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Poker face and steady voice: Gender and reactions to emotional neutrality in crowdfunding

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ABSTRACT

While emotional neutrality (e.g., maintaining a neutral face, speaking with a calm voice) can help entrepreneurs project a sought-after image of rationality, the effectiveness of such displays is context-dependent and gendered. In the emotionally resonant world of crowdfunding, the value of neutrality is ambiguous, as it may conflict with audience expectations of expressiveness. Building on the Emotions as Social Information (EASI) model, we argue that equivalent neutral cues from men and women are evaluated differently. Using pre-trained machine-learning algorithms to extract facial and vocal features from 548 crowdfunding videos, we examine how neutrality in pitches relates to funding success. We find that a neutral facial expression ("poker face") is penalized for women but has no discernible effect for men. In contrast, a neutral vocal tone lowers success for both sexes; however, further analysis reveals this penalty is concentrated in male-typed categories (e.g., technology, design) and largely absent in female-typed categories (e.g., fashion, craft). Our findings highlight that crowdfunding backers interpret emotional neutrality through the combined lens of gender and pitch context, which may create biases in entrepreneurial evaluation.

1. Introduction

Entrepreneurial pitches serve as a primary communication interface between entrepreneurs and potential supporters (Kalvapalle et al., 2024). In pitches, entrepreneurs present business plans and financial prospects, but their self-presentation and outward displays through verbal and non-verbal channels critically shape investor perceptions and decisions (e.g., Balachandra et al., 2019; Chen et al., 2009; Clarke et al., 2019). In these high-stake interactions, potential investors often infer an entrepreneur's capability to navigate uncertainty and challenges directly from their emotional display (Van Kleef, 2009). One powerful cue of composure under pressure is emotional neutrality, which signals the entrepreneur's capability to keep emotions from clouding rational judgment (Kopelman et al., 2006; Van Kleef et al., 2010). This study explores the effectiveness of emotional neutrality, conveyed through a composed facial expression and a steady vocal tone in crowdfunding pitches.

Importantly, the effectiveness of such cues depends on the specific audience and financial context. Crowdfunding has emerged as an alternative to traditional financing channels like venture capital, democratizing access to capital for a diverse range of projects and

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entrepreneurs (Mollick, 2014). Unlike professional venture investors, crowdfunding backers are often members of “the crowd” who may lack the expertise to rigorously evaluate new ventures' financial potential. Instead, their decisions are frequently driven by various factors, such as a general appetite for novelty (Seigner et al., 2022; Taeuscher et al., 2021), personal incentives to receive pre-sold products as rewards (Mollick, 2014), and prosocial motivations to help others achieve their dreams (Dai and Zhang, 2019). Consequently, crowdfunding backers may prioritize different signals than traditional investors, placing less emphasis on professional prototypes and long-term economic returns. Specifically, crowdfunding audiences generally reward emotional expressiveness that signals passion and enthusiasm, which enhances empathy and engagement (Anglin et al., 2018; Chen et al., 2009; Davis et al., 2021; Raab et al., 2020).

This creates a critical puzzle. Given that video pitches rely on salient and diagnostic emotional cues (Van Kleef, 2009), does a composed face and steady voice convey professionalism or does it undercut the engagement backers seek? The answer likely depends on gender norms regarding emotional expression. While often expected to be proper for men, emotional neutrality can be penalized as norm-violating and inappropriate for women (Eagly et al., 2000; Eagly and Karau, 2002). Therefore, understanding the boundary conditions of emotional neutrality is theoretically nontrivial and practically important for entrepreneurs crafting crowdfunding pitches.

While recent studies address emotional valence and gender (Hu and Ma, 2025; Warnick et al., 2021), research has largely overlooked emotional neutrality as an active signaling device in securing funding and how this varies for men and women. Furthermore, it is unclear whether emotional neutrality, often valued in traditional financing (e.g., Balachandra, 2020; Balachandra et al., 2019, 2021; Malmström et al., 2017), has similar implications in crowdfunding. This gap matters because, although crowdfunding may favor women entrepreneurs (Greenberg and Mollick, 2017; Wesemann and Wincent, 2021), it is unclear if this advantage persists when women attempt to communicate cognitive rationality through emotional neutrality, or if they are penalized for violating gender expectations. Drawing on 548 Kickstarter crowdfunding videos, this study uses pre-trained machine learning algorithms to extract facial and vocal features to examine how entrepreneurs' nonverbal emotional neutrality relates to crowdfunding success and how these associations differ by observed sex.[1]

Our findings reveal a sex-conditioned effect of emotional neutrality in pitch delivery. Building on EASI perspectives, we propose that emotional neutrality functions as a context-dependent cue whose interpretation hinges on gendered display rules. We find that the effect of emotional neutrality is asymmetric. Emotional neutrality in facial expressions triggers a significant penalty for women, whereas men are neither penalized nor rewarded for the same cue. In the vocal channel, neutrality is generally detrimental, though further analysis reveals this is largely confined to male-typed crowdfunding categories. These patterns help reconcile the conflicting advice regarding effective entrepreneurial pitch strategies for women in previous research. While some studies advocate for gender role congruence (Anglin et al., 2022; McSweeney et al., 2022), others highlight the benefits of counter-stereotypical characteristics (Davis et al., 2021; Seigner et al., 2022). Our findings suggest that, in rewards-based crowdfunding, women benefit when they align with a core gender norm of emotional expressiveness, consistent with prior work showing that stereotypical femininity can advantage women in this setting (Johnson et al., 2018; Li et al., 2022; Seigner & Milanov, 2023). Therefore, women may be more successful in crowdfunding than in traditional entrepreneurial finance because their typical expressive communication style better matches what the crowd expects and values, not the absence of gender bias.

2. Theory and hypothesis

2.1. *The context-dependent signal of emotional neutrality*

Emotional neutrality is not the absence of emotion; rather, it actively shapes audience judgments similar to basic emotional expressions (Carrera-Levillain and Fernandez-Dols, 1994). In organizational settings, it can signal effectiveness and professionalism in negotiation (Kopelman et al., 2006; Van Kleef et al., 2010) and task-oriented leadership (Humphrey, 2002; Sy and van Knippenberg, 2021). Accordingly, entrepreneurs often adopt it in pitches to convey control and poise. Yet its effectiveness depends on the audience expectations, because emotional expression and its interpretation are inherently social processes (van Kleef and Côté, 2022). In pitches to venture capitalists, entrepreneurs are often rewarded for avoiding stereotypical femininity (Balachandra et al., 2019, 2021; Malmström et al., 2017). However, crowdfunding decisions are more susceptible to emotional cues (Allison et al., 2022; Anglin et al., 2018; Warnick et al., 2021). This is because the audiences often lack the information, experience, and expertise to formally evaluate a project. Consequently, backer support is instead driven mainly by personal interest, emotional connection, or enthusiasm (Li et al., 2017; Raab et al., 2020; Seigner & Milanov, 2023).

According to the EASI model, observers use emotional expression to infer information and form affective reactions (Van Kleef, 2009). Facial emotions are easily recognizable, highly visible and quickly interpreted across cultures (Horstmann, 2003; Matsumoto et al., 2008), while vocal cues serve as a distinct and critical channel for signaling emotional and cognitive states (Guilford and Dawkins, 1991; Hawk et al., 2009). Observers frequently infer from neutral displays that a speaker possesses emotional control and, by

[1] Following prior research (e.g., Unger, 1979; Eagly et al., 1995; Balachandra et al., 2019; Seigner et al., 2022), we distinguish between sex—a biologically determined characteristic (typically man or woman)—and gender, a social construct reflecting culturally ascribed meanings (typically masculine or feminine). Consistent with these definitions, we use sex-related terminology (e.g., entrepreneur's sex, sex differences) when comparing men and women or describing representation, and gender-related terminology when referring to cultural products such as gender stereotypes, beliefs, and expectations (Eagly, 1987).

extension, objective reasoning under pressure. This inference rests on a common conflation: people often assume that suppressing outward displays equates to mitigating emotion's cognitive and behavioral biases (Brescoll, 2016; Shields, 2002).

However, this positive interpretation of neutrality is not guaranteed, since the inference depends on the audience and context. In professional settings like venture capital, neutrality may align with norms of analytical rigor and risk control, reinforcing perceptions of expertise. By contrast, in reward-based crowdfunding, where decisions are driven by affect and heuristics (Ren et al., 2021), expressive displays are more likely than neutral ones to drive discovery, liking, and willingness to help (Allison et al., 2022; Raab et al., 2020; Wang et al., 2017). At the same time, emotional neutrality may elicit unintended affective reactions, as observers interpret it through shared expectations, including gender norms (Van Kleef, 2009; van Kleef and Côté, 2022). In crowdfunding, these expectations may lead neutral displays to be read as cold or misaligned that provoke backlash.

2.2. Gendered display rules and crowdfunding outcomes

Gendered social norms, or "display rules", systematically shape expectations about how emotional expression is to be performed (Eagly et al., 2000; Eagly and Karau, 2002). In many cultures, women are expected to be more emotional, whereas men are expected to be more restrained (Brescoll, 2016; Shields, 2002; Van Boven and Robinson, 2012). Women are also more often expected to perform "emotional labor" and provide support in stressful situations (Guillén et al., 2018; Vial and Cowgill, 2022). These expectations reflect broader role-congruity theory, which emphasizes that behaviors are evaluated relative to prevailing gender norms (Anglin et al., 2022; Biddle, 1979, 1986).

When applied to emotional neutrality, these display rules create distinct expectations for men and women. Prior research shows that observers tend to view men's neutral displays as consistent with masculine norms that emphasize emotional restraint, while women's neutral displays may be seen as deviating from prescriptive expectations for expressiveness (Hareli et al., 2009; Hess et al., 2016). Specifically, audiences react positively when men remain emotionally neutral during challenging situations but prefer women to visibly express emotions like sadness or anger in leadership roles (Lewis, 2000). Therefore, in reward-based crowdfunding, where entrepreneurs rely on engaging pitches to connect with backers, such deviations can be especially consequential.

Building on the EASI theory (Van Kleef, 2009), we argue that equivalent neutral cues may be evaluated differently through the lens of opposing socially gendered expectations applied to the entrepreneur. Emotional neutrality is therefore unlikely to yield uniform effects, since gendered display rules create asymmetries in how neutral facial expressions and steady vocal tones are received. This perspective underpins our prediction that gender acts as a critical moderator, such that men and women face different payoffs when presenting neutral emotions. Specifically.

Hypothesis 1. Gender moderates the relationship between emotional neutrality (in face and voice) and crowdfunding success.

We break this prediction down into specific directional hypotheses for men and women.

Hypothesis 1a. For women, facial and vocal emotional neutrality in pitches is negatively associated with success in reward-based crowdfunding.

Hypothesis 1b. For men, facial and vocal emotional neutrality in pitches is positively associated with success in reward-based crowdfunding.

3. Sample and variables

To examine how variation in emotional neutrality affects entrepreneurial fundraising, we gathered videos from one of the world's largest reward-based crowdfunding platforms, Kickstarter (https://www.kickstarter.com/). Our sampling procedure began with 8614 projects in English launched from January 2020 to August 2023. We focus on technology, design, craft and fashion categories because: (1) they are distinct male-typed (technology, design) and female-typed (craft, fashion) domains[2]; (2) entrepreneurs in these categories are more likely to present themselves using their own face and voice compared to categories such as art, film, or photography, where pitches tend to be more work-centric. Among them, 4720 projects included pitch videos. One of the authors manually screened these videos to ensure that both the entrepreneur's face and voice could be reliably extracted.[3] We excluded videos that were advertisements or animations; in which the creator showed the face without speaking or spoke while the face was hidden; that focused primarily on the product and showed the creator's face for less than 10 seconds; in which other people appeared prominently due to the product presentation; or in which the face could not be easily recognized because of low resolution. The final analysis sample consists of 548 videos that feature a single entrepreneur whose face is visible for more than 60 % of the total video duration and who speaks using their own voice.

The full list of variables and their descriptive statistics are summarized in Table 1, with more detailed descriptive statistics in sex subsamples (cross tabs) shown in Table 2.

Dependent variable. Funding on Kickstarter is all-or-nothing; Only when the project's funding goal is reached within the pre-decided deadline will the project creator receives the full amount bid by backers. If the total amount bid is less than the goal, then

[2] The selection of male-typed and female-typed categories is based on prior studies (Greenberg and Mollick, 2017; Seigner et al., 2022; Seigner & Milanov, 2023).

[3] The number of eligible videos after screening by project categories is detailed in Table B1 of APPENDIX B.

Table 1
Descriptive statistics and correlations.

	Mean	SD	1	2	3	4	5
(1) Success	0.529	0.50	1				
(2) Pledged ratio	957.257	8078.554	0.111***	1			
(3) Pledged USD	31649.569	179248.758	0.159***	0.168***	1		
(4) Backer number	245	1208.80	0.179***	0.322***	0.947***	1	
(5) Neutral face	0.151	0.195	−0.05	−0.037	0.005	−0.02	1
(6) Neutral voice	0.553	0.158	−0.252***	−0.092**	−0.056	−0.084**	−0.093**
(7) Positive words	0.326	0.088	−0.001	−0.023	−0.011	−0.002	0.009
(8) Negative words	0.271	0.092	0.023	−0.026	0.006	0.02	0.011
(9) Woman	0.328	0.470	0.091**	0.068	−0.074*	−0.047	0.005
(10) Funding goal	9.087	1.744	−0.478***	−0.193***	0.068	0.014	0.016
(11) Duration	34.553	12.795	−0.282***	0.090**	−0.009	−0.004	0.045
(12) Staff pick	0.115	0.319	0.294***	0.219***	0.236***	0.241***	−0.002

	6	7	8	9	10	11	12
(6) Neutral voice	1						
(7) Positive words	−0.200***	1					
(8) Negative words	−0.221***	0.944***	1				
(9) Woman	−0.389***	0.068	0.049	1			
(10) Funding goal	0.147***	−0.024	−0.04	−0.113***	1		
(11) Duration	0.147***	0.033	0.041	−0.024	0.213***	1	
(12) Staff pick	−0.130***	0.043	0.026	0.04	−0.036	−0.071*	1

Notes: Sample Size (N) is equal to 548. Funding goal is measured as log (requested amount in USD + 0.0001). ***p < 0.001, **p < 0.01, *p < 0.05.

Table 2
Descriptive statistics of main variables by sex.

	Women Subsample (N = 180)		Men Subsample (N = 368)		Difference	p-Value
Dependent Variables	Mean	SD	Mean	SD	MeanDiff	
Success	0.595	0.492	0.497	0.501	0.097*	0.033
Pledged ratio	1743.406	13020.792	572.729	3758.869	1170.678	0.111
Pledged USD	12819.036	35509.283	40860.156	216828.931	−28041.12	0.086
Backer number	164	571.862	284	1419.018	−120	0.276
Independent Variables						
Neutral face	0.153	0.187	0.150	0.199	0.002	0.900
Neutral voice	0.466	0.143	0.596	0.146	−0.131***	0.000
Control Variables						
Positive words	0.334	0.083	0.322	0.090	0.013	0.114
Negative words	0.278	0.088	0.268	0.094	0.009	0.252
Project-level Controls						
Funding goal	8.805	1.677	9.225	1.762	−0.419**	0.008
Project duration	34.111	12.236	34.769	13.071	−0.658	0.573
Staff pick	0.134	0.341	0.106	0.308	0.028	0.347

Notes: Success is the main dependent variable of interest. We also include the alternative dependent variables we used for robustness checks: Pledged ratio, Pledged USD, and Backer number. Funding goal is measured as log(requested amount in USD + 0.0001). ***p < 0.001, **p < 0.01, *p < 0.05.

the creator receives no funding. The dependent variable *Success* is coded as a binary variable, 1 when the goal was met and 0 otherwise (Josefy et al., 2017; Seigner et al., 2022). We analyze final success because it centers the analysis on the platform's threshold outcome that determines resource allocation, which better aligns with our theory than continuous metrics (pledged ratio, backer number, pledged USD). The results of robustness checks are discussed in APPENDIX A.

Independent and interaction variable. *Neutral face* and *Neutral voice* are continuous measures ranging from 0 to 1. *Neutral face* captures the prominence of neutrality in the entrepreneur's facial expressions during the pitch, and *Neutral voice* captures the degree of emotional neutrality in the voice during the pitch. We used pre-trained algorithms implemented in iMotions[4] to detect emotions from facial expressions (Affectiva AFFDEX 2.0[5]) and vocal cues (audEERING[6]). AFFDEX has been widely applied in management research (Davis et al., 2021; Hodges and Chen, 2022; Stroe et al., 2020), while audEERING has been adopted in recent work in psychology and computer science (Hecker et al., 2025; Ravi et al., 2025; Scherer et al., 2024). Using the raw frame-level facial emotion metrics, we

4 https://imotions.com/?srsltid=AfmBOoqm7jGNwpdq9NZU9GT-nNGsnRrH0P3Ebp4CCdNr3g–KO_9mk91.
5 https://imotions.com/support/document-library/affdex-2-0-a-real-time-facial-expression-analysis-toolkit/.
6 https://imotions.com/products/imotions-lab/modules/voice-analysis/.

calculated the percentage of frames in which neutrality was the most dominant emotion across all detected face frames during the pitch. This percentage represents the average intensity of facial neutrality at the video level. The software generated voice metrics for each voiced segment, excluding pauses. We then computed a duration-weighted average of vocal neutrality across all segments. The detailed coding process of these variables and the cross-validation of algorithms in use are specified in Appendix B. To identify the entrepreneur's observed sex, we employed a three-step approach[7] to create the variable *Woman* (coded as 1 for women, and 0 for men). The representation of women is around 32.8 % of the sample for analysis (180 out of 548).

Control variables. In our analysis, we controlled for key project attributes that can influence crowdfunding outcomes. Appendix A details all control variables.

4. Results

We report Probit regression results in Table 3, with robust standard errors and fixed effects for launch date (year–quarter) and Kickstarter categories.

Facial Neutrality. We first tested Hypothesis 1, which posited that gender moderates the effect of emotional neutrality on campaign success. We focus on Model 5 for interpretation, as the results are consistent across the models. The coefficient of *Neutral face* × *Woman*

Table 3
Probit Regression of Crowdfunding Success (two-way interaction with sex).

	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
DV: Success					
Neutral face	−0.411	0.117	−0.401	0.140	0.126
	(0.363)	(0.455)	(0.365)	(0.456)	(0.457)
Neutral voice	−1.516**	−1.451**	−1.341*	−1.209†	−1.304*
	(0.520)	(0.519)	(0.624)	(0.619)	(0.630)
Woman	−0.113	0.193	0.155	0.583	−0.265
	(0.155)	(0.205)	(0.554)	(0.585)	(0.859)
Positive words	−5.631*	−5.950*	−5.583*	−5.882*	−6.198*
	(2.343)	(2.359)	(2.344)	(2.359)	(2.953)
Negative words	4.033†	4.536*	3.985†	4.471*	4.166
	(2.233)	(2.246)	(2.234)	(2.245)	(2.823)
Funding goal	−0.475***	−0.468***	−0.474***	−0.467***	−0.467***
	(0.058)	(0.059)	(0.058)	(0.059)	(0.059)
Duration	−0.020***	−0.021***	−0.020***	−0.021***	−0.021***
	(0.005)	(0.006)	(0.005)	(0.006)	(0.006)
Staff pick	1.621***	1.629***	1.631***	1.646***	1.644***
	(0.324)	(0.331)	(0.325)	(0.335)	(0.338)
Woman × Neutral face		−1.843*		−1.899*	−1.958*
		(0.783)		(0.789)	(0.792)
Woman × Neutral voice			−0.533	−0.760	−0.443
			(1.020)	(1.025)	(1.069)
Woman × Positive words					1.418
					(4.747)
Woman × Negative words					0.832
					(4.730)
Constant	6.659***	6.520***	6.539***	6.351***	6.576***
	(0.775)	(0.792)	(0.829)	(0.833)	(0.875)
Year Quarter FE	YES	YES	YES	YES	YES
Category FE	YES	YES	YES	YES	YES
Log pseudolikelihood	−226.008	−223.160	−225.877	−222.903	−222.169
Observations	548	548	548	548	548

Notes: This table reports Probit regressions of crowdfunding success examining the interaction between observed sex and emotional neutrality. Emotional neutrality is operationalized as neutral face and neutral voice. Model 1 estimates the main effects of emotional neutrality in both facial and vocal dimensions. Model 2 estimates the main effect of facial neutrality and its interaction with Woman. Model 3 estimates the main effects of vocal neutrality and its interaction with Woman. Model 4 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. Model 5 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. To isolate gendered effect of neutrality from textual valence cues, we include Woman × Positive words and Woman × Negative words. All models include project-level controls and fixed effects for launch year-quarter and project category. Robust standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$.

[7] First, we used the Genderize.io algorithm to classify gender based on first names (Greenberg and Mollick, 2017; Kuppuswamy and Mollick, 2016). Second, we verified these classifications using probability scores generated from facial images via the DeepFace library. Finally, we manually reviewed each video to ensure the accuracy of the gender coding.

($b = -1.958$, $p = 0.013$) is negative and significant. This indicates that the relationship between facial neutrality and success differs significantly between men and women, supporting H1 in the facial domain. Fig. 1a graphically presents the specific directions predicted for men and women. As predicted in H1a, an increase of one standard deviation (0.195) in neutral face expression is associated with a 22.7 % decrease in the probability of success for women ($dy/dx = -1.360$, $p = 0.002$). However, regarding H1b, the effect for men is positive but not significant ($dy/dx = 0.029$, $p = 0.783$). This shows that the interaction stems from the penalty on women rather than a gain for men, with the gap widening as neutrality increases. The predicted magnitude of this gap is shown in Fig. 1b, which indicates that the interaction effect *Neutral face* × *Woman* is statistically different from zero once the intensity of facial neutrality exceeds 0.25 (Zelner, 2009). Thus, in the facial dimension, although the moderating role of gender (H1) is supported as women are penalized (H1a), but the expected benefit from neutrality for men (H1b) is not.[8]

Vocal Neutrality. In the vocal dimension, the interaction *Neutral voice* × *Woman* is not statistically significant. Therefore, H1 is not supported for vocal neutrality. The main effect of *Neutral voice* is consistently negative and significant across models, suggesting that neutral voice is associated with lower success irrespective of sex. Therefore, we do not find support for our hypotheses in the vocal

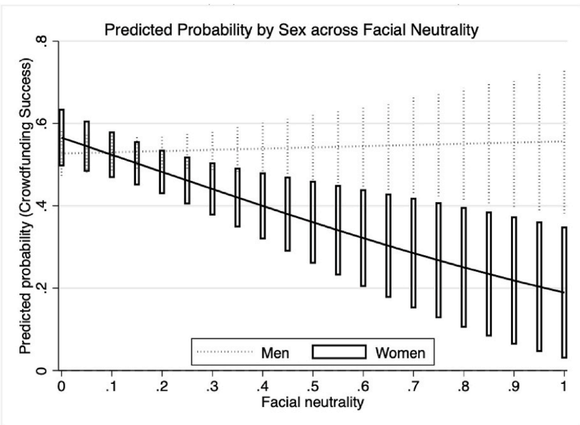

Fig. 1a. Predicted Probability by Sex across Facial Neutrality – Table 3, Model 5

Notes: This figure graphically presents the predicted probability of crowdfunding success for women (solid line, dark bars) and men (dotted line, light bars) across levels of facial neutrality (0–1), based on Probit estimates. Vertical bars indicate 95 % confidence intervals.

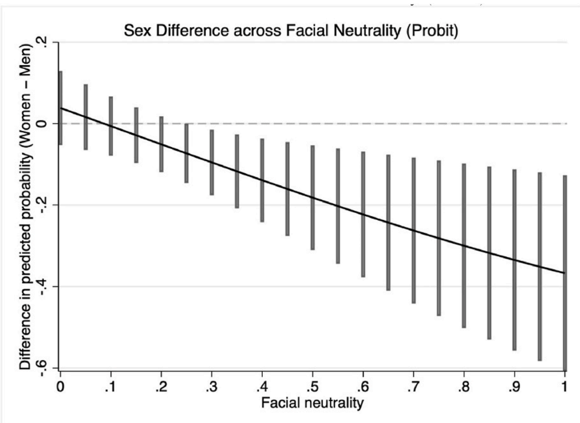

Fig. 1b. Predicted Sex Difference across Facial Neutrality (Probit) – Table 3, Model 5

Notes: This figure graphically presents the difference in predicted probability of success (women – men) across levels of facial neutrality, with 95 % confidence intervals. Values below zero indicate a penalty for women relative to men, and this difference becomes significant once facial neutrality exceeds 0.25.

[8] The split sample analyses within men and women confirm the same pattern, as shown in Table A1 of Appendix A.

Table 4
Probit Regression of Crowdfunding Success (three-way interaction with female-typed category).

	(1)	(2)	(3)
	Model 1	Model 2	Model 3
Success			
Neutral face	0.112		−0.241
	(0.514)		(0.534)
Neutral voice		−2.051***	−2.092***
		(0.585)	(0.606)
Woman	0.550**	0.320	0.708
	(0.211)	(0.617)	(0.628)
Positive words	−6.247**	−4.867*	−5.320*
	(2.209)	(2.225)	(2.230)
Negative words	5.823**	3.697†	4.273*
	(2.086)	(2.121)	(2.133)
Funding goal	−0.468***	−0.472***	−0.473***
	(0.056)	(0.057)	(0.056)
Staff pick	1.885***	1.788***	1.855***
	(0.321)	(0.320)	(0.334)
Duration	−0.024***	−0.022***	−0.023***
	(0.005)	(0.005)	(0.005)
Woman × Neutral face	−1.775*		−1.684†
	(0.861)		(0.936)
Female typed category	0.306	−0.843	−0.888
	(0.283)	(0.871)	(0.881)
Female typed category × Neutral face	0.004 (1.046)		0.301 (1.049)
Woman × Female typed category	−0.223 (0.409)	−0.148 (1.188)	−0.374 (1.189)
Woman × Female typed category × Neutral face	−0.431 (1.548)		−0.375 (1.576)
Woman × Neutral voice		−0.518	−0.768
		(1.127)	(1.114)
Female typed category × Neutral voice		2.006	1.982
		(1.544)	(1.543)
Woman × Female typed category × Neutral voice		−0.048	0.568
		(2.317)	(2.234)
Constant	5.627***	6.896***	7.034***
	(0.636)	(0.828)	(0.794)
Year Quarter FE	YES	YES	YES
Log pseudolikelihood	−247.763	−244.961	−240.087
Observations	548	548	548

Notes: This table reports Probit regressions of crowdfunding success examining the additional interaction between project category and the gender penalty of emotional neutrality. Emotional neutrality is operationalized as neutral face and neutral voice. Model 1 estimates the three-way interaction effects in the facial dimension. Model 2 estimates the three-way interaction effects in the vocal dimension. Model 3 estimates the three-way interaction effects in both the facial and vocal dimensions. Robust standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$.

domain, as neutral voice is penalized for both men and women.

Overall, we find partial support for our theoretical model. Gender significantly moderates the effect of facial expressions, driven by a penalty for women who display neutrality on their faces, whereas men are neither penalized nor rewarded by showing poker faces. In the vocal channel, a neutral vocal tone is associated with lower success probabilities for both women and men, which is contrary to our expectation that men would benefit from a steady, emotionally restrained voice.

Additional Analysis: The Moderating Role of Project Category. Prior work suggests that the success of woman entrepreneurs in reward-based crowdfunding depends not only on their own sex-related characteristics but also on the gender stereotypes associated with the categories in which they seek funding (e.g., Greenberg and Mollick, 2017; McSweeney et al., 2022; Seigner & Milanov, 2023; Wesemann and Wincent, 2021). To ensure our findings regarding gendered display rules are robust, we performed two additional analyses.

First, we examined the moderating role of project category (male-typed vs. female-typed) in the sex-conditioned effect of emotional neutrality on crowdfunding success to test if the penalty for women is category-specific. We focus on Model 3 in Table 4 for interpretation given consistent results across the models. The three-way interactions are not significant (*Woman* × *Female-typed category* × *Neutral face*: $b = -0.048$, $p = 0.812$; *Woman* × *Female-typed category* × *Neutral voice*: $b = 0.568$, $p = 0.799$), providing no evidence that the penalty women face for facial and vocal neutrality is confined to specific industrial contexts.

Second, given the unexpected finding that vocal neutrality was consistently associated with lower crowdfunding success for both sexes, we also examined how project category may alter the penalty of neutral voice to better understand the mechanism (See Model 4 in Table 5). The underlying rationale might be male-typed categories often involve higher uncertainty in evaluation; consequently, backers may rely more heavily on vocal expressiveness (Brucks et al., 2025). The main effect of *Neutral voice* is negative and significant ($b = -2.408$, $p < 0.000$), representing a strong penalty in the male-typed categories. The interaction term *Neutral voice* × *Female typed category* is positive and significant ($b = 2.378$, $p = 0.020$), offsetting this effect so that the penalty for vocal neutrality disappears in female-typed contexts (Fig. 2a). In male-typed categories, a one SD-increase in neutral voice (0.158) reduces success probability by 23.5 % ($dy/dx = -0.600, p < 0.000$), whereas in female-typed categories neutral voice is unrelated to success ($dy/dx = -0.008, p = 0.974$). As shown in Fig. 2b, the difference in slopes becomes statistically significant once vocal neutrality exceeds 0.65, suggesting that the

Table 5
Probit Regression of Crowdfunding Success (two-way interaction with female-typed category).

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	Model 4
DV: Success				
Neutral face	−0.562	−0.475	−0.699†	−0.592
	(0.360)	(0.424)	(0.364)	(0.432)
Neutral voice	−1.695***	−1.667***	−2.441***	−2.408***
	(0.490)	(0.485)	(0.530)	(0.528)
Female typed category	0.123	0.170	−1.086*	−1.037†
	(0.165)	(0.210)	(0.533)	(0.552)
Positive words	−5.216*	−5.254*	−5.079*	−5.129*
	(2.221)	(2.216)	(2.216)	(2.209)
Negative words	4.221*	4.254*	3.884†	3.927†
	(2.135)	(2.130)	(2.117)	(2.110)
Woman	−0.017	−0.017	−0.017	−0.017
	(0.148)	(0.148)	(0.148)	(0.148)
Funding goal	−0.477***	−0.477***	−0.481***	−0.481***
	(0.055)	(0.055)	(0.055)	(0.056)
Duration	−0.021***	−0.020***	−0.021***	−0.021***
	(0.005)	(0.005)	(0.005)	(0.005)
Staff pick	1.781***	1.778***	1.801***	1.796***
	(0.310)	(0.310)	(0.317)	(0.316)
Female typed category × Neutral face		−0.256		−0.312
		(0.798)		(0.803)
Female typed category × Neutral voice			2.364*	2.378*
			(1.022)	(1.020)
Constant	6.770***	6.737***	7.333***	7.296***
	(0.750)	(0.740)	(0.766)	(0.759)
Year Quarter FE	YES	YES	YES	YES
Log pseudolikelihood	−245.824	−245.761	−243.105	−243.013
Observations	548	548	548	548

Notes: This table reports Probit regressions of crowdfunding success examining the interaction between project category and emotional neutrality. Emotional neutrality is operationalized as neutral face and neutral voice. Model 1 estimates the main effects of emotional neutrality in both facial and vocal dimensions. Model 2 estimates the main effect of facial neutrality and its interaction with Female typed category. Model 3 estimates the main effects of vocal neutrality and its interaction with Female typed category. Model 4 estimates the main effects of both facial and vocal neutrality and their interactions with Female typed category. All models include project-level controls and fixed effects for launch year-quarter. Robust standard errors in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.10.

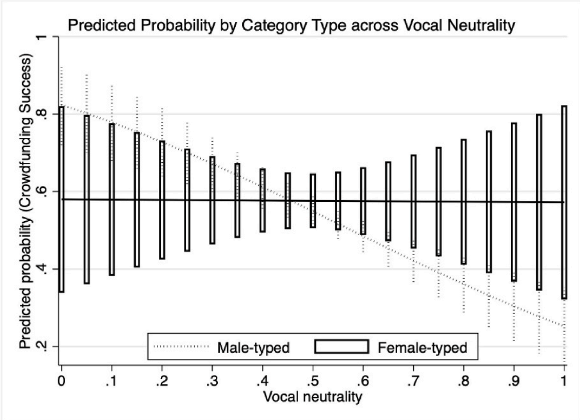

Fig. 2a. Predicted Probability by Category Type across Vocal Neutrality – Table 5, Model 4
Notes: This figure graphically presents the predicted probability of crowdfunding success for male-typed categories (solid line, dark bars) and female-typed categories (dotted line, light bars) across levels of vocal neutrality (0–1), based on Probit estimates. Vertical bars indicate 95 % confidence intervals.

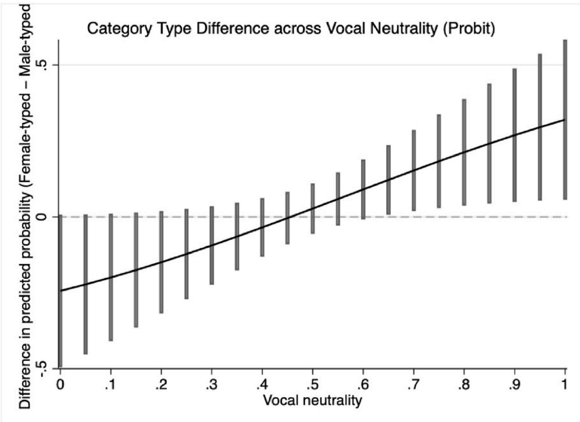

Fig. 2b. Category Type Difference across Vocal Neutrality (Probit) – Table 5, Model 4
Notes: This figure graphically presents the difference in predicted probability of success (female-typed category – male-typed category) across levels of facial neutrality, with 95 % confidence intervals. Values above zero indicate a penalty for male-typed category relative to female-typed category, and this difference becomes significant once vocal neutrality exceeds 0.65.

"universal" vocal penalty in our main models is largely driven by male-typed categories at high levels of neutrality. In contrast, the impact of facial neutrality does not vary across the two types of categories (*Neutral face* × *Female typed category*: $b = -0.311, p = 0.698$).

5. Discussion

Interpretation of Results. Our study explored the gendered effects of emotional neutrality in crowdfunding pitches. In the *facial channel*, we find that gender significantly moderates the effect of facial neutrality: maintaining a "poker face" is strongly penalized for women, whereas the effect for men is small and statistically indistinguishable from zero. This pattern is consistent with the idea that ostensibly equivalent neutral facial cues are filtered through gendered display rules. Crucially, our additional analyses reveal no significant three-way interaction with project category, suggesting that backlash against women's facial neutrality operates similarly across both male-typed and female-typed Kickstarter categories. Robustness checks using alternative dependent variables beyond the threshold-based success measure employed in the main analysis further show that the penalty associated with facial neutrality is strongest for the pledged ratio, weaker for total pledged dollars, and not significant for the number of backers (see Appendix A). This pattern suggests that different crowdfunding outcomes capture distinct dimensions of performance. Future research should therefore treat crowdfunding performance as multidimensional and test whether clearing the funding threshold (success), scaling resources (pledged amount or ratio), and mobilizing broad support (backer count) operate through different mechanisms and respond to different signals.

In the *vocal channel*, we observed a different pattern: a neutral voice was associated with lower success for both women and men, contrary to our expectation that men would benefit from a steady, emotionally restrained tone. However, our exploratory analysis reveals that the negative effect of a neutral voice is context dependent, which is almost entirely driven by male-typed categories (e.g., technology, design) and disappear in female-typed categories (e.g., fashion, craft). This divergence between facial and vocal results offers a nuanced insight into how backers process information. While facial expressions appear to be evaluated through gender norms, vocal cues appear to be judged in terms of their informational value. Expressive voice may matter more in functionally complex, high uncertainty categories, where backers rely on auditory cues to make sense of the pitch. Consequently, neutral voice may be penalized in male-typed categories, where backers face greater uncertainty, whereas in female-typed categories where product qualities are more visually apparent, vocal delivery is less diagnostic.

While our theory is largely consistent with the observed patterns, the results are unable to ensure causality. It would be valuable to manipulate facial and vocal neutrality in controlled experiments to provide a direct test of causal effects. Such designs could also clarify the underlying psychological mechanisms in entrepreneurial evaluation of nonverbal cues. For example, audience perceptions such as trustworthiness, authenticity, dominance, competence, as mentioned in related studies (e.g., Maxwell and Lévesque, 2014; Radoynovska and King, 2019).

Theoretical Contributions. First, we contribute to research highlighting the importance of context and audience in entrepreneurial pitches (e.g., Li et al., 2022; Seigner et al., 2023). We clarify that the value of emotional neutrality is not uniform. Unlike in formal financing, where professionalism and limited emotional expression are often rewarded (Balachandra et al., 2019), crowdfunding backers evaluate these cues through gendered expectations. With facial neutrality harming women and vocal neutrality helping no one, the presumed "rationality" signal of neutrality fails to resonate in this affective, subjective context (Ren et al., 2021).

Second, we offer a nuanced explanation for the "advantage for women" in crowdfunding (Greenberg and Mollick, 2017). This advantage is likely not due to a lack of bias, but because the crowd rewards communication styles that align with feminine stereotypes (Johnson et al., 2018; Li et al., 2022; Seigner & Milanov, 2023). Women succeed because their typical expressive style matches audience expectations; however, when women deviate from these norms by displaying neutrality, they face a severe penalty.

Finally, the discrepancy between facial and vocal channels suggests emotional expression is a multimodal information signal. Observers appear to integrate cues from face, voice, and content with different weights. Facial neutrality shapes inferences about social norms, whereas vocal neutrality—voice acting as the primary vehicle for the pitch's informational content—shapes message clarity and backers' cognitive engagement. This invites future research to examine how the importance of specific cues is dynamically re-weighted across modalities.

CRediT authorship contribution statement

Jennie Jiongni Mao: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Charles Williams:** Writing – review & editing, Methodology, Conceptualization. **Silvia Stroe:** Writing – review & editing, Conceptualization. **Charlotta Sirén:** Writing – review & editing, Methodology.

Declaration of generative AI in scientific writing

The authors received assistance from ChatGPT 5.1 Pro for language editing, including grammar, syntax, and style suggestions. Each recommendation was carefully reviewed by the authors to ensure that the original meaning and scientific accuracy were maintained. The final text is the sole responsibility of the authors.

Declaration of Competing interest

We have nothing to declare.

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APPENDIX A

1. Detailed Explanation of Control Variables

Project duration refers to the predetermined fundraising period established by the project creator upon launching the project. It is controlled as shorter durations give projects less time to raise funds (e.g., Anglin et al., 2022a,b; Mollick, 2014). Funding *goal,* determined as the logarithm of the sum of the requested goal amount for the project (plus 0.0001 so that zero values get logarithmic values), tends to influence backer expectations regarding successful funding (e.g., Colombo et al., 2015; Josefy et al., 2017). *Staff pick* is a dummy variable coded as 1 for campaigns that had "project we love" badge, 0 otherwise. This pre-evaluation from the staff is a quality signal that potentially impacts fundraising (e.g., Seigner et al., 2022; Taeuscher et al., 2021). We also include emotional valence of the speech: *Positive words* is the similarity between the average speech-text embedding and the average embedding of LIWC positive words, and *Negative words* is defined analogously using the LIWC negative word list (Chung and Pennebaker, 2018). This allows us to isolate neutrality from variation in textual valence frequently emphasized in related research (e.g., Anglin et al., 2018; Jiang et al., 2019).

2. Robustness Check of Sex Difference using Split Sample Analyses

Table A1
Sex Subsample Analysis of Emotional Neutrality and Crowdfunding Success

	(1)	(2)
	Model 1: Women	Model 2: Men
DV: Success		
Neutral face	−2.439***	0.087
	(0.720)	(0.436)
Neutral voice	−2.012†	−1.531*
	(1.123)	(0.619)
Positive words	−6.334	−5.650*
	(5.014)	(2.824)
Negative words	6.135	3.640
	(4.699)	(2.717)
Funding goal	−0.616***	−0.443***
	(0.126)	(0.067)
Duration	−0.027*	−0.018**
	(0.012)	(0.006)
Staff pick	1.361***	1.420***
	(0.325)	(0.357)
Constant	8.999***	6.192***
	(1.692)	(0.944)
Year Quarter FE	YES	YES
Category FE	YES	YES
Log pseudolikelihood	−240.087	−51.678
Observations	156	368

Notes: This table presents Probit regressions of crowdfunding success separately for women (Model 1) and men (Model 2). All models include project-level controls and fixed effects for launch year-quarter and project category. There are 24 observations omitted within women sample due to perfect collinearity with FE. Robust standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$.

3. Robustness Test of Alternative Dependent Variables

To complement the binary success models, we re-estimate alternative outcome variables widely used in prior work (e.g., pledged ratio, backer number, and pledged USD), using Poisson pseudo–maximum likelihood (PPML) with robust standard errors. PPML is well suited to nonnegative, right-skewed outcomes and yields multiplicative effects, which is now considered the most robust form of estimation for count and positive variables such as percentages (Wooldridge, 1999). Tables A2–A4 report PPML models for three scaling outcomes: pledged ratio (A2), backer number (A3), and pledged USD (A4). All models include year–quarter and category fixed effects and the same set of controls.

In the Probit models using success as the dependent variable, *Neutral face* × *Woman* interaction is significantly negative in most specifications, indicating a penalty for women who display a neutral face. In the PPML models, the results suggest gender penalty of facial neutrality on pledged ratio (e.g., Table A2, Model 5: $b = -2.597$, $p = 0.042$). However, this negative interaction effect is marginally significant on pledged USD (e.g., Table A4, Model 5: $b = -2.672$, $p = 0.054$), and not significant on backer number (e.g., Table A3, Model 5: $b = -1.952$, $p = 0.180$).

For voice, our main analysis show neutral voice is negative for both men and women. We find consistent results across all specifications, as neutral voice has a large, negative, and mostly highly significant effect. Substantively, a 10 % increase in neutral voice is associated with roughly a 20–40 % decrease in pledged amount of USD, pledged ratio, and number of backers.

Taken together, these results suggest that facial neutrality mainly operates as a gendered threshold penalty. It is most evident in whether women's projects succeed at all and, to a lesser extent, in the scale of funds raised. In contrast, vocal neutrality appears to be a general performance penalty that substantially reduces funding outcomes for all entrepreneurs, regardless of the observed sex.

We present a hurdle model that separates the probability of crowdfunding success from outcomes conditional on success in Table A5 to further understand the role of facial and vocal neutrality at different stages of campaign performance.

Among successful projects, the effect of neutral voice is significant on number of backers (Model 3: $b = -3.644$, $p = 0.001$) and pledged USD (Model 4: $b = -2.439$, $p = 0.017$) but has no significant effect on the pledged ratio. By contrast, neither *Neutral face* nor *Neutral face* × *Woman* is significant in the scaling equations, so the gendered facial penalty mainly appears at the threshold of success rather than in the level of funds raised once projects succeed. Overall, these patterns suggest that gendered reactions to facial cues operate at the entry stage, whereas neutral vocal delivery has broader, performance-related consequences for all campaigns that clear the initial success threshold.

Table A2
PPML Regression of Pledged Ratio

	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
DV: Pledged ratio					
Neutral face	0.550	0.838	0.569	0.877	0.825
	(0.529)	(0.623)	(0.540)	(0.631)	(0.677)
Neutral voice	−2.529***	−2.511***	−2.252*	−2.127*	−2.214*
	(0.746)	(0.760)	(1.006)	(1.010)	(1.072)
Woman	−0.034	0.177	0.274	0.633	−1.899
	(0.211)	(0.300)	(0.741)	(0.800)	(1.188)
Positive words	−6.648†	−6.550†	−6.640†	−6.563†	−13.919**
	(3.905)	(3.906)	(3.882)	(3.864)	(5.193)
Negative words	4.113	4.263	4.056	4.209	9.799^{+}
	(3.608)	(3.579)	(3.586)	(3.548)	(5.080)
Funding goal	−0.709***	−0.700***	−0.709***	−0.701***	−0.697***
	(0.046)	(0.047)	(0.046)	(0.046)	(0.046)
Duration	0.054***	0.052***	0.055***	0.052***	0.051***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)
Staff pick	1.979***	2.010***	1.961***	1.985***	1.963***
	(0.247)	(0.250)	(0.247)	(0.248)	(0.269)
Woman × Neutral face		−1.997		−2.198	−2.597*
		(1.352)		(1.346)	(1.276)
Woman × Neutral voice			−0.680	−0.974	−0.378
			(1.489)	(1.536)	(1.441)
Woman × Positive words					20.996**
					(6.985)
Woman × Negative words					−16.234*
					(7.675)
Constant	9.915***	9.704***	9.757***	9.473***	10.184***
	(1.263)	(1.354)	(1.342)	(1.432)	(1.493)
Year Quarter FE	YES	YES	YES	YES	YES
Category FE	YES	YES	YES	YES	YES
Log pseudolikelihood	−251206.47	−249114.28	−250929.94	−248578.08	−237958.43
Observations	548	548	548	548	548

Notes: This table reports PPML regression of pledged ratio examining the interaction between observed sex and emotional neutrality. Emotional neutrality is operationalized as neutral face and neutral voice. Model 1 estimates the main effects of emotional neutrality in both facial and vocal dimensions. Model 2 estimates the main effect of facial neutrality and its interaction with Woman. Model 3 estimates the main effects of vocal neutrality and its interaction with Woman. Model 4 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. Model 5 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. To isolate gendered effect of neutrality from textual valence cues, we include Woman × Positive words and Woman × Negative words. All models include project-level controls and fixed effects for launched date (year-quarter) and project category. Robust standard errors in parentheses. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$.

Table A3
PPML Regression of Backer Number

	(1)	(2)	(3)	(4)	(5)
	Model 1	Model 2	Model 3	Model 4	Model 5
DV: Backer Number					
Neutral face	−0.595	−0.374	−0.638	−0.413	−0.446
	(0.635)	(0.679)	(0.640)	(0.691)	(0.701)
Neutral voice	−3.747***	−3.703***	−4.211***	−4.167***	−4.265***
	(0.848)	(0.865)	(1.007)	(1.017)	(1.027)
Woman	−0.723*	−0.480	−1.623*	−1.381†	−2.226†
	(0.284)	(0.382)	(0.776)	(0.835)	(1.264)
Positive words	−16.569***	−16.386***	−16.769***	−16.559***	−19.099***
	(3.970)	(3.916)	(3.999)	(3.950)	(4.691)
Negative words	15.277***	15.203***	15.585***	15.492***	17.606***
	(4.191)	(4.106)	(4.209)	(4.128)	(4.648)
Funding goal	0.021	0.028	0.011	0.018	0.022
	(0.086)	(0.085)	(0.084)	(0.083)	(0.082)
Duration	0.016	0.015	0.015	0.014	0.015
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)

(continued on next page)

Table A3 (*continued*)

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
Staff pick	1.904***	1.899***	1.925***	1.921***	1.906***
	(0.320)	(0.317)	(0.313)	(0.311)	(0.314)
Woman × Neutral face		−1.993		−1.919	−1.952
		(1.527)		(1.464)	(1.455)
Woman × Neutral voice			2.095	2.073	2.237
			(1.446)	(1.475)	(1.555)
Woman × Positive words					8.621
					(8.429)
Woman × Negative words					−7.355
					(9.805)
Constant	6.829***	6.650***	7.151***	6.988***	7.170***
	(1.268)	(1.323)	(1.335)	(1.379)	(1.432)
Year Quarter FE	YES	YES	YES	YES	YES
Category FE	YES	YES	YES	YES	YES
Log pseudolikelihood	−138112.24	−137349.61	−137161.34	−136422.31	−135736.32
Observations	548	548	548	548	548

Notes: This table reports PPML regression of backer number examining the interaction between observed sex and emotional neutrality. Emotional neutrality is operationalized as neutral face and neutral voice. Model 1 estimates the main effects of emotional neutrality in both facial and vocal dimensions. Model 2 estimates the main effect of facial neutrality and its interaction with Woman. Model 3 estimates the main effects of vocal neutrality and its interaction with Woman. Model 4 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. Model 5 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. To isolate gendered effect of neutrality from textual valence cues, we include Woman × Positive words and Woman × Negative words. All models include project-level controls and fixed effects for launched date (year-quarter) and project category. Robust standard errors in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.10.

Table A4
PPML Regression of Pledged USD

	(1) Model 1	(2) Model 2	(3) Model 3	(4) Model 4	(5) Model 5
DV: Pledged USD					
Neutral face	0.263	0.455	0.218	0.426	0.398
	(0.614)	(0.621)	(0.621)	(0.632)	(0.636)
Neutral voice	−3.526***	−3.489***	−3.881***	−3.852***	−3.932***
	(0.849)	(0.867)	(0.930)	(0.940)	(0.952)
Woman	−1.186***	−0.808*	−2.252**	−1.917*	−2.513
	(0.302)	(0.394)	(0.804)	(0.869)	(1.486)
Positive words	−16.368***	−16.248***	−16.672***	−16.489***	−18.136***
	(4.505)	(4.431)	(4.547)	(4.476)	(5.345)
Negative words	14.542**	14.503***	14.920***	14.840***	16.222**
	(4.468)	(4.376)	(4.486)	(4.398)	(4.991)
Funding goal	0.194*	0.203*	0.186*	0.194*	0.195*
	(0.090)	(0.090)	(0.089)	(0.088)	(0.088)
Duration	0.012	0.011	0.012	0.011	0.012
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Staff pick	2.227***	2.220***	2.240***	2.234***	2.228***
	(0.418)	(0.413)	(0.413)	(0.408)	(0.413)
Woman × Neutral face		−2.724†		−2.682†	−2.672†
		(1.501)		(1.393)	(1.386)
Woman × Neutral voice			2.451	2.534	2.574
			(1.471)	(1.497)	(1.643)
Woman × Positive words					7.374
					(9.467)
Woman × Negative words					−6.628
					(10.897)
Constant	9.502***	9.347***	9.752***	9.618***	9.740***
	(1.333)	(1.337)	(1.370)	(1.362)	(1.416)
Year Quarter FE	YES	YES	YES	YES	YES
Category FE	YES	YES	YES	YES	YES
Log pseudolikelihood	−19132305	−18992953	−19017779	−18824440	−18824440
Observations	548	548	548	548	548

Notes: This table reports PPML regression of pledged USD examining the interaction between observed sex and emotional neutrality. Emotional neutrality is operationalized as neutral face and neutral voice. Model 1 estimates the main effects of emotional neutrality in both facial and vocal dimensions. Model 2 estimates the main effect of facial neutrality and its interaction with Woman. Model 3 estimates the main effects of vocal neutrality and its interaction with Woman. Model 4 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. Model 5 estimates the main effects of both facial and vocal neutrality and their interactions with Woman. To isolate gendered effect of neutrality from textual valence cues, we include Woman × Positive words and Woman × Negative words. All models include project-level controls and fixed effects for launched date (year-quarter) and project category. Robust standard errors in parentheses. ***p < 0.001, **p < 0.01, *p < 0.05, †p < 0.10.

Table A5
Hurdle model of Pr(success) and outcomes conditional on success

	(1)	(2)	(3)	(4)
	Model 1	Model 2	Model 3	Model 4
	Threshold	Scaling conditional on Success		
	DV: Success	DV: Pledged Ratio	DV: Backer Number	DV: Pledged USD
VARIABLES				
Neutral face	0.140	0.738	−0.880	0.286
	(0.456)	(0.630)	(0.811)	(0.825)
Woman	0.583	0.720	−1.792†	−2.097†
	(0.585)	(0.857)	(0.965)	(1.073)
Woman × Neutral face	−1.899*	−1.617	−0.994	−2.214
	(0.789)	(1.511)	(1.891)	(1.934)
Neutral voice	−1.209+	−1.683	−3.645***	−2.439*
	(0.619)	(1.046)	(1.097)	(1.027)
Woman × Neutral voice	−0.760	−1.567	2.903	3.557†
	(1.025)	(1.731)	(1.830)	(1.915)
Positive words	−5.882*	−3.727	−16.075***	−14.497***
	(2.359)	(3.571)	(3.755)	(3.888)
Negative words	4.471*	1.206	15.753***	13.713***
	(2.245)	(3.438)	(4.112)	(4.103)
Funding goal	−0.467***	−0.642***	0.245*	0.576***
	(0.059)	(0.048)	(0.108)	(0.124)
Duration	−0.021***	0.059***	0.036*	0.034*
	(0.006)	(0.006)	(0.015)	(0.016)
Staff pick	1.646***	1.650***	1.326***	1.411***
	(0.335)	(0.224)	(0.288)	(0.371)
Year Quarter FE	YES	YES	YES	YES
Category FE	YES	YES	YES	YES
Constant	6.351***	8.935***	4.992***	5.506**
	(0.833)	(1.353)	(1.413)	(1.678)
Log pseudolikelihood	−222.903	−199664.5	−92903.853	−11048285
Observations	548	290	290	290

Notes: This table reports a hurdle model that separates the probability of crowdfunding success from outcomes conditional on success. Model 1 ("Threshold") presents Probit estimates for whether a project succeeds (DV: Success). Models 2–4 ("Scaling conditional on Success") report regressions for the pledged ratio, number of backers, and pledged USD among successful projects only. The table shows coefficients for facial and vocal neutrality and their interactions with sex. Robust standard errors in parentheses. All models include project-level controls and fixed effects for launched date (year-quarter) and project category. ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$.

APPENDIX B. Video Screening and Analysis

1. Number of Eligible Videos After Screening, by Project Category

Table B1
Screening and Inclusion of Project Videos by Category

Category	#Total Videos	#Included Videos	Inclusion Rate_%
Design	1202	123	10.23
Crafts	286	48	16.78
Technology	2445	283	11.74
Fashion	787	94	11.94
TOTAL	4720	548	11.69

Notes: This table reports, by project category, the total number of campaigns with videos, the number of videos that passed our screening criteria (single identifiable entrepreneur, face visible for >60 % of the video, speaking in their own voice, non-advertising/animation, adequate resolution), and the resulting inclusion rate (included videos ÷ total videos).

2. Video Analysis Procedure Using Commercial Algorithms

This procedure to decompose videos into three channels of voice, text and face follows the method first proposed by Hu and Ma (2025).

(1) Verbal Analysis

Step 1. Text Extraction
- Transform video (.mp4) to audio (.mp3) using *FFmpeg* library.[9]
- Isolate background music and ambient noise in extracted audios using *Demucs*[10].
- Apply *OpenAI Whisper*[11] to process clean audios to have the whole transcript at the creator level

Step 2. Textual Emotion Analysis

LIWC emotion dictionary[12] is the most frequently used software for sentiment analysis in recent management research, acceptable to analyze sentiment in social media (Borah et al., 2015), CEO speech (e.g., Guo et al., 2021; Um et al., 2022), and media press (e.g., Antons et al., 2015; Zavyalova et al., 2012). The sentiment measure is based on word counts - calculate the frequency of each word corresponding to each sentiment category in each transcript.

To overcome the limitation of the dictionary-based method in terms of accuracy and universality, we improve the count-based measure to create a "geometric" measure by leveraging the "analogy-solving" capacity of word embeddings (Gennaro and Ash, 2022; Osnabrügge et al., 2021).

- Identify seed words for positive emotions and negative emotions from LIWC.
- Train a word-embedding model based on how words co-occur in the whole corpus using the Word2Vec algorithm from Mikolov et al. (2013).
- Generate a vector w corresponding to each word w_i in the vocabulary using the trained word-embedding model. For example, the vector POS_EMO represents the average of the vectors w for the words in the positive emotion word list, and the vector NEG_EMO represents the average of the vectors w for the words in the negative emotion word list
- Estimate vector representations for each transcript, using the same specification as for emotion vectors. Let the vector v for the transcript t_i be the average of the vectors w_i for the words in the transcript.
- Calculate the intensity of sentiment in each transcript as: $E_i = sim(t_i, EMO)$, where $sim(v, w) = (v \cdot w)/(\|v\|\|w\|)$ is the cosine similarity between vectors v and w.

(2) Facial Analysis

Step 1. Frame level metric generation
- Use *iMotions Affectiva's AFFDEX*[13] to predict facial emotions of each video: anger, disgust, fear, happy, sad, surprise, and neutrality.

Step 2. Video level facial metric generation
- There is a score to represent the confidence of each emotion category, by which we can also infer the most dominant emotion among the five categories that is with the highest score.
- Calculate the percentage of frames with neutrality as the most dominant emotion (number of frames with neutrality dominant divided by number of frames with face), which represents the main variable in our study, *Neutral face.*

(3) Vocal Analysis

Step 1. Raw metrics in audio chucks
- Use audEERING[14] to process the audios and obtain vocal emotions: angry, happy, neutral, sad.
- The software skips voice breaks/pauses to focus on the part with entrepreneur voice only. Therefore, each audio file is automatically processed in separate audio chunks with human voice.

Step 2. Video level vocal metric generation
- There is a score to represent the confidence of each emotion category, and we focus on the confidence score of neutral to infer the intensity of vocal neutrality.

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[9] https://www.ffmpeg.org/documentation.html.
[10] https://github.com/facebookresearch/demucs.
[11] https://github.com/openai/whisper.
[12] https://liwcsoftware.onfastspring.com/.
[13] https://imotions.com/products/imotions-lab/modules/fea-facial-expression-analysis/.
[14] https://imotions.com/products/imotions-lab/modules/voice-analysis/.

- For each audio file, compute the average intensity of its chunks, giving greater weight to longer chunks based on their duration. This resulting measure represents the other main variable in our study, *Neutral voice.*

3. Video Analysis Procedure Using Publicly Accessible Algorithms

(1) Verbal Analysis

Step 1. Text Extraction
- Transform video (.mp4) to audio (.wav) using *MoviePy* library.[15]
- Split each audio file of the project creator where silence is 700 ms or more and get chunks.
- Apply speech recognition on each of these chunks using Google *SpeechRecognition* library[16] (two ways as below, and we refer to the first option that is free).
  - o Google Speech Recognition (free; Google Speech Recognition service by default)
  - o Google Cloud Speech API[17](paid service; Google API Client Library is required)
- Use *Diction* function in Microsoft word 365 to have a double-check.
- Join all the processed audio chunks to have the whole transcript at the creator level.

Step 2. Textual Emotion Analysis
- Split the whole transcript into sentences.
- Use *NRC Lexicon* [18] to generate a score to represent the confidence of each emotion category (happiness, sadness, surprise, anger, fear) for each sentence. The scores range from 0 to 1, representing the frequency of words related to a certain emotion.
- Calculate the average score of sentences for each emotion category to determine the verbal emotions at the creator level.
- Positive verbal emotion is the score that denotes happiness, negative verbal emotion is the average score that denotes sadness, anger, and fear.

(2) Facial Analysis

Step 1. Image Extraction
- Use *OpenCV* library[19] to capture frame in each 0.1 s in a video.
- Create a folder for each video.
- Save the captured frames as JPG file for each video in separate folders.

Step 2. Face Detection
- Use pre-trained *Haar Cascade* from the *OpenCV* library to detect face in each frame.
- Calculate the probability of face appearance in each video (number of frames with faces divided by the number of captured frames).

Step 3. Facial Emotion Analysis
- Use *FER* library [20]to predict facial emotions of each video: anger, disgust, fear, happy, sad, surprise, and neutrality.
- There is a score to represent the confidence of each emotion category, by which I can also infer the most dominant emotion among the five categories that is with the highest score.
- Calculate the percentage of frames with neutrality as the most dominant emotion (number of frames with neutrality dominant divided by number of frames with face), which represents the main variable in our study, *Neutral face*.

(3) Vocal Analysis

Step 1. Process Audio
- Use *pydub* library [21]to slice audio and transform to mono channel.

Step 2. Vocal Attribute Extraction
- Manually check each audio file to keep the part with entrepreneur voice only and save it as a separate file for further analysis.
- In *Praat*[22] software, the pitch of the women voices was measured within a range of 100–600 Hz, and for voices of men within a range of 75–500 Hz. All other system settings were set to their defaults.
- Use *Praat* to generate the average voice pitch level (mean fundamental frequency F_0), and voice pitch variation (standard deviation of the mean fundamental frequency). Pitch variation is the other main variable in our study, *Neutral voice.*

[15] https://pypi.org/project/moviepy/.
[16] https://pypi.org/project/SpeechRecognition/.
[17] https://cloud.google.com/speech-to-text.
[18] https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm.
[19] https://opencv.org/author/opencv/.
[20] https://pypi.org/project/fer/.
[21] https://pypi.org/project/pydub/.
[22] https://www.fon.hum.uva.nl/praat/.

Step 3. Vocal Valence Classification (Gorodnichenko et al., 2023)

- Extract 180 voice features, including 128 Mel spectrogram frequencies, a complete spectrum encompassing 12 chroma coefficients, and 40 MFCCs using the Librosa package (Pan et al., 2010) in the audio sample for both training, testing and prediction.
- Use 80 % of TESS and RAVDESS data to train Convolutional Neural Network (CNN) based on Keras, a deep learning API run on top of Google's machine learning platform TensorFlow, and test the CNN model on the remaining 20 %.
  - o The architecture of this neural network includes three linearly activated dense layers, each with 200 nodes: the first layer processes 180 features (128 Mel coefficients, 40 MFCCs, and 12 chroma coefficients), while the second and third layers build on the outputs of their preceding layers. It is a fully connected network with four layers, with a node in the next layer connected with all inputs I_i in the previous layer through weight ($w_{k,i}$) and bias (b_k): $\sum_{i=1}^{j} I_i + w_{k,i} + b_k$. The network culminates in an output layer with five nodes, each corresponding to one of five emotions: happy, pleasantly surprised, neutral, sad, and angry.
  - o To prevent overfitting, 30 % of inputs are randomly set to 0 at each step during the training time and only 70 % of inputs are retained for training. The number of training epochs is set to 2,000, enabling the entire training dataset passed forward and backward through the network 2000 times. The batch size of 64 indicates that the model updates its weights after processing 64 training audio files through the network. The way weights are updated is determined by Adam (adaptive moment estimation) optimizer.
  - o The trained model attains an accuracy rate of 85 %. The accuracy scores for each emotion class—angry, happy, neutral, pleasantly surprised, and sad—are 92 %, 71 %, 87 %, 93 %, and 83 %, respectively.
- Predict the vocal emotion categories using the trained CNN model.

4. Validation of Measures

(1) Facial Metric Validation

To validate our facial neutrality measure, we first compare fer and Affectiva within a smaller sample (N = 183). Raw frame-level outputs and video-level aggregates correlate at 0.775 and 0.780 respectively, indicating strong convergence across tools (Table B2).

We then benchmark both algorithms against human judgments on 30 randomly selected videos, dichotomizing their neutrality scores (≥0.5 = neutral, <0.5 = expressive).

Agreement with the human coder is substantial for both systems, with 23 of 30 cases for Affectiva and 18 of 30 for fer (Table B3). Together with the strong correlations between the two tools, these results support the reliability of our facial-neutrality measure.

Table B2
Measure Comparison of fer and Affectiva for Facial Emotion (N = 183)

Facial Emotion	Video Level Measure	Raw Metrics
Anger	0.374***	0.228*
Disgust	0.380***	0.151
Fear	0.428***	0.304**
Joy	0.939***	0.868***
Sadness	0.797***	0.539***
Surprise	0.662***	0.502**
Neutrality	0.775***	0.780***

***p < 0.001, **p < 0.01, *p < 0.05.

Table B3
Number of Consistent Cases for Face with Human Coding (N = 30)

	fer	Affectiva
Facial EmotionNeutrality	18	23

(2) Vocal Metric Validation

To validate our vocal-neutrality measure, we compare Praat (the open-source tool used previously) with audEERING (the commercial tool used in the revised analysis) on two core voice features: mean pitch and pitch variation. The correlations between the tools are very high (r = 0.832 and r = 0.840, respectively) and statistically significant (p < 0.001; Table B4), indicating that the two independent algorithms yield highly consistent estimates of pitch-related vocal characteristics. This convergence shows that audEERING extracts fundamental vocal features that closely align with those obtained from Praat, supporting the reliability of our vocal-neutrality measurement.

Next, we assess how closely two vocal-neutrality measures match human judgments in a subset of 30 randomly selected videos. The Gorodnichenko-style classifier (a binary neutral/non-neutral algorithm) matches human coding in 12 of 30 cases, whereas audEERING's continuous neutrality measure—dichotomized for comparability—matches in 25 of 30 cases (Table B5). The classifier is limited by its binary output, which compresses a graded signal. We considered segmenting pitch contours into meaningful units and computing the share of neutral segments, but we could not identify a principled segmentation rule; as a result, we could not use the pre-trained algorithm in a more fine-grained way. Overall, audEERING captures vocal neutrality more accurately and consistently than the binary classifier and supports the construct validity with its strong agreement with human judgments.

Taken together, these results indicate that audEERING provides the valid and appropriate measure of vocal neutrality for this study.

Table B4
Measure Comparison of Praat and audEERING for Vocal Emotion (N = 183)

Voice Pitch Measure	Correlation
Average Pitch	0.832***
Pitch Variation	0.840***

***$p < 0.001$, **$p < 0.01$, *$p < 0.05$.

Table B5
Number of Consistent Cases for Voice with Human Coding (N = 30)

	Gorodnichenko-style classifier	audEERING
Vocal EmotionNeutrality	12	25

Data availability

Data will be made available on request.

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