEOGRAPHY* is constructed using one of two proxies: (1) *D_CSEDUCATION*, indicating whether the project is in a US state with above-median access to high school CS education; and (2) *D_POLITICS*, indicating whether the Democratic candidate won the 2020 US presidential election in that state. *Controls* denote the set of control variables present in Model (1). Detailed variable definitions are provided in Appendix B**.**

Table 7 presents the results of geographic conditions as the moderator. Panel A reveals the role of CS education in high schools. The coefficients of interaction terms ($AIPROJECT \times D\_CSEDUCATION$) are positive and significant ($\beta_2 = 0.373, p < 0.05$; $\beta_2 = 0.543, p < 0.05$; $\beta_2 = 0.234, p < 0.05$). These results indicate that AI projects located in states with greater access to CS education (which represents greater AI literacy in this study) perform better in financing performance. The positive interaction suggests that AI projects in states with greater access to CS education are more likely to be understood and appreciated. Panel B reveals the influence of regional political climate, measured by whether a project is located in the state where the Democratic candidate won the 2020 presidential election. The interaction term (*D_AIPROJECT* × *D_POLITICS*) shows a consistently positive coefficient across specifications, indicating that AI projects perform better in Democratic-leaning states. This suggests that such regions may provide a more favorable environment for AI-driven innovation, potentially due to greater ideological alignment with progressive values such as technological advancement, sustainability, and social impact.

[Insert Table 7 Here]

4.5.3. Backer sentiment

Investor influence plays a more decisive role in the success of AI startups securing funding than do technological factors (Siddik et al., 2024). This suggests that in entrepreneurship, soft signals such as social verification and trust may carry more weight than technical merit alone in influencing financing outcomes. In RBC, Backer comments serve as a valuable lens for understanding their sentiments and perceptions. Positive comments not only reflect satisfaction but also act as social signals visible to potential backers (Bao et al., 2022). To assess emotional reactions tied to financing outcomes, we analyze the comments section for all 10,692 projects. After removing remove boilerplate platform messages and creator responses, we retain 101,973 original backer comments across 5,665 projects. Comment volume per project ranges from 1 to 1,786.

Prior studies have explored the potential of replacing human annotation with a deep learning tool to conduct text classification (Smit et al., 2020; Pangakis & Wolken, 2024), suggesting that large language models provide a cost-effective alternative by being significantly faster, cheaper, and free from issues such as human fatigue and inconsistency. Building on this, we assess backer sentiments using the BERT framework. Specifically, we use the *cardiffnlp/twitter-roberta-base-sentiment*[2] model (Barbieri et al., 2020), deployed on Amazon Web Services, to score comment sentiment. Each project's average sentiment score is calculated. Based on these scores, we construct a binary variable (*D_COMMENTS*), which is coded as 1 if the sentiment is positive, and 0 otherwise.

As shown in Table 8, the interaction term between AI projects and backer sentiment is positive and significant across all outcomes. For example, in Column (1), the coefficient of the interaction term (*D_AIPROJECT ×D_COMMENTS)* is positive and significant ($\beta = 0.391, p < 0.05$), indicating that positive backer comments mitigate the negative effect of AI projects on financing

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[2] For further information about this model, please refer to https://huggingface.co/cardiffnlp/twitter-roberta-base-sentiment.

performance. The findings emphasize the interactive role of backer sentiment in shaping financing performance, underscoring the importance of building emotional connections as a key strategy for financing success in crowdfunding.

[Insert Table 8 Here]

4.6. Additional analyses

4.6.1. subsample analysis

To consider the results based on the type of AI project, we draw on Kickstarter's AI policy, which requires creators to specify how AI is used during the project registration and review process. The platform provides three standardized disclosure options: (1) 'I plan to use AI-generated content in my project'; (2) 'My project seeks funding for AI technology'; and (3) 'I am incorporating AI in my project in another way'. Based on this guidance, we classify AI projects into three types: projects with AI-generated content; projects developing AI technology; and projects incorporating AI in another way. The analysis reveals there are 335 projects with AI-generated content, 81 projects developing AI technology, and 334 projects incorporating in another way.

Table 9 presents the heterogeneous effects of these AI project types on the financing performance of AI projects. While all forms of AI use have a negative effect on fundraising performance, the magnitude of the effect varies significantly. Projects developing AI technology (D_TYPE_2) have the strongest negative effect on financing performance ($\beta = -2.245, p < 0.01$; $\beta = -1.907, p < 0.01$; $\beta = -1.278, p < 0.01$), suggesting that backers are particularly averse to projects involving automation and complex technical development. Post-estimation tests confirm that *D_TYPE_2* has a significantly stronger negative effect on financing performance than do the other two types of AI projects ($p < 0.01$). Projects with AI-generated content (*D_TYPE_1*) ($\beta = -0.906, p < 0.01$; $\beta = -0.917, p < 0.01$; $\beta = -0.475, p < 0.01$) and those incorporating AI in other ways (*D_TYPE_3*) ($\beta = -0.957, p < 0.01; \beta = -0.944, p < 0.01; \beta = -0.630, p < 0.01$) also have clear negative effects on financing performance, although the effect is smaller than it is for projects developing AI technology. These results suggest that backers differentiate between types of AI use and respond most negatively to projects perceived as highly technical.

[Insert Table 9 Here]

4.6.2. Topic modeling

While the type of AI project explains part of the variation in backer response, it does not fully capture the drivers of financing outcomes. In particular, projects classified as 'other' often reflect diverse motivations, such as varying degrees of human versus AI involvement or simply following trends in AI adoption. To further unfold these nuances, we conduct a thematic analysis of the 'Use of AI' sections.

Drawing from Bao and Datta (2014), we apply a LDA topic model to find hidden topics. Topic quality is assessed using semantic coherence, which measures the co-occurrence of top words in a topic. As illustrated in Figure D.1 of Appendix D, the coherence scores range from 0.4442 (27 topics) to 0.6952 (3 topics), with the highest coherence observed for a three-topic solution. Table D.1 outlines keywords defining each theme. *TOPIC_1* reflects meaningful human involvement given that keywords such as '*drawing*' and '*cropping*' point to hands-on creativity, and keywords such as '*functional*', '*control*' and '*impossible*' imply that AI is used as a tool for supporting complex tasks rather than replacing human effort. *TOPIC_2* centers on data sourcing and consent, with keywords such as '*consent*', '*database*' and '*source*' highlighting legal and ethical concerns about how AI systems access personal data. *TOPIC_3* focuses on the disclosure of AI-generated content. Keywords such as '*aigenerated*', '*images*' and '*content*' suggest attempts to clarify which parts of the project are created by AI.

Table 10 reports the regression results assessing the effect of various AI-related topics on the financing performance of AI projects. The findings reveal that AI adoption tends to reduce financing outcomes across two of the three thematic areas. *TOPIC_2* exhibits the most pronounced negative effect ($\beta = -2.656, p < 0.01$; $\beta = -2.111, p < 0.01$; $\beta = -1.609, p < 0.01$), suggesting that backers are particularly cautious about projects that emphasize issues such as data usage, privacy or consent. *TOPIC_3* also has negative but comparatively smaller effects ($\beta = -0.955, p < 0.01$; $\beta = -0.928, p < 0.01$; $\beta = -0.600, p < 0.01$). This suggests that transparency alone does not ease backer skepticism. However, *TOPIC_1* shows no statistically significant effects across all models ($\beta = -0.080, p > 0.1$; $\beta = -0.603, p > 0.1$; $\beta = 0.231, p > 0.1$), highlighting a clear preference among backers for human-centered innovation, where technology supports rather than substitutes human creativity and judgement. Overall, these findings underscore a persistent skepticism towards AI projects in crowdfunding, particularly when projects focus on abstract, technical or ethically sensitive aspects of AI. Even transparency alone is insufficient to alleviate backer concerns. Instead, creators should priorities communicating how AI complements human effort to build backers' trust and engagement with the project.

[Insert Table 10 Here]

4.6.3. Quantile regression

Hopp et al. (2025) use quantile regression to show that sustainable projects underperform conventional ones at higher funding levels in RBC. This study extends that analysis to AI versus non-AI projects to examine the impact of AI adoption. Figure 1 presents the kernel density estimation (KDE) for three proxies of financing performance. Across all measures, AI projects show greater density in the lower tail of the distribution, indicating that AI projects are overrepresented among campaigns with weaker financing outcomes. In contrast, non-AI projects tend to cluster around higher values. These differences imply that the effect of AI adoption varies across performance levels, rather than being uniform. This provides motivation for the use of quantile regression, which allows for the estimation of heterogeneous effects at different points in the outcome distribution. Unlike OLS, which captures only the average effect across the full sample, quantile regression can uncover effects that are stronger or weaker at specific quantiles. This approach offers a more nuanced view of how AI adoption affects financing outcomes.

[Insert Figure 1 Here]

Table 11 presents the results of quantile regressions at the 25th, 50th and 75th percentiles for three outcomes: pledged amount, donation amount and number of backers. The results reveal that the negative effect of AI adoption is most pronounced at the 25th percentile across all specifications. For example, in Column (1) of Panel A, the effect of *D_AIPROJECT* on *LnPLEDGED* is strongly negative ($\beta = -1.879, p < 0.01$), indicating that, among projects at the lower end of the funding distribution, AI projects tend to attract significantly less financing than their non-AI counterparts. This may reflect greater skepticism in AI projects within this performance segment. In the median (Column (2)), the negative effect persists but is smaller in magnitude ($\beta = -0.791, p < 0.01$). At the 75th percentile (Column (3)), the effect is weakest, although still negative ($\beta = -0.155, p < 0.05$), implying that high-performing AI projects are able to narrow the funding gap. Overall, these results suggest that the low performance in financing associated with AI adoption is concentrated among projects with the lowest funding outcomes but diminishes at higher performance levels, indicating that the AI projects that are the best performing in attracting financing may be able to overcome initial backer skepticism.

[Insert Table 11 Here]

5. Conclusion

This study investigated the funding implications of AI adoption in RBC. Using Kickstarter data from US projects launched between 2023 and 2024, the results reveal that, on average, AI projects attract lower pledged amounts, fewer donations and fewer backers than non-AI projects. This funding gap is partly explained by the presence of an abnormal tone in AI project narratives, which can misalign with backer perceptions and erode trust. Cross-sectional results reveal that the negative effect of AI adoption on funding performance is weaker in AI projects with clearer disclosures, in those in supportive regional contexts and when backer sentiment is positive. Moreover, AI projects with a strong technical focus attract less financing, and those that emphasize human effort attract more financing. Quantile regression further reveals that the negative effect of AI adoption on financing performance is not uniform across the funding distribution, in that it is more pronounced in campaigns that attract less funding.

This study offers several key insights. First, AI projects face structural disadvantages in RBC because of a persistent trust gap between creators and backers. Backers often exhibit AI aversion, expressing doubts about the reliability and authenticity behind AI-driven campaigns. To improve financing outcomes, creators should emphasize meaningful human involvement and apply AI only when necessary. Second, ethical AI use remains a governance challenge. While transparency policies now require AI disclosure, current enforcement mechanisms are limited. Platforms should consider implementing pre-launch verification systems for AI-related disclosures, either through internal reviews or third-party audits. These systems could flag high-risk projects for further inspection, ensure that AI use cases are clearly described and appropriately framed. Third, platform-level endorsement can play a pivotal role in reshaping perceptions and encouraging ethical AI adoption. Labels such as 'Projects We Love' can boost visibility and credibility, signaling institutional support for ethical AI use. Over time, such endorsement may shift public perception and encourage broader adherence to responsible practices among creators.

This study has several limitations. First, it focuses on U.S. Kickstarter projects, which may limit the generalizability of the results to other regions or platforms with different regulatory and cultural contexts. Second, due to the recent implementation of the AI policy, the analysis is restricted to short-term financing performance, leaving long-term project sustainability unexamined. Future research could address these gaps by exploring international datasets, examining backer behavior over longer periods, and analyzing the effect of AI adoption on post-funding project execution.

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Appendix A. Sample selection

	Dropped	Sample Size
Projects downloaded	18,535	18,535
Less: Duplicate projects	(6,609)	11,926
Less: Live projects	(844)	11,082
Less: Cancelled projects	(400)	10,682
Final number		10,682

Appendix B. Variable definition

Variable	Definition
Dependent variables	
LnPLEDGED	Natural log of the sum of one and the total amount (in US dollars) pledged
LnDONATION	Natural log of the sum of one and the total amount (in US dollars) donated (part of the pledged amount without any rewards)
LnBACKERS	Natural log of the sum of one and number of backers
Independent variable	
D_AIPROJECT	Dummy=1 if project contains 'Use of AI' section; 0 otherwise
Control variable	
LnGOAL	Natural log of the sum of one and the total amount (in US dollars) sought
LnDURATION	Natural log of the sum of one and the total project duration in days
D_VIDEO	Dummy=1 if project contains a video; 0 otherwise
D_FACEBOOK	Dummy=1 if project contains a Facebook link; 0 otherwise
D_WEBSITE	Dummy=1 if project contains a personal website link; 0 otherwise

D_STAFFPICK	Dummy=1 if project is labelled as 'Projects We Love'; 0 otherwise
LnTOTOALWORDS	Natural log of the sum of one and the total number of words in the campaign section
LnCREATORWORDS	Natural log of the sum of one and the total number of words in the 'About the Creator' section
LnPASTCREATED	Natural log of the sum of one and the total number of campaigns previously created by the creator
LnPASTBACKED	Natural log of the sum of one and the total number of campaigns previously backed by the creator
LnGDP	Natural log of the sum of one and the real GDP in the year the project is launched and in the state the project is located
Mediating variables	
NTONE	Net tone in the campaign section. It is calculated as the net positive words in the description (positive words minus negative words), then divided by the total story word count
ABTONE	The residual component of campaign tone from a campaign tone model, capturing deviations from the predicted tone. It reflects the extent to which a campaign's communication style is unexpectedly positive or negative relative to typical expectations based on campaign characteristics
Moderating variables	
D_SMOG	Dummy=1 if the SMOG index is above the median across all projects; 0 otherwise
D_FLESCHKINCAID	Dummy=1 if the Flesch–Kincaid grade level is above the median across all projects; 0 otherwise
D_CSEDUCATION	Dummy=1 if project is located in a state where the proportion of public high schools teaching foundational computer science exceeds the median across all projects; 0 otherwise (Source: AI index report 2024)
D_POLITICS	Dummy=1 if project is located in a state where the Democratic candidate won the 2020 presidential election; 0 otherwise
D_COMMENTS	Dummy=1 if the average sentiment of backer comments for a project is classified as positive, and 0 otherwise
Variables of AI type	
D_TYPE_1	Dummy=1 if the 'Use of AI' section contains 'I plan to use AI-generated content in my project'; 0 otherwise
D_TYPE_2	Dummy=1 if the 'Use of AI' section contains 'My project seeks funding for AI technology'; 0 otherwise
D_TYPE_3	Dummy=1 if the 'Use of AI' section contains 'I am incorporating AI in my project in another way'; 0 otherwise
Variables of AI topic	

TOPIC_1	The probability of disclosure of AI section related to human involvement and functional support
TOPIC_2	The probability of disclosure of AI section related to data privacy, ownership and consent
TOPIC_3	The probability of disclosure of AI section related to AI-generated content

Appendix C. Tone model

VARIABLES	(1)
	NTONE
LnGOAL	0.001*** (9.28)
LnDURATION	0.001** (2.13)
D_VIDEO	0.003*** (5.60)
D_FACEBOOK	–0.001 (–0.90)
D_WEBSITE	–0.002*** (–3.73)
D_STAFFPICK	–0.003*** (–5.19)
LnTOTALWORDS	–0.001*** (–3.43)
Year-Month FE	Yes
Category FE	Yes
State FE	Yes
N	10,682
Adj. R^2	0.136

Appendix D. Topic modeling

Figure D.1: Topic coherence

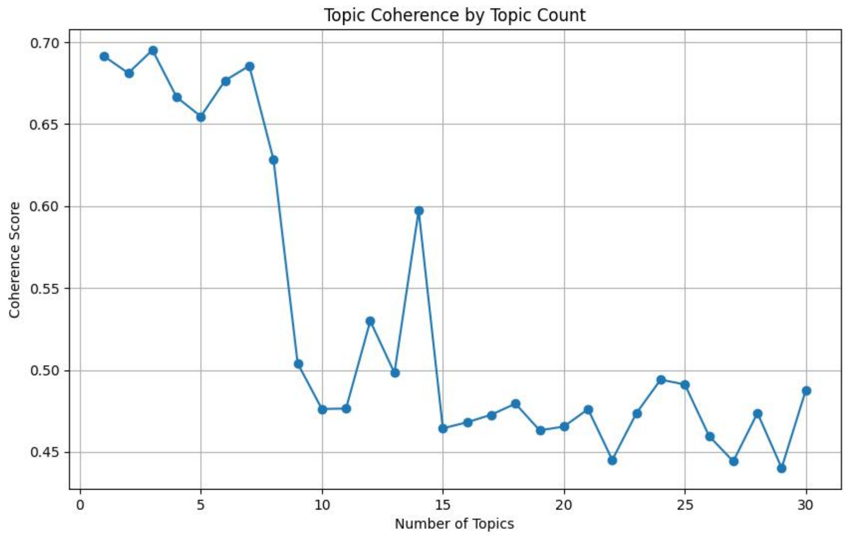

Table D.1: Top 20 terms by topics

TOPIC 1	TOPIC 2	TOPIC 3
know	owners	art
live	work	explain
texture	otout	projects
program	credit	portion
hard	way	works
textures	receiving	owners
designing	incorporating	produce
correction	consent	consent
drawing	use	possible
perks	works	parts
avoid	create	specific
increasingly	technology	plan
impossible	funding	incorporating
nearly	seeks	way
fundraiser	source	images

mapping	obtained	aigenerated
cropping	persons	used
itjust	information	use
tshirt	database	generated
concert	incorporated	content

Figure 1: Distributional differences: AI vs. non-AI projects

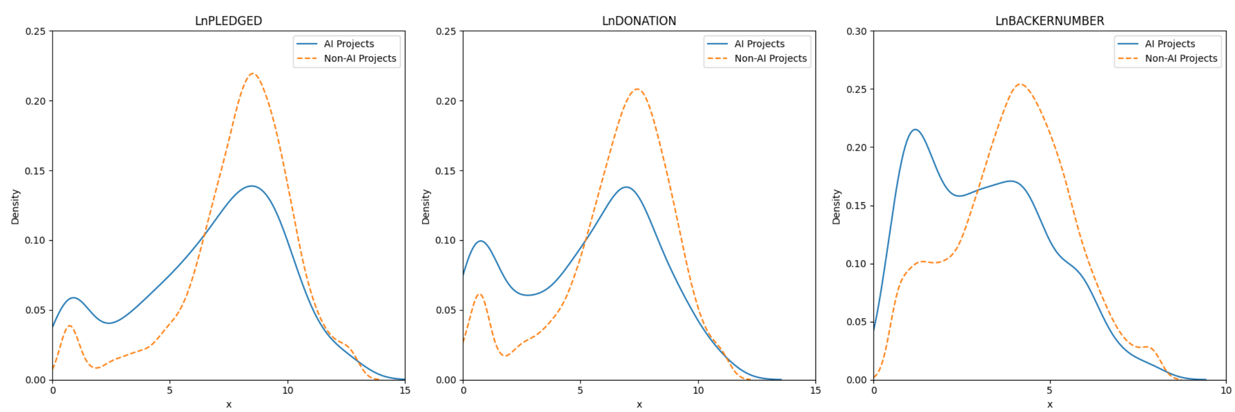

Table 1: Descriptive statistics

	N	Mean	Std.	Min	P25	P50	P75	Max
LnPLEDGED	10,682	7.850	2.528	0.693	6.815	8.249	9.437	12.760
LnDONATION	10,682	6.412	2.553	0.000	5.283	6.929	8.152	11.060
LnBACKERS	10,682	3.907	1.685	0.693	2.773	4.007	5.056	7.948
D_AIPROJECT	10,682	0.066	0.248	0.000	0.000	0.000	0.000	1.000
LnGOAL	10,682	8.131	1.585	4.605	6.909	8.294	9.210	11.951
LnDURATION	10,682	3.411	0.407	2.079	3.258	3.434	3.526	4.111
D_VIDEO	10,682	0.650	0.477	0.000	0.000	1.000	1.000	1.000
D_FACEBOOK	10,682	0.111	0.314	0.000	0.000	0.000	0.000	1.000
D_WEBSITE	10,682	0.752	0.432	0.000	1.000	1.000	1.000	1.000
D_STAFFPICK	10,682	0.234	0.423	0.000	0.000	0.000	0.000	1.000

LnTOTOALWORDS	10,682	6.544	0.774	4.419	6.057	6.589	7.085	8.174
LnCREATORWORDS	10,682	3.686	0.961	1.386	3.045	3.738	4.357	5.778
LnPASTCREATED	10,682	0.907	1.090	0.000	0.000	0.693	1.609	4.043
LnPASTBACKED	10,682	1.653	1.764	0.000	0.000	1.099	2.996	6.089
LnGDP	10,682	13.573	1.075	10.607	12.953	13.458	14.420	15.026
NTONE	10,682	0.044	0.025	–0.100	0.029	0.043	0.059	0.177
ABTONE	10,682	0.000	0.022	–0.054	–0.014	–0.001	0.013	0.062
D_SMOG	10,682	0.488	0.500	0.000	0.000	0.000	1.000	1.000
D_FLESCHKINCAID	10,682	0.498	0.500	0.000	0.000	0.000	1.000	1.000
D_CSEDUCATION	10,682	0.485	0.500	0.000	0.000	0.000	1.000	1.000
D_POLITICS	10,682	0.680	0.467	0.000	0.000	1.000	1.000	1.000
D_COMMENTS	5,665	0.794	0.404	0.000	1.000	1.000	1.000	1.000

This table presents the descriptive statistics for the variables used in the empirical analysis. Specifically, it presents the summary statistics of main variables for 10,682 Kickstarter projects covering the sample period of Aug. 29, 2023, to Aug. 29, 2024. Variable definitions can be found in Appendix B. To mitigate the influence of extreme outliers, all continuous variables are winsorised at the 1st and 99th percentiles.

Table 2: Baseline results

VARIABLES	(1)	(2)	(3)
	LnPLEDGED	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	-1.111^{***}	-1.057^{***}	-0.670^{***}
	(–13.37)	(–11.92)	(–13.39)
LnGOAL	0.230^{***}	0.261^{***}	0.137^{***}
	(15.06)	(16.03)	(14.89)
LnDURATION	-0.180^{**}	-0.116^{*}	-0.077^{**}
	(–3.18)	(–1.92)	(–2.26)
D_VIDEO	0.495^{***}	0.405^{***}	0.230^{***}
	(10.94)	(8.40)	(8.46)
D_FACEBOOK	–0.031	–0.017	–0.007
	(–0.46)	(–0.24)	(–0.18)
D_WEBSITE	0.406^{***}	0.383^{***}	0.221^{***}
	(8.28)	(7.31)	(7.50)

D_STAFFPICK	1.566*** (29.79)	1.312*** (23.39)	1.230*** (38.88)
LnTOTALWORDS	0.513*** (17.79)	0.401*** (13.04)	0.320*** (18.42)
LnCREATORWORDS	–0.100*** (–4.64)	–0.079*** (–3.43)	–0.108*** (–8.27)
LnPASTCREATED	0.227*** (8.63)	0.131*** (4.65)	0.232*** (14.61)
LnPASTBACKED	0.150*** (8.87)	0.161*** (8.90)	0.141*** (13.86)
LnGDP	–8.251* (–1.67)	–5.552 (–1.05)	–1.781 (–0.60)
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	10,682	10,682	10,682
Adj. R^2	0.354	0.278	0.474

This table examines the association between AI adoption and financing performance. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. This specification controls for launching year-month, the project category and the creator's state fixed effect. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 3: PSM and Entropy balancing approaches

	LnPLEDGED		*LnDONATION*		*LnBACKERS*	
	PSM	Entropy	PSM	Entropy	PSM	Entropy
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
D_AIPROJECT	–1.123*** (–7.79)	–0.760*** (–14.97)	–1.236*** (–8.49)	–0.777*** (–15.01)	–0.687*** (–8.64)	–0.486*** (–17.62)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
N	1,402	10,682	1,402	10,682	1,402	10,682
Adj. R^2	0.360	0.363	0.316	0.315	0.471	0.477

This table presents the outcomes of the PSM and entropy balancing sample by estimating Model (1). The PSM results are shown in Columns (1), (3) and (5). The entropy balancing results are shown in Columns (2), (4) and (6). This specification controls for launching year-month, the project category and the creator's state fixed effect. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 4: Instrumental variable approach with 2SLS

Panel A: The average proportion of AI projects				
	(1)	(2)	(3)	(4)
	1st stage	2nd stage	2nd stage	2nd stage
VARIABLES	*D_AIPROJECT*	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
Fit_AIPROJECT		–1.359*** (–9.52)	–1.295*** (–8.50)	–0.757*** (–8.81)
IND_AI	0.991*** (73.24)			
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	10,682	10,682	10,682	10,682
Adj. R^2	0.389	0.358	0.283	0.478
Weak instrument test:				
Cragg-Donald Wald F statistic	5364.14***			
Panel B: Lewbel's IV				
	(1)	(2)	(3)	(4)
	1st stage	2nd stage	2nd stage	2nd stage
VARIABLES	*D_AIPROJECT*	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
Fit_AIPROJECT		–1.574*** (–5.12)	–1.657*** (–5.54)	–0.985*** (–5.56)
Lewbel_D_VIDEO	0.392*** (5.15)			

Lewbel_D_FACEBOOK	–0.637***			
	(–3.20)			
Lewbel_D_STAFFPICK	–0.659***			
	(–5.49)			
Lewbel_LnCREATORWORDS	0.125***			
	(3.78)			
Controls	Yes	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
N	10,682	10,682	10,682	10,682
Adj. R^2	0.203	0.357	0.281	0.476
heteroskedasticity test:				
Breusch–Pagan test	4369.60***			
Weak instrument test:				
Cragg-Donald Wald F statistic	386.463***			
Overidentification test:				
Hansen-J statistic (*p*-value)		0.510	0.740	0.275

This table presents the two-stage IV regression results. Panel A reports estimates. The IV is the average proportion of AI projects in the same year-month, category and state on Kickstarter. Panel B presents results using Lewbel's (2012) heteroscedasticity-based IV approach, which generates instruments by exploiting heteroscedasticity in the first-stage regression. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 5: The mediating effect of abnormal tone

	(1)	(2)	(3)	(4)
VARIABLES	*ABTONE*	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	0.002***	–1.096***	–1.042***	–0.659***
	(2.68)	(–13.21)	(–11.77)	(–13.21)
ABTONE		–6.642***	–6.467***	–4.659***
		(–7.33)	(–6.68)	(–8.55)
Controls	Yes	Yes	Yes	Yes

Year-Month FE	Yes	Yes	Yes	Yes
Category FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Adj. R^2	0.012	0.357	0.281	0.478
Proportion of total effect mediated		1.4%	1.5%	1.7%
Sobel Test		No Sobel test is required		

This table examines the mediation effect of the abnormal tone in the relationship between AI adoption and financing performance by estimating Model (2). The abnormal tone, calculated as the residual, is derived by estimating the tone model. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 6: The moderating effect of information readability

Panel A. SMOG index			
	(1)	(2)	(3)
VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	-0.650^{***}	-0.533^{***}	-0.379^{***}
	(–4.73)	(–3.63)	(–4.58)
D_AIPROJECT × *D_SMOG*	-0.705^{***}	-0.804^{***}	-0.444^{***}
	(–4.15)	(–4.44)	(–4.35)
D_SMOG	–0.061	–0.055	-0.051^{*}
	(–1.39)	(–1.18)	(–1.94)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	10,682	10,682	10,682
Adj. R^2	0.355	0.279	0.475
Panel B. Flesch–Kincaid grade level			
	(1)	(2)	(3)

VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	–0.656***	–0.545***	–0.399***
	(–4.99)	(–3.89)	(–5.04)
D_AIPROJECT ×	–0.737***	–0.832***	–0.439***
D_FLESCHKINCAID	(–4.43)	(–4.68)	(–4.39)
D_FLESCHKINCAID	–0.069	–0.039	–0.035
	(–1.62)	(–0.86)	(–1.36)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	10,682	10,682	10,682
Adj. R^2	0.355	0.279	0.475

This table Panel A (Panel B) examines the moderation effect of SMOG (Flesch–Kincaid) on the AI adoption and financing performance. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 7: The moderating effect of geographic conditions

Panel A. AI literacy			
	(1)	(2)	(3)
VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	–1.283***	–1.306***	–0.777***
	(–11.55)	(–11.02)	(–11.63)
D_AIPROJECT ×	0.373**	0.543**	0.234**
D_CSEDUCATION	(2.32)	(3.17)	(2.42)
D_CSEDUCATION	–8.805*	–5.835	–2.143
	(–1.74)	(–1.08)	(–0.70)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes

N	10,682	10,682	10,682
Adj. R^2	0.354	0.278	0.474

Panel B. Political climate

	(1)	(2)	(3)
VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	-1.323^{***}	-1.302^{***}	-0.763^{***}
	(–9.68)	(–8.92)	(–9.27)
D_AIPROJECT × D_POLITICS	0.327^{*}	0.377^{**}	0.144
	(1.95)	(2.11)	(1.42)
D_POLITICS	3.654^{**}	2.721	1.144
	(2.13)	(1.49)	(1.11)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	10.682	10.682	10.682
Adj. R^2	0.354	0.278	0.474

This table Panel A (Panel B) examines the moderation effect of AI literacy (political climate) on AI adoption and financing performance. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 8: The effect of backer sentiment

	(1)	(2)	(3)
VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_AIPROJECT	-0.643^{***}	-0.719^{***}	-0.481^{***}
	(–4.80)	(–4.13)	(–4.39)
D_AIPROJECT × D_COMMENTS	0.391^{**}	0.498^{**}	0.303^{**}
	(2.43)	(2.38)	(2.30)
D_COMMENTS	-0.156^{***}	0.018	-0.116^{***}
	(–3.73)	(0.32)	(–3.40)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes

Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	5,665	5,665	5,665
Adj. R^2	0.451	0.274	0.403

This table examines the moderation effect of backer sentiment on AI adoption and financing performance. The analysis is based on a sample of 5,665 projects, as only 5,665 out of the total 10,682 projects have comments. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 9: By type of AI project

	(1)	(2)	(3)
VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
D_TYPE_1	-0.906^{***}	-0.917^{***}	-0.475^{***}
	(–7.83)	(–7.41)	(–6.81)
D_TYPE_2	-2.245^{***}	-1.907^{***}	-1.278^{***}
	(–9.53)	(–7.58)	(–9.01)
D_TYPE_3	-0.957^{***}	-0.944^{***}	-0.630^{***}
	(–8.24)	(–7.61)	(–9.00)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	10,682	10,682	10,682
Adj. R^2	0.357	0.281	0.476

This table examines the effect of different AI types on financing performance. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 10: By topic of AI project

	(1)	(2)	(3)

VARIABLES	*LnPLEDGED*	*LnDONATION*	*LnBACKERS*
TOPIC_1	–0.080 (–0.08)	–0.603 (–0.60)	0.231 (0.40)
TOPIC_2	–2.656*** (–7.58)	–2.111*** (–5.64)	–1.609*** (–7.64)
TOPIC_3	–0.955*** (–7.87)	–0.928*** (–7.16)	–0.600*** (–8.21)
Controls	Yes	Yes	Yes
Year-Month FE	Yes	Yes	Yes
Category FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
N	10,682	10,682	10,682
Adj. R^2	0.355	0.278	0.474

This table examines the association between AI topics and financing performance. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix A. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.

Table 11: By performance quantiles

Panel A. Pledged amount			
	(1)	(2)	(3)
VARIABLES	*25th*	*50th*	*75th*
D_AIPROJECT	–1.879*** (–12.35)	–0.791*** (–12.03)	–0.155** (–2.45)
Controls	Yes	Yes	Yes
N	10,682	10,682	10,682
Pseudo R^2	0.186	0.203	0.231
Panel B. Donations			
	(1)	(2)	(3)
VARIABLES	*25th*	*50th*	*75th*
D_AIPROJECT	–2.328*** (–14.16)	–1.100*** (–11.34)	–0.390*** (–5.99)
Controls	Yes	Yes	Yes

N	10,682	10,682	10,682
Pseudo R^2	0.160	0.146	0.182

Panel C. The number of backers

	(1)	(2)	(3)
VARIABLES	*25th*	*50th*	*75th*
D_AIPROJECT	-0.835^{***} (−12.22)	-0.826^{***} (−12.22)	-0.368^{***} (−5.97)
Controls	Yes	Yes	Yes
N	10,682	10,682	10,682
Pseudo R^2	0.283	0.234	0.226

This table presents the quantile regression results. The first row displays the estimated coefficient, while the second row (in parentheses) shows the corresponding *t*-value. Variable definitions can be found in Appendix B. * indicates $p < 0.1$; ** indicates $p < 0.05$; *** indicates $p < 0.01$. All tests are conducted using a two-tailed approach.