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Subtle Cues and Substantial Challenges in Early-Stage Financing:

Essays on Pitch Evaluation and Women in Entrepreneurship

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Abstract

This dissertation primarily address scholarly conversations on (1) communication strategy in entrepreneurial pitches and (2) the inclusivity of women in entrepreneurship, in both formal and informal early-stage financing settings. Empirically, I employ machine learning algorithms to analyze large unstructured data, including texts, images, and videos of entrepreneurs collected from publicly accessible websites like YouTube and Kickstarter. I also refer to large scale archival database of funding deal records from Crunchbase. Recognizing the challenge in quantifying subtle nonverbal cues within entrepreneurial pitches, my dissertation began with a comprehensive review of coding tools used in published social science papers, complemented by practical applications to 50 accelerator pitch videos. This study wraps up with targeted algorithm suggestions for facial and vocal analysis, alongside a qualitative discussion about emotional disclosure in accelerator pitches of successful entrepreneurs. Transitioning from methodological exploration to practical application, the next study analyzed 183 pitch videos to uncover gender differences in the evaluation of nonverbal emotional neutrality in the crowdfunding context. I observed that gender-conforming expressions of emotion tend to be favored over non-conforming ones among informal investors. Building on these insights about gender difference in early-stage financing evaluation, the third study examines a potential solution to early-stage funding access of female entrepreneurs. Contrary to the implications of gender homophily between female investors and entrepreneurs, I find that the representation of female-founded startups securing initial funding rounds decreased when a female venture capitalist is involved, in states with heightened public attention post Elizabeth Holmes scandal. Overall, this dissertation critically explores gender and entrepreneurship, focusing on the subtle cues that may benefit women in pitch evaluations and substantial challenges they face in securing early-stage financing.

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Chapter 1

1 Introduction

It is noteworthy that most entrepreneurs fail very early, facing challenges in the financial resource acquisition (e.g., Artinger & Powell, 2016; Zunino et al., 2022). In the context of early-stage entrepreneurship where performance history is often scarce, investors leverage a multifaceted set of criteria to assess the venture's potential. Key indicators they consider include tangible assets like the quality of the product (e.g., Bapna, 2019; Kleinert et al., 2022) and the presence of the patent application (e.g., Audretsch et al., 2012; Haeussler et al., 2014). Investors also value the social capital of a startup, often evidenced by its media exposure and the strength of its networks in the entrepreneurial ecosystem (e.g., Courtney et al., 2017; Gomulya et al., 2019; Hallen & Eisenhardt, 2012; Tumasjan et al., 2021). Furthermore, academic or industry specific expertise can serve as markers of its operational capacity and market knowledge (e.g., Backes-Gellner & Werner, 2007; Chan et al., 2020). While these hard metrics of tangible assets are crucial, the intangible qualities of entrepreneurs are not overlooked. The passion and commitment displayed during entrepreneurial pitches can be projections of an entrepreneur's dedication and resilience (e.g., Allison et al., 2022; Cardon et al., 2017; Chen et al., 2009). It is crucial to recognize that while the entrepreneurial pitch primarily presents the vision and business plan, it often encompasses elements showcasing an entrepreneur's intangible capabilities like passion, resilience, or charisma. These elements can influence investors, even if they don't directly forecast the venture's forthcoming profitability or expansion.

From this observation arises a pertinent question: How do intangible capabilities inferred from entrepreneurial pitches influence investor decisions in early-stage resource mobilization? Contemporary research predominantly emphasizes verbal communication within pitches, particularly the role of storytelling in shaping financing outcomes (Anglin, Wolfe, et al., 2018; Spina & Williams, 2021; Steigenberger & Wilhelm, 2018). In contrast, nonverbal communication, though critical, is frequently overshadowed. The past decade has seen a growing theoretical interest in the relationship between nonverbal cues in pitches and financing decisions (Clarke et al., 2019; Momtaz, 2021a). Notably, these subtle nonverbal cues often serve as the vehicle to communicate emotions. Yet, the complexities in capturing and interpreting nonverbal emotions led to an incomplete comprehension of their theoretical meaning with very limited empirical studies. Consequently, it becomes imperative to delve deeply into the current coding tools used in affective computing and to examine the impact of nonverbal emotion communication on early-stage resource mobilization, as well as its assessment from investment selection.

Furthermore, entrepreneurship has historically been a male-dominant sector, continuing to exhibit a pronounced disparity between the two genders. Notably, investor gender can significantly impact the success of female entrepreneurs, since the professional prototype of a successful entrepreneur appears to share traits more associated with men (Danbold & Bendersky, 2020; Solal, 2021). This reality has impacted the communication of entrepreneurs during the pitch process and different investor responses they receive. For instance, feminine behaviors during the pitch (Balachandra et al., 2019) and feminine style in the language of their pitches (Balachandra et al., 2021; Malmström et al., 2017) are negatively associated with fundraising from venture capitalists. Investors are prone to pose “prevention-oriented” questions about potential for loss rather than “promotion-oriented” questions associated with gains to woman entrepreneurs (Kanze et al., 2018), and are likely to penalize female founders for lack of industry fit (Kanze et al., 2020). One of the potential solutions to support female entrepreneurs is the increased representation of women in the investor side based on the theory of gender homophily (Greenberg & Mollick, 2017; Wesemann & Wincent, 2021), but the same gender support seems not sustainable considering the stigma of incompetence of women in entrepreneurship (Snellman & Solal, 2023). Therefore, this dissertation centers theoretically on the gender dynamics within entrepreneurship, aiming to cultivate a nuanced understanding that can inform advocacy for gender equity in the entrepreneurial landscape.

In my dissertation, I employ leading-edge coding methods to collect and analyze a range of unstructured data, including texts, images, and videos from publicly accessible websites. To quantitatively measure nonverbal emotion cues, I employ computational psychometrics, building upon an in-depth exploration of contemporary coding tools. With a theoretical focus on gender and entrepreneurship, I investigated how the strategy to show facial and vocal emotional neutrality (e.g., maintaining a neutral face, talking with a calm voice) during the pitch brings about different crowdfunding outcome for male and female entrepreneurs, and how the attention to a female-centric fraud event may change the same-gender support female venture capitalists provide for female entrepreneurs after the high-profile Elizabeth Holmes scandal. My dissertation includes three papers as specified below:

"**Quantify Nonverbal Emotions: Review and Brief Technical Exploration Using Video Analysis**" (<u>Chapter 2</u>) seeks to deepen knowledge of the emerging automatic coding tools for analyzing nonverbal emotion cues, thereby advancing future research with the application of machine learning to code entrepreneurial pitch communication. I investigate affective computing techniques as applied in 36 recent studies across social science domains of economics, finance, accounting, management, and marketing. The coding tools range from off-the-shelf software toolkits to trained models serving for specific purposes. The paper discusses the "black box" aspects of the features offered by these tools, clarifying the processing procedure that often confuse the business scholars. Further, this comprehensive review is complemented by the analysis of 50 finalist pitch videos from Antler Demo Day spanning 2019-2022, aiming to evaluate the consistency of those noncommercial opensource approaches. After comparing the generated metrics, I find Praat is appropriate for empirical voice pitch analysis, while Librosa excels in Python-based deep learning projects. For facial emotion recognition, the FER library is more reliable than DeepFace. The paper also provided a qualitative discussion about emotional disclosure in accelerator pitches of successful entrepreneurs. The results from the video analysis uncover gender-based differences in emotional expression, with men displaying a wider range of emotions and more negative facial expressions, whereas women predominantly express happiness and surprise.

"Poker Face and Steady Voice: Nonverbal Emotional Neutrality and Gender in Crowdfunding Pitches" (Chapter 3) examines how showing nonverbal emotions (e.g., maintaining a neutral face, talking with a calm voice) results in different crowdfunding outcomes for male and female entrepreneurs. Although entrepreneurs can project a sought-after image of rationality with neutral emotional expressions, it is essential to consider societal expectations toward entrepreneurs regarding emotional expressiveness, particularly the gender norm that dictate women should be more emotionally expressive than men. Leveraging pre-trained machine learning algorithms, we analyzed 183 crowdfunding videos and extracted features from verbal contents, facial expressions, and vocal tones. The findings reveal a positive correlation between demeanors that showing facial and vocal emotional neutrality and crowdfunding success for male entrepreneurs, whereas the correlation is negative for female entrepreneurs.

Notes: The early version of this project received AIDEA Grants in Rome in December 2021 and was presented at the 2022 SMS 42nd Annual Conference at London, 2023 5th IDEC *at Singapore. The recent version was presented at 2024 INFORMS OSWC at Zurich, 2024 BCERC at Munich and will be presented at AOM Chicago.*

"Women Support Women? Public Attention to Fraud Scandal and Gender Homophily in Venture Capital" (Chapter 4) builds upon previous research that suggests greater female investor participation could alleviate the funding challenges faced by female entrepreneurs, especially in early rounds. However, this same-gender support may be undermined by heightened scrutiny in the wake of high-profile fraud scandals, prompting investors to enhance their due diligence. Using the Google Trends API, I measure public attention to Elizabeth Holmes' fraud scandal and divide U.S. states into treatment and control groups based on the median keyword search index for "Elizabeth Holmes". The findings indicate that in states with heightened public attention post-scandal, startups securing initial funding rounds are less likely to have female founders when a female VC partner is involved, particularly in industries associated with Theranos.

Notes: The early version of this paper was included as the best paper in the ENT division at AOM Chicago. A 6-page abridged version is published in the Academy of Management Proceedings (Mao, 2024).

Chapter 2

2 Quantify Nonverbal Cues: Review and Brief Technical Exploration Using Video Analysis

"People's emotions are rarely put into words, far more often they are expressed through other cues. The key to intuiting another's feelings is in the ability to read nonverbal channels, tone of voice, gesture, facial expression, and the like."
(Psychologist and Author of Emotional Intelligence, Daniel Goleman)

2.1 Introduction

The past decade has seen a growing theoretical interest in the relationship between communication in entrepreneurial pitches and early stage resource mobilization (Clingingsmith & Shane, 2018; Martens et al., 2007). Notably, the subtle nonverbal cues conveyed through the tone of voice and facial expressions often serve as the vehicle to communicate emotions, showcasing personal characteristics like passion or commitment that are pivotal to an entrepreneur's appeal (Chen et al., 2009; Hu & Ma, 2021a; J. Jiang et al., 2022). These nonverbal cues can sway investor decisions when performance history is scarce, even if they do not directly forecast the new venture's forthcoming profitability or growth. However, the complexities in capturing and interpreting nonverbal emotions have led to a paucity of empirical research in this domain.

Existing research has largely concentrated on the verbal aspects of entrepreneurial pitches, with particular attention to the influence of narrative structures on funding decisions

(Anglin, Wolfe, et al., 2018; Lounsbury & Glynn, 2001; Spina & Williams, 2021; Steigenberger & Wilhelm, 2018). This emphasis is likely because verbal content is more readily quantifiable and amenable to systematic analysis than the more nuanced nonverbal cues. The prevalence of verbal analysis also stems from a possible investor bias towards concrete, logical content over the abstract interpretation of nonverbal communication, directing researchers to focus on these aspects. The trend toward verbal analysis is further reinforced by the availability of advanced text analysis tools suitable for rich verbal datasets (Gentzkow et al., 2019; Jung et al., 2024; Marshall et al., 2023), as opposed to the more sophisticated and resource-intensive methods required for video-based nonverbal behavior analysis, which also suffers from limited archival data. Therefore, management scholars exploring theoretical insights about nonverbal cues in entrepreneurial pitch often refer to experimental studies (Chen et al., 2009; Clark, 2008; Clarke et al., 2019).

Despite the mentioned challenges, the nonverbal cue analysis is on the rise across various social science domains, increasingly leveraging affective computing based on machine learning applications to enhance analyses of facial expressions, vocal cues, bodily motions, gestures, and postures during events such as financing roadshows, CEO talks, earnings conference calls, and government communications. These innovative studies have introduced opportunities to systematically quantify large-scale unstructured data derived from nonverbal interactions. A comprehensive understanding of the tools and approaches employed in such studies is crucial to advance management research concerning early-stage selection and evaluation based on a candidate's "authentic" perspective on a given matter (Choudhury et al., 2019). For instance, the integration of affective computing in analyzing nonverbal cues can enhance our insights into the elements that define a compelling entrepreneurial pitch in financing (Hu & Ma, 2021a) and the correlation between CEO facial affect and firm valuation (Momtaz, 2021b). Yet, there persists a lack of understanding surrounding the available tools, the features they offer, and the potential strengths and weaknesses associated with these approaches.

This study aims to provides clarity in the emerging affective computing application in nonverbal cue analysis. Drawing insights from 36 papers spanning the social science domains of economics, finance, accounting, marketing, and management, this article summarizes the operational functions and mechanisms of off-the-shelf pre-trained tools, as well as the processes involved in developing specialized models from scratch, highlighting their application in these studies. The detailed review is complemented by actual employment of budget-friendly options in Python environment, including Parselmouth, Librosa and openSMILE for voice feature extraction, DeepFace and FER libraries for facial emotion analysis, and a self-trained CNN model for voice emotion classification. These tools are utilized to analyze 50 finalist winner pitch videos from Antler Demo Day events between 2019 and 2022 held in Europe and Singapore.

The findings from coding tool application highlight the inconsistencies emerged from the metrics generated by opensource tools. The average pitch level and pitch variation generated by Parselmouth, Librosa and openSMILE are very different, although Parselmouth and Librosa are more closely aligned in their measurements. The DeepFace library demonstrates heightened sensitivity to the detection of negative emotions including disgust and fear, whereas the FER library more consistently identifies non-negative emotions, such as happiness and neutrality. Despite the discrepancies, the data consistently shows the pattern that entrepreneurs successfully selected by Antler accelerator predominantly exhibited happiness and anger, with women showing fewer negative emotions then men both vocally and facially. This observation aligns with the important role of positive emotions in previous literature (Hu & Ma, 2021a; L. Jiang et al., 2019) and suggests the possible difference in emotion expression bewteen men and women in entrepreneurial pitches (Davis et al., 2021).

The contribution of this study lies in enhancing the understanding of the emerging affective computing based on machine learning in nonverbal cue analysis, rather than providing definitive methodological validation or advancements. This paper presents a timely methodological review of affective computing techniques in recognized published work within various domains. The technical exploration within this study serves as a provisional guideline for codifying nonverbal cues in an entrepreneurial setting, delineating both the capabilities and the limitations of current opensource tools, while also noting the risks of potential biases in each step of the analysis. Although the study breaks new ground by applying automatic coding tools for nonverbal cue analysis in the entrepreneurial domain—a practice previously confined to neuroscience and psychology—it is imperative to recognize that these tools are still evolving. The insights primarily cater to empirical scholars in entrepreneurship, who are examining the role of nonverbal cues in securing early-stage financing, and to strategy theorists exploring the influence of individual characteristics on stakeholder engagement.

2.2 Review Framework and Theoretical Rationale

To review the research leveraging automatic coding tools for affective computing to analyze nonverbal cues in public communication, I searched for the terms “pitch video,” “video analysis,” “nonverbal communication,” “voice analysis,” and “facial analysis” for the relevant articles in peer-reviewed academic journals in business and economics domain with acknowledgement, evidenced by high impact factors in parentheses[1]. These included Academy of Management Journal (10.979), American Economic Review (11.49), American Political Science Review (8.048), Journal of Accounting and Economics (7.293), Journal of Accounting Research (4.446), Journal of Applied Psychology (11.802), Journal of Behavioral Finance

[1] The reported impact factors are updated in 2023.

(1.798), Journal of Business Venturing (13.139), Journal of Consumer Research (8.612), Journal of Corporate Finance (5.107), Journal of Financial Economics (8.238), Journal of Monetary Economics (4.63), Management Science (6.172), Review of Accounting Studies (4.011), Review of Finance (5.059), Strategic Management Journal (7.815), and The Journal of Finance (7.87). It is noteworthy that journals such as Journal of Behavioral Finance and accounting journals with smaller research community size can have lower impact factors compared to management or economics subjects with broader audience. While the impact factor may not fully reflect the research rigor of the journal, it serves as an important reference about the scholarly focus and research advancement. As such, my analysis of nonverbal communication research includes an interdisciplinary set of 17 journals with academic prestige. While nonverbal cue analysis using automatic tools is of recent growing interest, the number of published works is limited. Therefore, several SSRN and NBER working papers which share similar topics and apply affective computing are also included to constitute a meaningful review[2]. Those working papers have already received citation although not having been published yet. My search yielded 36 articles quantifying nonverbal cues in vocal, facial, and bodily dimensions from 2011 to 2023.

Clearly, the limited number of publications underscores the emerging nature of research about nonverbal cues in communication. One may question the significance of a review paper in a field where the body of literature is still in its infancy. However, it is precisely in such nascent domains that comprehensive reviews hold the most profound value. More importantly, this paper primarily aims to illuminate the methodological contributions made by each study and shed light on the available tools for the automated coding of nonverbal cues. Therefore, it

[2] SSRN (Social Science Research Network) is a repository for preliminary reports on original research in the social sciences and humanities and covers a wide range of topics. NBER (National Bureau of Economic Research) is a private, non-profit research organization dedicated to promoting a greater understanding of how the economy works. Both types of working papers are not typically peer-reviewed at the time of initial release but serve as a means for researchers to share their findings and receive feedback from the academic community.

serves as an indispensable foundational resource for researchers venturing into investigations of nonverbal cues, particularly those grappling with the complexities of measuring and interpreting them.

In fact, the importance of nonverbal cues in shaping judgments has been studied through sophisticated human-coded experiments in the fields of management, marketing, and political science. For instance, Chen et al. (2009) investigated how displaying energetic body movements, expressive body language, animated facial expressions, abundant gestures, diverse tones, and pitch variations in business plan presentations form venture capitalists' perceptions of entrepreneurial passion and their investment decisions. Clarke et al. (2019) found that entrepreneurs' use of symbolic gestures when pitching can significantly boost the appeal of their business propositions. Furthermore, Wang et al. (2017) found that the intensity of a smile shapes perceptions of warmth and competence, with broader smiles often associated with greater warmth but reduced competence. Additional research by Klofstad et al., (2015) showed that a lower voice pitch may help leaders craft favorable impressions, although vocal fry in females can be perceived negatively in contexts such as job interviews (Anderson et al., 2014). These findings underscore the critical role of nonverbal communication—encompassing vocal, facial, and bodily cues—in interactions, especially under conditions where substantial performance data is limited. Despite the rich theoretical framework surrounding nonverbal communication and its recognized influence, empirical investigations have been historically constrained by the high costs and resource demands of experimental designs, a limitation increasingly mitigated by advancements in machine learning technologies.

In finance, accounting, and economics, scholars have attempted to apply automatic coding tools in capturing and interpreting nonverbal cues to discern implications for financial systems and corporate behavior. On the one hand, nonverbal cues in voice and face are used to retrospectively detect financial misreporting or corporate misconduct (Hobson et al., 2012a;

Jia et al., 2014; Kamiya et al., 2019). On the other hand, nonverbal cues are indicators to anticipate stock returns and predict future earnings (Baik et al., 2023; Banker et al., 2021; Dávila & Guasch, 2022; Mayew & Venkatachalam, 2012). These insights suggest that nonverbal communication can exert an immediate influence on investor perceptions and actions, particularly in high-stakes scenarios where any form of disclosure holds significant value. Although the body of literature on the automatic quantification of nonverbal cues is still burgeoning, these pivotal research has already made notable contributions.

The current literature, although not extensive, as marked important advances in identifying and interpreting these subtle yet influential cues in communication. In the pages that follow, I describe, categorize, and apply the publicly accessible tools employed in reviewed studies. Detailed summaries of the extracted features, as well as inferred metrics and dependent variables used in these studies. The review and comparison of coding tools for voice analysis, face analysis, and other nonverbal cue analysis are presented in Table 2-1, Table 2-2, and Table2-3.

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2.3 Detailed Review of Automatic Coding Tools

Nonverbal communication is multifaceted, consisting of several distinct modalities: (1) kinesics, which involves body movements, encompasses gestures, facial expressions, ocular activity, and posture; (2) vocal attributes beyond spoken language, including tonal variations, pitch, and non-linguistic utterances such as laughter and yawns; (3) proxemics that deals with the perception and use of personal and interpersonal space; (4) scent and smell; (5) skin sensitivity to touch and temperature; (6) use of artifacts, like clothing and cosmetics (Duncan, 1969). Among these, affective cues in facial expressions and vocal attributes have been most extensively researched in the reviewed publications. Specific coding tools can be categorized into two main types: software based on pre-trained algorithms and those utilizing self-trained algorithms.

2.3.1 Coding Tools for Vocal Analysis

(1) Pre-trained Commercial Software

The transformative trajectory of nonverbal communication analysis began from the pioneering work of Hobson et al. (2012), which initiated the discourse on quantifying CEO voice dissonance to predict financial misreporting by employing vocal emotion analysis software developed by Nemesysco (https://www.nemesysco.com/), an Israeli provider of voice analysis technologies. Notably, Nemesysco's innovative software solution backed by Layered Voice Analysis (LVA) technology enables the meticulous extraction of nuanced voice data for emotion analysis, stress detection, personality, and risk assessment, as detailed in its validation study (Elkins & Burgoon, 2010). Further research in accounting has investigated the nuanced impacts of managerial vocal cues on future performance (Mayew & Venkatachalam, 2012) and investor response after earnings conference calls (Price et al., 2016). Additionally, Wang et al., (2021) relied on the same tool for audio mining in crowdfunding pitch videos, contributing to marketing research by revealing the persuasive role of vocal tones denoting focus, low stress, and stable emotions on crowdfunding success.

LVA technology is adept at identifying and quantifying nuanced variations in the human voice. By digitizing vocal signals without delving into the spoken content, it discerns patterns correlated with distinct emotional states, stress levels, and other notable characteristics (X. Wang et al., 2021). The graphical user interface make it easy for users to navigate and use algorithm applications. Despite the myriad of features and user-friendly advantage offered by LVA technology, its adoption is often hindered by cost considerations. Nemesysco's research support, for instance, comes with a hefty price tag, ranging from thousands to tens of thousands of US dollars. Beyond the monetary factor, LVA's "black box" aspect poses another challenge when transparency is appreciated in academic research. Since the algorithms and intricate details of their voice analysis remain Nemesysco's patented knowledge, the detailed inner workings of the algorithms are not made publicly available.

(2) Pre-trained Opensource Software for Feature Extraction

Scholars rely on pre-trained opensource software to extract fundamental features in the voice such as pitch, amplitude, and spectral components, known as low level descriptors. Tools such as Praat, openSMILE, and Librosa facilitate the automated generation of voice descriptors, streamlining the analysis process significantly. Fundamental vocal metrics, such as the average pitch over a specified time frame, can hint at aspects like emotionality and masculinity (Hu & Ma, 2021). The major body of related literature refer to Praat to generate easily interpretable voice pitch attributes (e.g., Dietrich et al., 2019; Klofstad et al., 2015; Mohliver et al., 2023), while Librosa appeared in one recent publication for extracting spectral and cepstral features, which are valuable input for supervised machine learning algorithms to predict vocal emotions (Gorodnichenko et al., 2023a). Although Hwang et al. (2021) employed openSMILE to extract loudness, pitch, and talking duration from the online influencer video data, there is currently no recognized published work that acknowledges this application. To eliminate the confusion, we detail the features of each software, and clarify the processes involved in their application.

Praat (https://www.fon.hum.uva.nl/praat/) stands as a robust audio processing tool tailored for phonetic analysis. Developed in the C programming language, it leverages pre-defined algorithms to conduct speech analysis, synthesis, and manipulation (Hwang et al., 2021). It offers a suite of tools for analyzing, editing, and visualizing various aspects of speech, such as waveforms and pitch, with notable capabilities for in-depth spectrographic analysis and visual annotations. Parselmouth library, a Python interface for Praat software, has bridged the gap between Praat's powerful phonetic analysis capabilities and the Python programming environment. While it may not be the optimal tool for feature extraction in machine learning tasks, the features it can extract are readily applicable for use in statistical empirical analyses. The features include average pitch, pitch variation, intensity or loudness in the voice, and voice quality indicators like jitter, shimmer, and the harmonics-to-noise ratio.

On another note, Librosa is a Python library originally developed to analyze and extract audio features, especially from music signals, with a focus on the needs of the Music Information Retrieval (MIR) community (McFee et al., 2015). It can extract and visualize voice features like Mel-frequency cepstral coefficients (MFCCs), spectral entropy, chroma-based features, etc. While these features do not have an intuitive or clear meaning to most people without specialized knowledge, they represent unique fingerprints of voice signals that are essential inputs in machine learning for speech recognition tasks. Librosa also works in pitch detection, able to extract average pitch and pitch variation with defined algorithm.

openSMILE (https://github.com/audeering/opensmile/releases/tag/v3.0.0, fully named as open Speech & Music Interpretation by Large-space Extraction) was originally developed using C programming language by the Auditory Vocal Signal Processing group at TUM (Technical University of Munich). Engineered for efficiency and scalability, openSMILE excels at deriving large-scale numeric voice features, establishing itself as a premier choice for a variety of tasks such as emotion recognition, speaker identification, and music classification (Eyben et al., 2010). It operates through various configurations tailored to specific applications, while it is important to note that the complete range of these configuration files might not be fully accessible within the Python environment.

In the common manner of audio processing, audio analysis tools often employ techniques such as windowing and the Fast Fourier Transform (FFT) to dissect continuous audio signals into manageable frames, extracted at specific time intervals and sizes. This procedure entails dividing the continuous audio signal into frames, determined by a selected window length, followed by the application of FFT to produce a frequency-domain representation for each frame.

Importantly, the sample rate, frame size and frame step can significantly influence the results of audio processing, so choosing the appropriate parameters to achieve desirable attributes for the task at hand is crucial. For example, given the sample rate of 22.05 kHz (22050 samples per second) using Librosa default, the frame and spacing can be calculated as below:

The actual window function applied to each frame can be specified with the window parameter in the librosa.stft() function. By default, the window function used is the 'hann' window with the size of the frame at 2048 samples[3]. The duration of each frame (determined by frame size) is:

$$\text{Duration} = \frac{Default\ FFT}{Sample\ Rate} = \frac{2048\ samples}{22050\ samples/second} = 0.093 \text{ seconds} = 93 \text{ milliseconds}$$

So, each frame of the whole audio file spans 128 milliseconds. Additionally, the number of samples between successive frames is set to frame step of 512 by default, which is a common choice for a 50% overlap between frames when using the 'hann' window (Babu et al., 2021; McFee et al., 2015). Since there is a new frame every 512 samples, frames are spaced apart by:

$$\text{Spacing} = \frac{Default\ Frame\ Step}{Sample\ Rate} = \frac{512\ samples}{22050\ samples/second} = 0.023 \text{ seconds} = 23 \text{ milliseconds}$$

Therefore, with the default parameters and a 22.05kHz sampling rate processed in Librosa, each frame spans 93 milliseconds and there is a new frame every 23 milliseconds. For openSMILE, the frame duration and spacing can be computed similarly, though the parameters for frame size and frame step might differ across its various configuration files. These parameters can be located and adjusted as needed. In contrast, Praat determines the appropriate FFT frame size internally based on user-specified values such as desired frame duration,

[3] The 'hann' window, commonly used in signal processing, applies a weighted cosine function to each frame to minimize the signal discontinuities at the beginning and end. This process, using 2048 samples per frame, reduces spectral leakage and improves the accuracy of the spectral analysis. Other windowing options include Hamming, Rectangular, Blackman, Kaiser, and Gaussian.

frequency resolution, or time step. While the underlying principles for calculating frame duration and spacing remain consistent across audio processing software, default values and the ease of configuration can differ significantly between them.

Once the unit of analysis is determined, the three tools operate to extract a variety of low-level descriptors of rudimentary voice features. The extracted features are categorized in Table 4. It is crucial to recognize that while many of these features provide valuable insights into emotions, the interpretation can be subjective and varies depending on the context, cultural norms, and individual differences. By integrating multiple features and employing machine learning models, researchers can substantially improve the precision of emotion detection from vocal indicators. This sets the stage for my exploration of pre-trained models or self-trained models designed to predict emotional states from voice.

***** INSERT TABLE 2-4 ABOUT HERE *****

(3) Pre-trained Opensource Models for Vocal Emotion Detection

There is only one paper that applied pre-trained models for higher level voice analysis to detect emotions in my review list. In a study by Hu & Ma (2021), emotional states reflected in vocal cues during entrepreneurial pitches were extracted using an SVM model from the PyAudioAnalysis library (Giannakopoulos, 2015) for emotion valence and arousal, and an LSTM (Long Short-Term Memory) model from the speechemotionrecognition library (https://github.com/hkveeranki/speech-emotion-recognition) for vocal positivity and negativity. LSTM model is a type of RNN architecture designed to recognize patterns over sequences of data, thus is highly suitable for time series data and speech recognition tasks. However, the creator of PyAudioAnalysis library has updated the opensource library mainly for audio feature extraction, classification, segmentation, and visualization issues since 2021, and the pre-trained models for emotion valence and arousal classification are not available anymore. While it provides Deep Audio API for higher level audio analysis such as musical classification, speech to text, speaker characteristics including gender and speaking style, etc. (https://labs-repos.iit.demokritos.gr/MagCIL/deep_audio_api.html), these pre-trained models serve for commercial purposes in corporation with formal projects only. Another library appears to be outdated since it requires the Python 2 series for operation and is not compatible with Python 3. Notably, Python 2 reached its end of life on January 1, 2020, meaning it no longer receives updates, bug fixes, or security patches. This suggests that the library hasn't been actively maintained, making it a potentially less reliable reference. Consequently, publicly available pre-trained models for voice emotion analysis are scarce, though a few options exist for commercial purposes.

(4) Self-trained Deep Learning Models for Vocal Analysis

With scarcity of established opensource software available, many researchers and developers use Librosa and openSMILE to extract features from audio data when building speech-emotion recognition systems (Babu et al., 2021; Eyben et al., 2010). By combining the extracted features with deep learning methods, such as convolutional neural networks (CNNs) or recurrent neural networks (RNNs), they can create models that recognize and classify emotions in speech. openSMILE has its strengths and is favored in many academic and industry applications where robust and standardized feature extraction is required, while Librosa is especially popular in Python-based projects. For instance, in a study by Gorodnichenko et al.(2023) published on American Economic Review, Librosa was used to extract 180 vocal features, including 128 mel coefficients, 40 MFCCs, and 12 chroma coefficients, from audio materials in two labeled audio databases, the Ryson Audio-Visual Database of Emotional Speech and Song (RAVDESS) and Toronto Emotional Speech Set (TESS). These features were then employed to construct a CNN model using 80% of the two labeled database as training data, which achieves the accuracy rate of 84% in the rest 20% data for test. Specifically, the algorithm achieves accuracy scores of 87%, 84%, 74%, 87%, and 80% for angry, sad, neutral, pleasantly surprised, and happy, respectively. This self-trained model was applied to predict the economic impact of vocal emotion cues in Federal Open Market Committee (FOMC) communication. After controlling for the Federal Reserve's actions and the sentiment in policy texts, the detected positive tone in the voices of Federal Reserve chairs was found to significantly increase share prices in the first 15 days after the policy communication.

Overall, the reviewed papers leveraging automated coding tools to quantify vocal cues in communication primarily depend on library toolkits to extract fundamental voice features that are intuitively meaningful as an inference about certain emotional states for empirical analysis. For more advanced emotion detection in voices, the trend is either to rely on specialized commercial software or to directly apply pre-trained models without further finetuning; while validated pre-trained software and building deep learning models are not common practices.

2.3.2 Coding Tools for Facial Analysis

(1) Pre-trained Commercial Software

Facial analysis has seen significant development partially because facial data can be incredibly rich in information and there is a high demand for understanding and interpreting this data in various fields such as security, marketing, psychology, and entertainment. Several established commercial software are available for researchers to generate affective metrics from human face, including AFFDEX and FACET in iMotions's software suite and FaceReader marketed by Noldus as mentioned in the published work (Lewinski et al., 2014; Stöckli et al., 2018; van Kuilenburg et al., 2005). AFFDEX, initially developed by Affectiva, features technology that has been integrated into the iMotions platform. On the other hand, FACET originated from a foundation built upon another software known as CERT (Littlewort et al., 2011) and was distributed by Emotient. In 2016, iMotions announced a switch to AFFDEX after the acquisition of Emotient by Apple Inc. (*Guides and Product Information - iMotions*, 2022). Meanwhile, FaceReader had its beginnings in the development efforts of VicarVision (Uyl & Kuilenburg, 2006). The validation studies conducted on AFFDEX, FACET (Stöckli et al., 2018) and FaceReader (Version 6; Lewinski et al., 2014; Uyl & Kuilenburg, 2006) yielded classification accuracies of 70% (AFFDEX), 96% (FACET) and 88% (FaceReader) for faces within the two datasets that contain publicly available validated facial expressions of emotions - Warsaw Set of Emotional Facial Expression Pictures (WSEFEP) and the Amsterdam Dynamic Facial Expression Set (ADFES).

These three software tools identify faces within images or video streams, recognize key facial landmarks such as eyes, nose, mouth, and eyebrows, and utilize unique underlying deep learning models trained on extensive databases to categorize basic emotional expressions, including anger, disgust, fear, happiness, sadness, surprise, and neutrality. Recent studies have started using these machine classification tools to derive facial emotion metrics based on the returned confidence scores associated with specific emotions. A few studies relied on iMotions's FACET module to extract the facial emotions of crowdfunding entrepreneurs and microlenders to predict their persuasion performance in early stage resource mobilization (Davis et al., 2021; Warnick et al., 2021). Furthermore, Jiang et al. (2019) revealed the advantages of incorporating a higher level of peak displayed joy, particularly in the initial and concluding phases of a crowdfunding pitch using FaceReader, while the duration an entrepreneur maintains the peak level of displayed joy demonstrates an inverted U-shaped relationship with funding performance. FaceReader is also utilized in economics and finance domains. For instance, Zhang et al. (2022) measured emotions expressed on the faces of Fed chairs during congressional testimonies and found that increases in facial emotionality during these testimonies generally raise the S&P500 index and lower the VIX, ultimately shaping market responses to Fed communications. Besides, Breaban & Noussair (2018) found a positive correlation between traders' positive emotional states and asset market purchases and overpricing, with facial fear correlating with selling, low prices, and price decreases.

Similar to the commercial software for voice analysis, the expense of acquiring a single system for facial analysis usually falls within the higher four- or lower five-digit range, leaving researchers with limited flexibility to reassess their decision once they have invested. Owing to advancements in computer vision and deep learning, commercially viable alternatives have emerged, including Application Programming Interfaces (APIs) offered by leading technology companies. APIs are characterized by more affordable pricing options, making them accessible to a broader range of users. These APIs use machine learning algorithms trained by the provider, often deep learning models like convolutional neural networks (CNNs), to detect and process human faces within digital images or video streams. Users can also choose to access the service locally by requesting authentication keys and run it on their own device or server or access over the internet. Advanced APIs may offer related functionalities like facial recognition or emotion detection. The notable examples of API include Google Cloud Vision, Microsoft Azure and Amazon Rekognition. However, the availability of validation studies assessing the accuracy of these APIs is somewhat limited, with only one conference paper offering insights into their performance in predicting specific emotions using the Karolinska Directed Emotional Faces Database (KDEF) (Al-Omair & Huang, 2018). Google Cloud Vision API supports detecting anger, joy (happiness), sorrow (sadness), and surprise. It delivers numeric likelihood scores, ranging from 0 (indicating uncertainty) to 5 (indicating a high likelihood). It achieves accuracies of 45% (anger), 100% (joy), 95% (sorrow), and 99% (surprise). In contrast, Microsoft and Amazon APIs furnish precise results representing confidence percentage rates with significant variations. Amazon Rekognition can predict emotions such as anger (31%), calmness (94%), disgust (32%), happiness (100%), sadness (49%), and surprise (77%). Meanwhile, Microsoft Azure Face API demonstrates varying accuracies for anger (59%), disgust (72%), fear (18%), happiness (100%), neutrality (100%), sadness (86%), and surprise (96%). Overall, these commercial APIs seem to perform better for emotions like happiness and surprise.

Numerous studies have harnessed the capabilities of Microsoft Azure Face API to extract confidence scores representing positive or negative facial emotions, employing these metrics as crucial predictors of audience responses. For instance, in a study by Curti & Kazinnik (2022), it was observed that investors exhibited adverse reactions when confronted with negative facial expressions during a press conference. Notably, this reaction persisted even after controlling for the verbal content of the conference and other explanatory variables. Additionally, Zhang et al. (2022) generated emotionality metrics in the facial dimension, further showcasing the versatility of this tool. Choudhury et al. (2019) identified distinct facial features to explore and analyze CEO communication styles. Using Face ++ API, Hu & Ma (2021) found that investors demonstrated a greater willingness to finance startup founders who displayed positive facial expressions in accelerator application videos, of which the accuracy has not been examined in the published validation study yet. Flam et al. (2020) applied Amazon Rekognition in their study to investigate the CEO facial expressions of anger during television interviews. Their findings revealed that CEO expressions of anger were more likely to manifest when CEOs exhibited higher overall expressiveness, when journalists displayed angry facial expressions, and when recent stock returns were on the lower side. Importantly, the study also illuminated the negative impact of CEO facial expressions of anger on investor reactions. CEO anger, it was found, could effectively nullify the positive effects of a journalist's otherwise favorable message.

(2) Pre-trained Opensource Software

Earlier work in this area applied Image J (https://imagej.nih.gov/ij/download.html) to calculate the facial width-to-height ratio (fWHR), which is a basic facial feature measuring masculinity. Previous studies extracted this features for the purpose of deducing aggression, dominance, or risk-taking behavior and identifying its connections to financial misreporting (Jia et al., 2014), financial analyst achievement (He et al., 2019), firm risk (Kamiya et al., 2019) and CEO succession (Gomulya et al., 2017). Image J is a Java-based, freely available image processing program that can be accessed online as an applet or downloaded as an application, compatible with any computer equipped with a Java 1.4 or later virtual machine. In recent years, it has introduced pyimagej module in Python that integrate ImageJ functionality with Python. We did not include this measure in the application, since fWHR is not directly used to measure emotionality. Moreover, the findings on fWHR are mixed, and its usage is a subject of ongoing debate within the scientific community.

As for the extraction of advanced facial features like emotions and attractiveness, the previously mentioned commercial solutions have served as the mainstream option for researchers, and published work applying opensource libraries is rare. This trend may stem from the comprehensive capabilities of commercial software, which comes equipped with all necessary models to detect and analyze human faces, as well as for computing confidence scores for sophisticated facial attributes (age, gender, emotion, and race). In contrast, open-source toolkits and pre-trained models are often constructed with a narrower focus, usually optimized for a select few functions. In the review, only one study utilized DeepFace to categorize YouTube influencer race and gauge seven distinct emotions, using the results to shape demographic control variables in their empirical analysis (Hwang et al., 2021). DeepFace (https://github.com/serengil/deepface) is a versatile toolkit for face recognition and facial attribute analysis. While DeepFace might hold an advantage in accuracy due to its advanced model support, the real-world performance can differ based on specific context. Rigorous testing and evaluation are essential, especially given the current lack of validation studies in this domain.

(3) Self-trained Deep Learning Models for Facial Analysis

Since pre-trained models are often developed on datasets that might not be representative of the specific demographic or conditions of interest, training a model on a dataset curated for the research ensures the model is fine-tuned to relevant facial attributes is not uncommon. For instance, Hwang et al. (2021) trained a CNN model on the SCUT-FBP5500 dataset (Liang et al., 2018) to score each influencer's attractiveness to account for a possible attractiveness premium. From a similar vein, a study by Banker et al. (2021) utilized Dlib face recognition algorithm (King, 2009) to create a metric that quantifies the dynamic hemifacial asymmetry (HFAsy) of facial expressions. Their findings indicated that the stock market reacted negatively when confronted with CEO's HFAsy as displayed in interview videos. Additionally, they observed that the market's response to positive earnings news was inversely correlated with the CEO's HFAsy. The development of deep learning algorithms broadens the range of information extracted not only from facial cues but also from general visual cues. Research has begun to build deep learning algorithms to detect general visual information like affective visual expression from frames both with and without faces (Y. Huang et al., 2023), and to identify facial trustworthiness from certain combinations of facial features (Duan et al., 2020; Hsieh et al., 2020).

Overall, employing fundamental facial features as a metric for investigating research questions is less prevalent in comparison to voice analysis. Researchers predominantly depend on well-established commercial software or APIs to extract facial emotions or other psychometrics. Leveraging the abundance of readily available resources, the development of deep learning models tailored for specific innovative classifications is also gaining popularity in studies applying automatic tools for facial analysis.

2.4 Application of Automatic Coding Tools

2.4.1 Potential Source of Inconsistence Prior to Analysis

From pre-trained commercial software, Python-based library toolkits and models, to custom deep-learning algorithms, these tools empower researchers to explore and decode the subtle yet powerful expression of nonverbal communication in the voice and face. The choice of which approach to adopt hinges on several critical factors, including the specific nonverbal features to analyze, the importance of validity and accuracy in the project, the allocated research budget, available computational resources, and the level of technical proficiency within the team. A careful consideration of these factors will guide the selection of the most suitable approach for nonverbal cue analysis endeavors.

Nonetheless, the significance of adept preprocessing—deciphering input data from audio, visual, or video content—cannot be understated, as it profoundly influences the outcome's accuracy and consistency. Paramount among these considerations is the quality of data. For auditory information, eliminating background noises or disturbances can help in isolating the speaker's voice and more accurately analyzing it. When working with facial imagery, actions such as rotation, scaling, flipping, and meticulous face isolation can circumvent the examination of extraneous data. It's also vital to elucidate the segmentation protocols employed for both audio and video content, ensuring that the extraction of pertinent features is transparently detailed. As an illustration, variations in audio data's sample rate, frame size, and frame step can result in disparate segmentations of the entire audio file, leading to discrepancies in metrics like average pitch. For facial expressions, the specific facial landmarks, the dimensions of facial embeddings and the approach used to calculate the distance between them might introduce variances in facial recognition outcomes. Finally, it is imperative to navigate the ethical landscape with caution when it comes to nonverbal cues of human beings. Models can sometimes mirror biases present in the training data, leading to skewed or discriminatory outcomes. Being aware of these inherent biases beforehand can mitigate their influence on the metrics derived.

After conducting an extensive review of the various coding tools presented in contemporary literature, this paper has sought to apply the publicly accessible options in practical settings. The opensource utilities are prioritized because of the cost constraints and the intention to explore opensource yet potent methods in nonverbal cue analysis. The application aims to shed light on the nonverbal interactions and emotional expressions of successful entrepreneurs during accelerator programs' initial selection phases. Our focus is on extracting the average pitch level and pitch variability—key indicators of emotionality in the voice—alongside machine predicted metrics of vocal and facial emotions.

2.4.2 Data Collection

I gathered data from Anteler's YouTube channel, a Singapore-based accelerator committed to supporting entrepreneurs from the outset. Anteler carefully chooses and invests in startups, offering valuable services such as co-founder matching, thorough business model validation, initial capital injection, expansion support, and follow-on funding (https://www.antler.co/). As part of my data-gathering process, I correlated publicly accessible pitch videos from Anteler Demo Day. During this event, each startup is allotted around 3 minutes to present their venture, showcase their progress, and seek potential funding support. Subsequently, I matched these pitch presentations to the startups that were officially selected and featured on the Anteler website. Given that Anteler's YouTube channel does not publish all of its Demo Day videos, the matched sample comprises a total of 50 entrepreneurs who have received recognition and support from Anteler and showcased through these available videos between 2019 and 2022. Twenty-five entrepreneurs attended the event in Singapore, while the remaining 25 were present at events in three European cities: London, Amsterdam, and Stockholm. There are 11 female entrepreneurs in total in the sample.

2.4.3 Video Data Preprocessing

The video data is decomposed into auditory and visual components (Hu & Ma, 2021a; Hwang et al., 2021). Each dimension, whether vocal audio or visual stream, is further dissected into smaller units for in-depth examination. After individual unit analysis, the results are averaged and aggregated to provide an overarching insight at the video level. The entire procedure was executed within the Python environment.

The initial step involves extracting audio from the video utilizing the moviepy library and transitioning it from an mp4 format to a wav format. The derived raw audio files possess a sample rate of 44.1 kHz at stereo channel, a standard in audio CDs and a prevalent choice for professional audio recording and playback. Using Librosa, we processed these audio files for noise reduction and subsequently exported them at mono channel and two distinct sample rates: 44.1 kHz and 16 kHz, organizing them into separate directories. The frequency range of the human voice generally spans from 80 Hz to 14 kHz. Specifically, an average adult male's voiced speech exhibits a fundamental frequency between 85 to 155 Hz, while an adult female's lies between 165 to 255 Hz (Baken, 1987). As such, the original 44.1 kHz sample rate is optimal for listening and rudimentary feature extraction. In contrast, the 16 kHz sample rate offers an efficient option for deep learning, striking a balance between capturing essential human speech nuances and ensuring reduced computational demands.

Subsequently, we extracted frames from the video at 0.1- second intervals, generating a sequence of images that encapsulated the video's essence, all stored in a singular folder. It is worth noting that the algorithm could potentially classify the faces of founding members in slides and audience members in archival pitch videos as facial objects, which is not the focal presenter for analysis. To address this, it is necessary to pinpoint an image emblematic of the presenter to serve as a benchmark in advance. This reference image will guide the algorithm to track only the presenter throughout the analysis, minimizing distractions from extraneous faces. To determine the reference image, potential strategies could involve the algorithm detecting the most frequently occurring face over the image folders, or manually identifying the presenter. After that, the face recognition algorithm can employ facial embedding comparisons to accurately identify the presenter in the images containing multiple faces based on the facial similarity. To make it easier, many commercial software tools and APIs come with built-in capabilities to identify the primary speaker automatically. This paper follows the manual check procedure. The video data processing framework is illustrated in Figure 2-1.

***** INSERT FIGURE 2-1 HERE *****

2.4.4 Vocal Analysis

(1) Extract Basic Voice Features Using openSMILE, Librosa and Parselmouth

In this section, we employed openSMILE, Librosa, and Parselmouth to calculate directly interpretable low-level voice descriptors of a presenter and to assess each software's functionality. To enhance comparability of the extracted features, this study concentrates on universally recognized variables such as voice pitch and its variability. These attributes are not only prevalent but also offer straightforward interpretability and possess tangible implications in practical scenarios.

We utilized the default "emobase" configuration of the openSMILE to extract average pitch level and pitch variability, as cited by Hwang et al. (2021). Since openSMILE presents a challenging interface for parameter adjustments within its unique configuration files, we took the parameters used in the "emobase" configuration file as the reference for other two software. As detailed in the configuration, pitch detection involves 40ms frames with a 10ms step, using an autocorrelation method.

To ensure consistency between the processing of Librosa and openSMILE, the FFT (Fast Fourier Transform) size and the window length parameters in Librosa were adjusted to correspond with those utilized by openSMILE. Parselmouth, a Python interface for Praat, differs by determining the optimal window length based on minimum pitch, rather than an exact parameter set by the user. Therefore, we can only maintain a 10ms frame step to keep consistency with openSMILE and Librosa. As for the pitch detection method, there are a variety of pitch calculation algorithms such as YIN algorithm, PYIN (probabilistic YIN) algorithm, and dynamic wavelet algorithm. The pitch analysis in Praat is performed using an autocorrelation method, calculating the similarity between the signal and delayed versions of itself to find the pitch frequency. Librosa provides several algorithms for pitch detection, including YIN and probabilistic YIN (pYIN). The YIN algorithm is also an autocorrelation-based method that is particularly designed for estimating the fundamental frequency or pitch of a sound. pYIN is a more advanced version that includes a probabilistic model for handling the uncertainty inherent in pitch detection and providing a smoother pitch contour. openSMILE utilizes three primary methods for pitch tracking: the Autocorrelation Function (ACF) and the Cepstrum method, as well as the Subharmonic-Summation (SHS) method. While we can stick to the method sharing the conception of autocorrelation when estimating pitch levels, the actual processing steps vary.

As such, the inherent algorithmic differences, configuration settings, and intended uses of these tools likely lead to variations in the pitch outputs. As present in Table 4, mean average pitch is around 174.66 Hz for Praat, compared to higher mean average pitch generated by Librosa at 183.93 Hz and much lower mean average pitch estimated by openSMILE at 100.67 Hz. Pitch variability indicates how much the pitch changes, while this statistical descriptor of Librosa and Praat are nearly double to that eatimated by openSMILE. Figures 2-2 and 2-3 graphically depict the inconsistency among the average pitch and pitch variability measurements when compared across three distinct software tools. In Figure 2-2 that visualized the mean values in histograms, Praat and Librosa show similar mean for average pitch measurements, although Librosa's mean is slightly higher, while for pitch variability, Librosa and openSMILE report higher mean values than Praat, indicating potential differences in their variability estimation methods. As shown in boxplots of Figure 2b, Praat tends to measure a lower average pitch and less pitch variability, while Librosa reports higher values for both average pitch and pitch variability. openSMILE sits in the middle for average pitch but closer to Librosa in terms of pitch variability. As such, Praat generally measures a lower average pitch compared to Librosa and openSMILE, with openSMILE showing a higher sample median average pitch than Praat but lower than Librosa. Regarding pitch variability, Librosa and openSMILE display higher sample median values than Praat, suggesting they might be more aligned in measuring pitch variability. Interestingly, the three tools consistently show that the outliers of high voice pitch comes from Asian women, while the outliers of high pitch variability comes from white men.

***** INSERT TABLE 2-4 and FIGUREs 2-2 & 2-3 ABOUT HERE *****

Furthermore, the correlation coefficients between the outputs of Praat, Librosa, and openSMILE shown in Table 2-5 reinforce the inconsistence in their measurements. Praat and Librosa are generally more closely aligned in their measurements of pitch average and variability, whereas openSMILE does not seem to correlate well with either Praat or Librosa for these pitch measurements.

***** INSERT TABLE 2-5 ABOUT HERE *****

The consistency in average pitch level between Praat and Librosa, and the inconsistencies in pitch variability metrics across all three tools, can be due to a combination of methodological and implementation differences, despite efforts to standardize the measurement conditions. The difficulty of adjusting parameters in openSMILE could mean that its settings are not perfectly matched with the other tools, even if the intention was to align them. Adjusting the FFT size and window length in Librosa to match openSMILE's was an effort to standardize the resolution and the amount of signal processed in each frame. However, if the FFT algorithm or windowing function is not identical, this can lead to differences in the spectral content analysis, which affects pitch estimation. Praat, through Parselmouth, adjusts window length based on the minimum pitch. This means Praat's analysis is more adaptive to the signal's content, which can lead to more accurate results for some types of voices but can also cause inconsistencies when compared to tools using fixed parameters. Furthermore, each tool might have different underlying models and assumptions. For instance, they might handle noise and harmonics differently, have different thresholds for considering what constitutes a voiced versus unvoiced frame, or use different methods to handle octaves or harmonics errors. It's a complex challenge to normalize different signal processing tools for comparative studies because even small differences in how signals are analyzed can lead to significant variations in the output.

Subsequently, we compared pitch metrics across three voice coding tools in a more detailed way, separated by gender and temporal segments. As illustrated in Table 2-6 and Figure 2-4, Praat and Librosa reports similar average pitch values for both genders, while openSMILE reports significantly lower average pitch values compared to the other two tools. Overall, there is a clear distinction between the average pitch of males and females, with women at higher average pitch levels. As for pitch variability, Librosa tends to show higher pitch variability for both genders compared to Praat, while openSMILE shows the least variability. Furthermore, male voices show more pitch variability than female voices when using Praat, whereas the metrics generated by openSMILE and Librosa demonstrate the opposite trend. The boxplots in Figure 2-5 give a more detailed view of the sample distribution of average pitch and pitch variability values for males and females across the three tools. For males, Praat and Librosa have similar sample median and interquartile ranges, while openSMILE's sample median for males is much lower, and the data is tightly clustered. For females, the same pattern is observed, but with higher pitch values, consistent with the typical differences between male and female voice pitches. The spread and central tendency of pitch variability data in both gender groups are consistent with previous findings from the full sample.

***** INSERT TABLE 2-6 and FIGUREs 2-4 & 2-5 ABOUT HERE *****

To validate the observed gender pattern, we conducted the t tests of the average pitch and pitch variability between men and women. As shown in Table 2-7, significant differences were found in average pitch across all three audio analysis tools ($p = 0.001$). Similarly, pitch variability generated using openSMILE exhibited significant disparities ($p = 0.001$), whereas Praat and Librosa showed no significant gender differences in pitch variability. Overall, the three tools consistently reveal the gender pattern that men have a lower average pitch than women, despite previously documented inconsistencies in the specific values they generated.

***** INSERT TABLE 2-7 ABOUT HERE *****

When splitting pitch metrics across different segments of audio recordings, Librosa consistently measures a higher average pitch than Praat and openSMILE, and Praat generally report lower pitch variability compared to Librosa and openSMILE. This could suggest that the tools are consistent in their measurement approach across different parts of the audio samples. Moreover, it appears that average pitch levels reported by Librosa are higher in the opening and closing 30 seconds compared to the average pitch level during the video. Conversely, average pitch levels decreased in the first and last 30 seconds according to openSMILE. This suggests that there might be a changing trend of average pitch at the beginning and end of the presentation, but the direction is unclear. As for pitch variability, the values across three tools are uniformly higher in the first 30 seconds of the video. Librosa shows a slight increase in the last 30 seconds compared to the first 30 seconds, while Praat's and openSMILE's variability remain relatively consistent with their initial values. This could imply that pitch variability tends to be higher at the beginning of the entrepreneurial pitch sample. As shown in Table 2-8, while the observed differences in pitch variability across the tools do not reach statistical significance, the variation produced by Librosa approaches the threshold of significance ($p = 0.05$). Therefore, we are not confident about the temporal patterns observed from the descriptive visualization of data.

***** INSERT TABLE 2-8 ABOUT HERE *****

When interpreting these results, it is important to consider that the extracted voice feature during the entrepreneurial pitch speech can be influenced by many factors, such as the method of pitch extraction, the type of audio processed, and the specific settings used in each tool. Despite standardizing the pitch extraction parameters and audio type for the software tools, the differing algorithmic strategies for pitch measurement have contributed to the discrepancies in their results. These variations underline the critical need for corroborating findings with additional methods or analyses to ensure the reliability and validity of conclusions drawn from vocal features. Interestingly, despite these challenges, the consistency observed in the gender pattern across the three tools offers valuable insights, which enlighten further understanding of the nuances in entrepreneurial pitches. Therefore, this analysis not only underscores the necessity of a multifaceted approach to validate the robustness and defensibility of conclusions drawn from vocal feature analysis but also unveils theoretically intriguing prospects for future research in entrepreneurial pitch studies.

(2) Vocal Emotion Prediction Using CNN Model

As mentioned earlier, the commercial software for emotion prediction is costly, and the financially friendly options are prioritized. Due to the scarcity of validated pre-trained models in this domain, we replicated the method of Gorodnichenko et al. (2023) to train a deep learning model for classifying audio tracks by emotion in the following section. We processed audio files with a sampling rate of 16 kHz and a mono channel configuration using the Librosa package (Pan et al., 2010). For analysis, the video frames are extracted at intervals of 0.032 seconds with a duration of 0.128 seconds. The extracted features include 128 Mel spectrogram frequencies, a complete spectrum encompassing 12 chroma coefficients, and 40 MFCCs. The number of Mel spectrogram frequencies typically ranges from 32 to 128, while the common range for MFCCs lies between 12 and 40. Utilizing a greater number of features facilitates finer frequency resolution, albeit at the expense of increased computational complexity. Therefore, this chosen feature set is tailored for a more detailed analysis of the audio, striking a balance between comprehensive frequency representation and computational manageability in the neural network.

The neural network is built using Keras, a deep learning API run on top of Google's machine learning platform TensorFlow. We used 80% of TESS and RAVDESS data to train the network and tested the CNN model on the remaining 20%, as suggested by Gorodnichenko et al. (2023). 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. 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 2,000 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. Finally, the categorical cross-entropy loss function which minimizes the distance between the distribution over pre-defined emotions and the "model" distribution over predicted emotions is used to optimize the parameter values.

The model attains an accuracy rate of 85%, closely aligning with the 84% accuracy of the replicated model. The accuracy scores for each emotion class—angry, happy, neutral, pleasantly surprised, and sad—are 92%, 71%, 87%, 93%, and 83%, respectively, paralleling the performance of the original model in the published work.

We implemented the trained algorithm to analyze the vocal emotions within 50 entrepreneurial pitch recordings, assessing the entire audio, as well as segments from the opening and closing 30 seconds. Figure 2-6 shows that "happy" is the most frequently detected emotion, which could suggest that entrepreneurs tend to convey positive emotions more often to strategically project optimism and confidence about their ventures. The heatmap on the right compares the prevalence of emotions both overall and specifically within the initial and final 30-second segments. It reinforces the observation that "happy" is the most consistently expressed emotion throughout the pitches, with no significant variation between the beginning and end. The consistent representation of emotions across all three categories suggests a uniform approach to emotional expression throughout the pitches.

***** INSERT FIGURE 2-6 ABOUT HERE *****

Figure 2-7 provides a detailed analysis of emotional expression by gender across various time segments in the pitches. "Happy" and "angry" are the predominant emotions for both genders, with a broader emotional range displayed by males. Happiness serves as a compelling indicator of passion for the venture, whereas anger effectively emphasizes the urgency and significance of the issues addressed by the business. Notably, "sad" and "neutral" are more frequently manifested by males, potentially reflecting a strategy to end pitches on a serious note, underscoring the importance of the challenges their ventures seek to overcome.

Conversely, female entrepreneurs predominantly exhibit happiness or anger in their voice, seemingly limiting the expression of negative emotions. This may be more than a mere strategic choice; it could also be a response to societal norms that expect women to maintain a warm demeanor. The data on the proportion of emotions expressed by different gender groups shown in Figure 2-7 could hint gender-specific communication styles and emotional responses utilized by different gender groups within the entrepreneurial domain.

***** INSERT FIGURE 2-7 ABOUT HERE *****

Additionally, we offer nuanced analysis of the acoustic characteristics of voice data, categorized by emotional expression, by correlating the identified vocal emotions with the previously extracted basic voice features. The first figure of Figure 2-8 shows the distribution of Praat extracted features across the vocal recordings for each emotion category. The angry vocal emotion appears to have a higher median pitch compared to other emotions, followed by the happy emotion in the voice. Moreover, the happy and angry emotions show higher intensities than other emotions, which may reflect strong, energetic vocal expressions. The rest figures provide parallel analysis using basic voice features extracted by Librosa and openSMILE. The patterns are consistent with Praat outputs. It is noteworthy that there appears to be a discrepancy with the observations of average pitch and intensity for neutral emotional expression. Praat and Librosa outputs demonstrate a tendency for entrepreneurs to express neutrality with a higher pitch and greater intensity, while openSMILE shows the opposite, which suggests there may be a lack of precision in the feature extraction performed by openSMILE. However, it is crucial to approach this conclusion cautiously based on a single observation of neutral voice emotion, which might not be representative.

***** INSERT FIGURE 2-8 ABOUT HERE *****

(3) Discussion about Vocal Emotion Expression of Entrepreneurs

In analyzing the vocal expressions of entrepreneurs during pitch presentations for the accelerator selection, a consistent trend emerges that happiness is the most frequently detected emotion. Such a trend persists throughout the pitches from start to finish, indicating a possible uniform approach to emotional delivery during these entrepreneurial pitches. Additionally, gender-specific patterns in emotional expression are evident. Both male and female entrepreneurs frequently express “happiness” and “anger”, yet there is a notable gender difference in the range of emotions displayed. Male entrepreneurs exhibit a wider array of emotions, while female entrepreneurs predominantly express “happiness” and “anger”, with a less frequent display of negative emotions. These observations may reflect both strategic communication choices and societal expectations regarding gender and emotional expression. Overall, the emotional landscape in the vocal dimension within entrepreneurial pitches is consistent with previous literature.

Furthermore, the acoustic examination that associates vocal emotions with basic voice features uncovers discrepancies in measurements of pitch and intensity when using different coding tools. Notwithstanding these variations, the overall data using Praat suggest that “neutral” vocal expressions tend to have a lower median pitch and less variability, indicating a more stable tone of voice. However, discrepancies in pitch and intensity for “neutrality” when analyzed by openSMILE hint at potential inconsistencies in feature extraction methods. As shown in Table 2-9, the average pitch and pitch variability are not correlated to any of the predicted vocal emotions in this dataset. As such, this inconsistency suggests the challenges in capturing voice feature extraction and emotions.

***** INSERT TABLE 2-9 ABOUT HERE *****

2.4.5 Facial Analysis

Our investigation delves into the "black box" of machine learning algorithms by analyzing facial emotions in entrepreneurs' pitch videos. We do this not to assess the validity of various machine learning tools but to compare their predicted outcomes and to understand the workings behind them. To achieve this, we've chosen the FER and DeepFace libraries for their accessibility and cost-effectiveness, which could prove beneficial for researchers with limited budgets. These tools diverge from the commercial software typically used in current publications for facial emotion prediction.

The FER library (available at https://pypi.org/project/fer/) is designed to detect faces in images and estimate the expressed emotions, offering two models for face detection: OpenCV and MTCNN. DeepFace (accessible at https://github.com/serengil/deepface) goes further by providing a suite of state-of-the-art models for facial recognition and facial feature analysis, including age, gender, emotion, and race prediction. In our application, we utilized both OpenCV and MTCNN models for face detection, noting significant differences between them in terms of computational speed and accuracy. OpenCV uses a Haar Cascade classifier for face detection, which is a supervised learning model relies on pre-trained Haar features and a cascade function to detect faces. MTCNN, on the other hand, is a deep learning model that uses a cascaded structure with three stages of convolutional networks, able to detect faces in different scales. MTCNN is more sophisticated and tends to yield higher accuracy, especially in detecting faces under various conditions then OpenCV, while its computational intensity makes it slower than Haar Cascade in processing. We can have the outcome generated from the following four combinations: FER – opencv, FER – mtcnn, DeepFace – opencv, DeepFace – mtcnn.

Furthermore, due to time and computational constraints, we streamlined the process by focusing solely on emotion analysis and excluding the facial recognition step typically used to identify the presenter in multi-face images. We manually selected a subset of images from the pitch videos, specifically focusing on moments that showcase only the presenter, excluding introductory and concluding greetings, as well as team introductions. This selective approach concentrates our analysis on the core presentation, offering a detailed examination of the emotional expressions during the most critical moments of the pitch.

(1) Raw Confidence Score Comparison

The analysis deconstructed each video into a sequence of images, each tagged with confidence scores for seven emotional states: anger, disgust, fear, happiness, sadness, surprise, and neutrality. We initially conducted a comparison of the mean confidence scores derived from all images captured throughout the entire pitch process. This comparison reflects the average confidence level associated with each identified emotion, as determined by four distinct analytical tools. Notably, the FER library outputs confidence scores with two decimal places, whereas the DeepFace library presents its results as percentages. By converting the DeepFace percentages to a similar two-decimal format, a more equitable comparison was achieved. As shown in Table 2-10, there is a notable uniformity in the detection of sadness across all tools, whereas other emotions were characterized by more pronounced variability. The FER library displayed a propensity to assign higher scores for neutral, angry, and happy emotions, aligning with the positive emotional range often presented in entrepreneurial pitches. In contrast, DeepFace was inclined to assign greater mean scores to disgust, fear, and neutrality, indicating a possible algorithmic sensitivity to more negative or subdued affective states.

***** INSERT TABLE 2-10 ABOUT HERE *****

We visualized the mean confidence scores, as well as the maximum and minimum confidence scores attained by each tool for the respective emotions in Figure 2-9. A pronounced divergence is observed in the detection of disgust emotions, with DeepFace exhibiting significantly higher peak scores compared to the FER library. This may indicate DeepFace's acute sensitivity to negative emotions such as disgust and fear. The FER library, which demonstrated high confidence scores for neutral expressions and moderation in its peak scores for emotional expressions, offered a more restrained assessment of emotional intensity. Further, the DeepFace library's tendency to report lower confidence scores for a broad spectrum of emotions, as opposed to its significantly higher confidence levels at moments of intense emotional expression, may indicate a conservative methodology in recognizing more nuanced emotional states. Conversely, FER generally reported higher minimum scores, notably for the neutral emotions, implying a robust baseline confidence in detecting a lack of emotional display.

***** INSERT FIGURE 2-9 ABOUT HERE *****

Table 2-11 presents an analysis of the correlations among raw confidence scores for each predicted emotion, as obtained from various facial analysis coding tools. Notably, the scores generated by DeepFace, when coupled with two disparate face detection algorithms, exhibited a strong positive correlation, significant at the 0.001 level. A similar degree of positive correlation is observed within the outputs of the FER library across different detection methods. Despite a near absence of correlation is noticeable when comparing the results between the two libraries, DeepFace and FER, the confidence scores of happy and sad facial expressions are barely correlated among the four tools at the 0.05 level. However, the overall lack of correlation reinforces divergent detection paradigms or differing sensitivity to the emotions being analyzed.

***** INSERT TABLE 2-11 ABOUT HERE *****

Furthermore, Table 2-12 provides correlation coefficients for the raw confidence scores of opposite emotions as recognized by the four facial analysis coding tools. It expands upon the concept of emotion detection by contrasting certain emotions against their opposites and examines how similarly or differently the tools score these opposing emotional states. For instance, anger refer to the confidence scores of anger, while non-anger is the sum of the rest of emotions including disgust, fear, happy, sad, and surprise. A negative coefficient indicates that as the tool's confidence in detecting one emotion increases, its confidence in the opposite emotion is expected to decrease. However, a positive coefficient would be counterintuitive, suggesting that the tool's confidence increases for both the emotion and its opposite, which should theoretically not occur. The statistically positive correlation between confidence scores of the emotion and the sum of the others of the DeepFace library suggests that it may not differentiate as reliably between a certain emotion and the absence of this emotion, as their confidence scores to increase together. In the further examination of correlations between positive and negative emotions, as well as neutral and non-neutral emotions, the coefficients are statistically positive for the DeepFace library, but statistically negative for the FER library at 0.001 level. As such, the FER library shows better internal consistency in emotion prediction than the DeepFace library.

***** INSERT TABLE 2-12 ABOUT HERE *****

(2) Comparison of Dominant Emotions

In the subsequent phase of analysis, we identified the maximum confidence score for each image and determined the corresponding emotion as the dominant emotion shown on the face in that image. This process involved computing the frequency of the dominant emotions across all images within the folder corresponding to the video. The emotion that most frequently occurred was marked as the dominant emotion throughout the pitch process. Consequently, the computation process enabled the quantification of the prevalence of each specific emotion, as well as the determination of the most pronounced emotional expression at the level of the entire video. As shown in Figure 2-10, the FER tools most frequently identified a neutral state, followed by happiness. In contrast, DeepFace predominantly recognized disgust and fear throughout the full video. The detailed descriptive statistics of dominant emotion frequency of 50 videos across the four tools are presented in Table 2-13.

***** INSERT FIGURE 2-10 & TABLE 2-13 ABOUT HERE *****

Furthermore, the robust positive correlations evident in the DeepFace library outputs, irrespective of the face detection methods employed, coupled with the equally significant positive correlations in frequency computations from the FER library, demonstrate the internal consistency within each tool when using different face detection methods. As shown in Table 14, this underscores the distinct paradigms for emotion prediction that each library employs.

***** INSERT TABLE 2-14 ABOUT HERE *****

Figure 2-11 illustrates gender difference in the frequency of expressing various emotions, including anger, disgust, fear, happiness, sadness, surprise, and neutrality. It demonstrates that, across four coding tools, women are generally less likely to express positive emotions and more inclined to express negative ones. To corroborate these observed patterns, we employed t-tests to assess the differences in emotional expression between the two gender groups, as shown in Table 2-15. Our analysis, leveraging the DeepFace library, revealed that female entrepreneurs exhibited significantly lower levels of disgust during pitch presentations. Furthermore, although marginally significant ($p < 0.05$), these women displayed a greater tendency towards neutrality compared to their male counterparts, as per the DeepFace analysis. However, these patterns were not consistent across all tools used for analysis. Specifically, the FER library provided evidence that female entrepreneurs showed higher levels of happiness compared to male entrepreneurs, with this difference also approaching significance at the 0.05 level. We further examined whether the frequency of expressed emotions differ in the beginning and the ending of the pitch. The temporal pattern did not hold, as shown in the t tests of Table 2-16. No significant differences are observed in the average frequencies of emotional expressions between the first 30 seconds and the entirety of the pitch video, as well as between the last 30 seconds and the whole entrepreneurial pitch process.

***** INSERT FIGURE 2-11 and TABLE 2-15 & 2-16 ABOUT HERE *****

(3) Discussion about Facial Emotion Expression of Entrepreneurs

The facial analysis of entrepreneurial pitch videos using FER and DeepFace libraries has surfaced gender-specific differences in emotional expression, with male entrepreneurs tending to exhibit more negative emotions, whereas females more frequently displayed happiness, surprise, or a neutral affect. This tendency is consistent with the established knowledge about difference in emotional expression of men and women (e.g., Brescoll, 2016), while differences in emotional expression are not observed across different temporal sections of the whole pitch process.

Notwithstanding, the present findings revealed that current publicly accessible automated tools may not be sufficiently advanced for operational use, considering the inconsistencies and noncorrelations emerged from the output generated by the two libraries. Compared to the DeepFace library, however, the FER library appears to offer more internally aligned and reflective evaluation of emotional expressions in the context of entrepreneurial endeavors, as shown in Figure 2-12 & 2-13. Importantly, there is an ongoing debate regarding biases in these tools that stem from gender and ethnic disparities within their training datasets. It is also critical to acknowledge that the emotions detected represent only the outward display of emotions on the face, which may not reflect the genuine emotional state and may be inconsistent with the actual perceptions and judgement held by the audience. Previous research often favored commercial software and APIs for their relatively higher reliability, despite the substantial financial investment required for analyzing large datasets. For researchers with limited budgets, the FER library would be an ideal option to provide basic and superficial insights.

***** INSERT FIGURE 2-12 & 2-13 ABOUT HERE *****

We also investigated the correlation between the vocal and facial outputs, as presented in Table 2-17 and Table 2-18. Since the facial outputs of the DeepFace are not reliable according to the previous analysis, we mainly focused on the FER library outputs and its correlation with vocal features and vocal emotions. Furthermore, the absence of happiness as the dominant facial emotion according to the DeepFace library coupled with opencv detection algorithm serves as another evidence of the lack of face validity of the DeepFace library. Vocal anger is positively correlated with facial surprise at a slightly significant level with the same correlation value among the two face detection tools. Vocal anger is also positively correlated with facial sadness generated by the FER libarary coupled with mtcnn model for face detection. As for the voice features, it is observed that the average pitch level is positively correlated with FER generated facial happiness across the three tools for voice feature extraction, with the significant level higher for Praat and Librosa than OpenSMILE.

***** INSERT TABLE 2-17 & 2-18 ABOUT HERE *****

2.5 Discussion and Conclusion

This paper provides an evaluation and overview of different analytical tools for voice and facial analysis. Its aim is to delineate the characteristics of emerging automatic coding tools and to explore the face validity of existing non-commercial tools. When it comes to the extraction of voice pitch, baseline level consistency is observed in the pitch measurements produced by Praat and Librosa, in contrast to the distinct values obtained from openSMILE. Specifically, Praat's metrics are directly applicable to the subsequent empirical analysis, making it a suitable choice for such studies. On the other hand, Librosa demonstrates its strength in Python-based deep learning projects due to its compatibility and specialized features in quantifying voice signals. In the realm of facial emotion recognition, our analysis reveals that the FER library achieves internal consistency, as evidenced by the stark contrast it identifies between the presence and absence of specific emotions. This contrasts with the DeepFace library, where the FER library's observable consistency in facial emotion prediction lends it greater reliability for analyzing emotional expressions in entrepreneurial pitches. This comprehensive evaluation underscores the importance of selecting appropriate tools based on the specific requirements of voice and facial emotion analysis tasks.

Despite the inconsistency of outputs using different set of coding tools, the analysis of successful accelerator pitch videos uncovers patterns indicative of universal phenomena. Our findings underscore a distinct gender-based variance in both vocal and facial emotional expressions. Specifically, men demonstrated a consistently lower average pitch compared to their female counterparts. Furthermore, across all participants, happiness emerged as the predominant emotion detected in voice analyses, highlighting a universal trend towards positive emotional expression in entrepreneurial pitches. It is also observed that both male and female entrepreneurs were frequently noted to express emotions of happiness and anger, yet the range of emotions displayed revealed a notable gender discrepancy. It appears that male entrepreneurs are more comfortable in expressing various emotions in the accelerator pitch. Moreover, the analysis of facial emotions unveiled additional findings that male entrepreneurs were more prone to display negative facial emotions, which contrasts sharply with the tendency among female entrepreneurs to show expressions of happiness, surprise, or to maintain a neutral affect. These observations are intriguing for theoretical advances in both unconscious and strategic nonverbal communication as one of the import inputs to managerial cognitive capabilities (Helfat & Peteraf, 2015).

Notably, much of the current literature has examined the impact of nonverbal cues at the individual level, particularly how they affect evaluations and outcomes in selection processes. Moving forward, research could expand to explore how these nonverbal cues function within the group, such as among team members or board interactions. Beyond the consequence of nonverbal cues, it is also essential to investigate what causes certain types of nonverbal communication to occur. For example, the working paper by Hwang et al. (2021) provides insights into online influencer communication, illustrating how sponsorship endorsement influences voice loudness and its subsequent effect on consumer sentiment. Future research could further explore how different nonverbal cues interact and influence each other across various contexts. Another promising direction is the study of bidirectional nonverbal interactions, considering the responses and interplay between communicators and their audiences. Such research would extend beyond mere judgments to encompass the reciprocal nature of nonverbal communication.

While methodologically, the study highlights the integration of video analysis as a means to better understand at both individual and team levels in the business context. Nonetheless, it calls for a formalized approach in reporting necessary methodological details to enhance reproducibility and facilitate subsequent research endeavors. Challenges also exist in the complexities involved in interpreting aggregate measures at the video level. The prevalent measures applied in current research primarily reflect the average level during the whole video, such as the frequency of certain emotion predominance in the captured image (Choudhury et al., 2019; Curti & Kazinnik, 2022; Flam et al., 2020; Hu & Ma, 2021a) or peak confidence scores of a specific emotion over the video (Y. Huang et al., 2023; L. Jiang et al., 2019). Future research will probably need to focus on a specific time segment within the video or generate measures that reflect time dynamics.

Moreover, it is imperative to acknowledge the limitations inherent in this study. The evaluation of coding tools was conducted on a constrained sample size, which can limit the strength of the results. While the reliance on publicly available and pre-trained tools mitigated the necessity for extensive coding, it precluded a thorough appraisal encompassing proprietary tools and dedicated deep learning training endeavors. Furthermore, the analysis was narrowly tailored to the principal elements of facial expressions and vocal features and tones, thereby omitting a consideration of additional nonverbal indicators that could yield informative insights.

In conclusion, this study offers a broad introduction to the current state of the tools available for the analysis of nonverbal communication in the context of entrepreneurship. By advancing the use of affective computing in this domain, the paper not only describe and categorize the methodological toolkit available to researchers but also encourage the bridging of theoretical concepts with practical, machine learning-driven applications. This convergence promises to enrich the discourse on voice and facial communication in entrepreneurship and beyond, fostering a more profound comprehension of the subtle yet powerful language of emotions.

2.6 Figures

Figure 0-1:Data Processing Flowchart

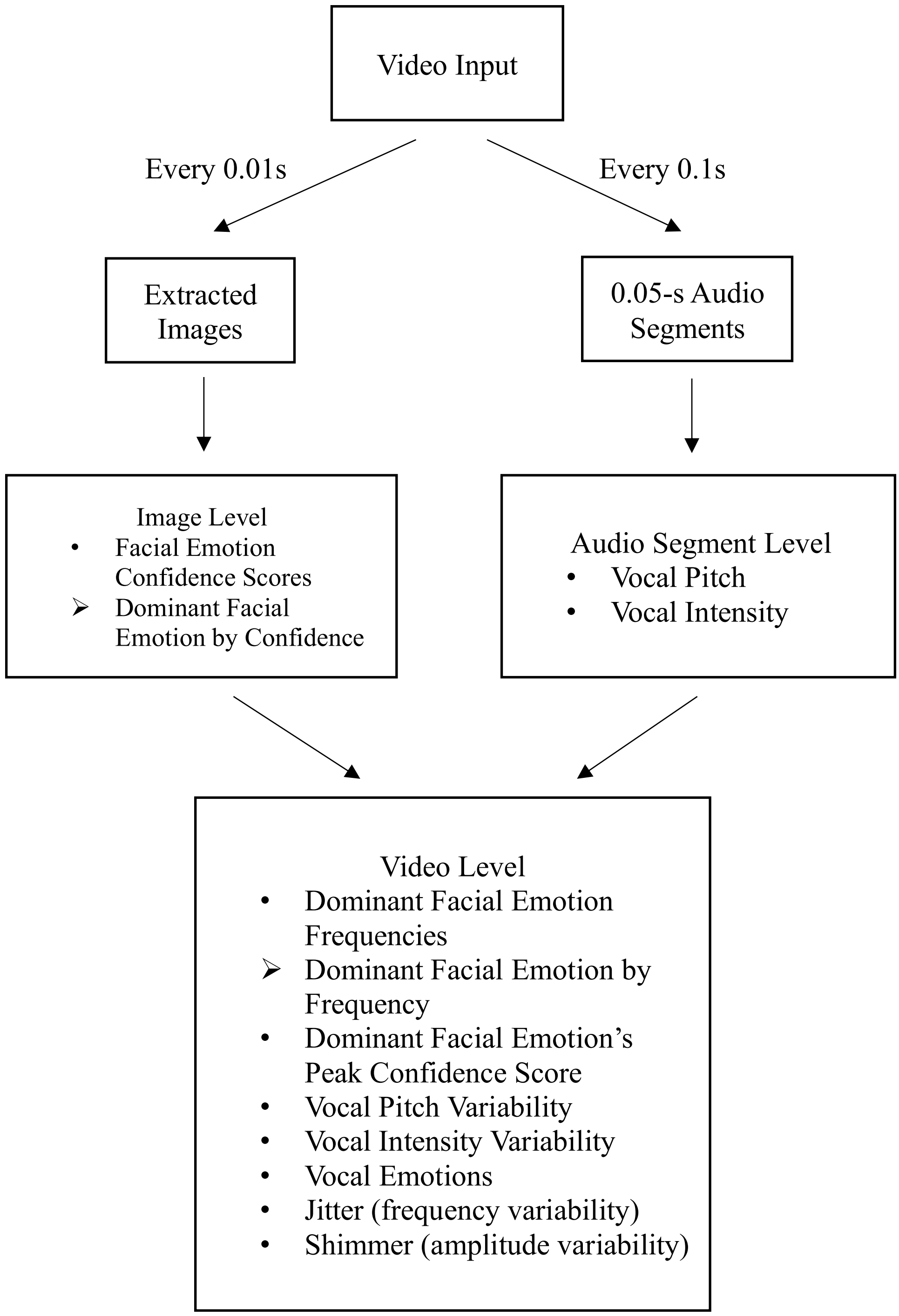


Figure 0-2: Pitch Comparison across Three Voice Analysis Tools - Histograms

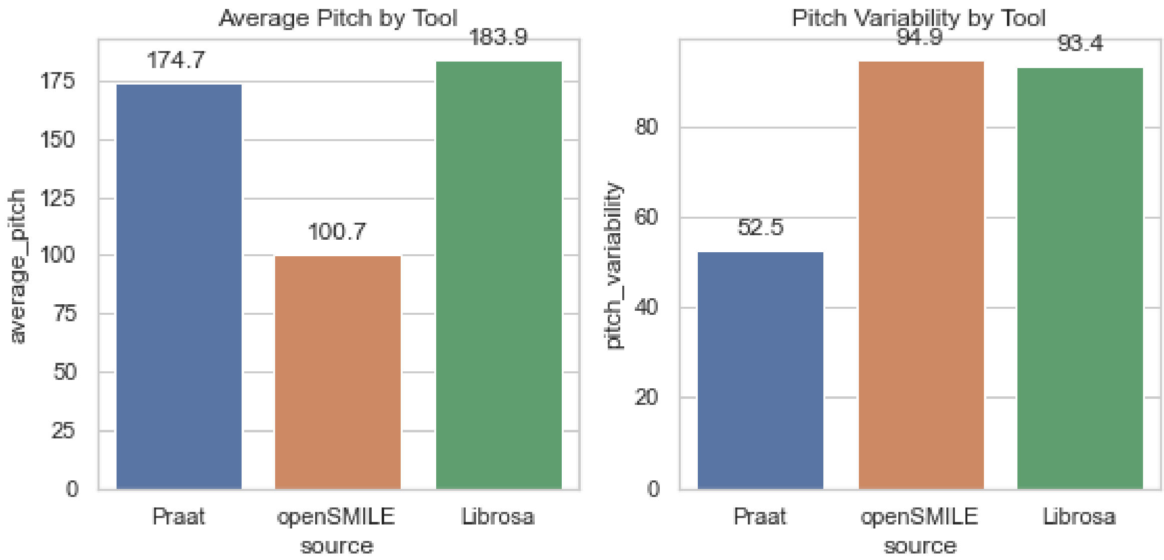


Figure 0-3: Pitch Comparison across Three Voice Analysis Tools – Boxplots

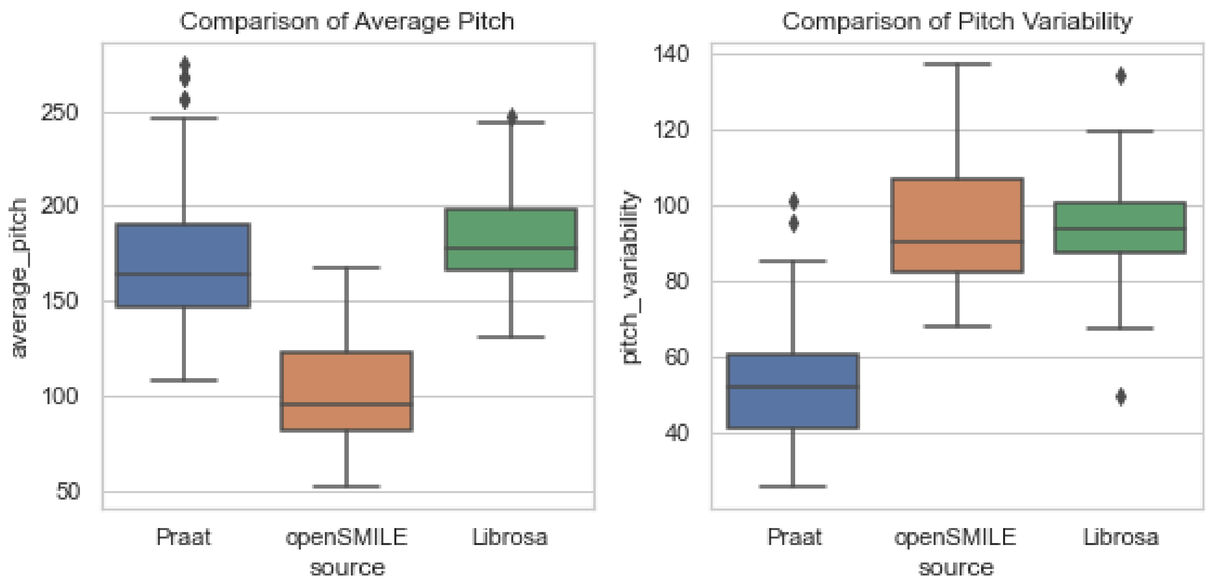


Figure 0-4: Pitch Comparison across Three Voice Analysis Tools by Gender – Histograms

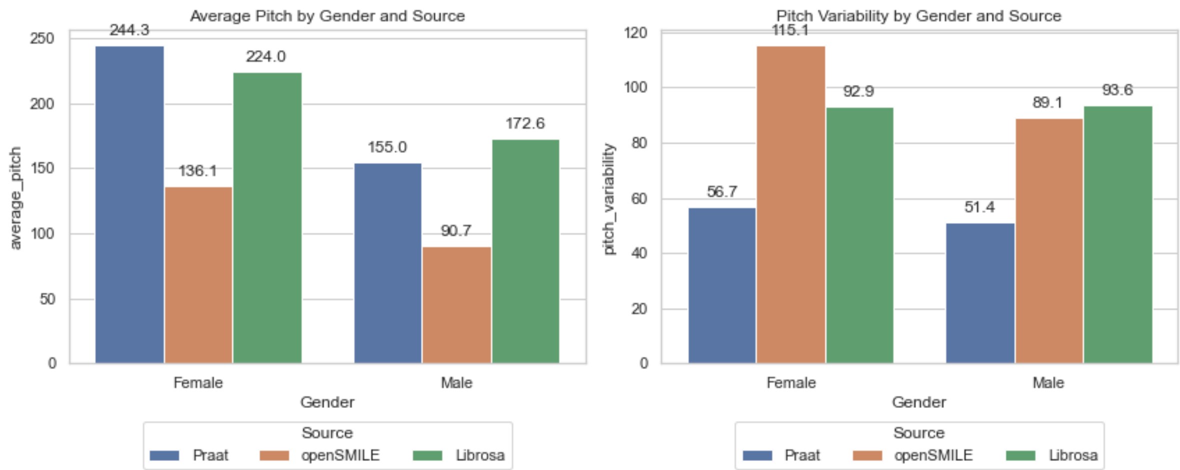


Figure 0-5: Pitch Comparison across Three Voice Analysis Tools by Gender - Boxplots

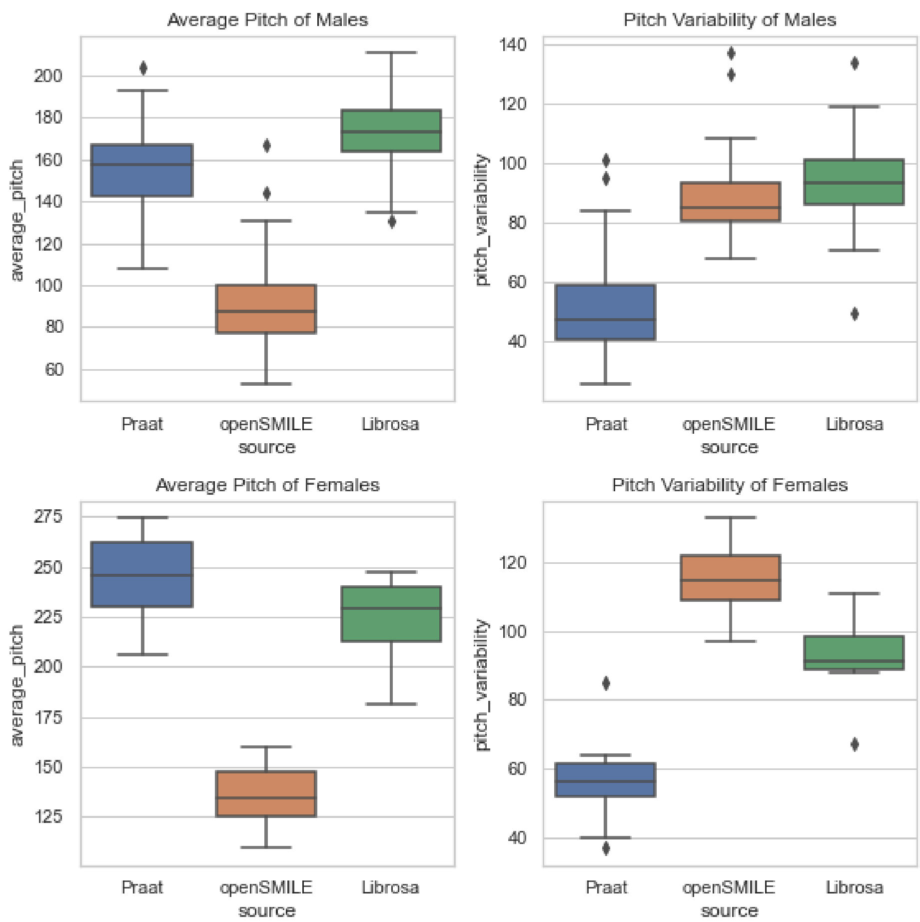


Figure 0-6: Voice Emotion Distribution

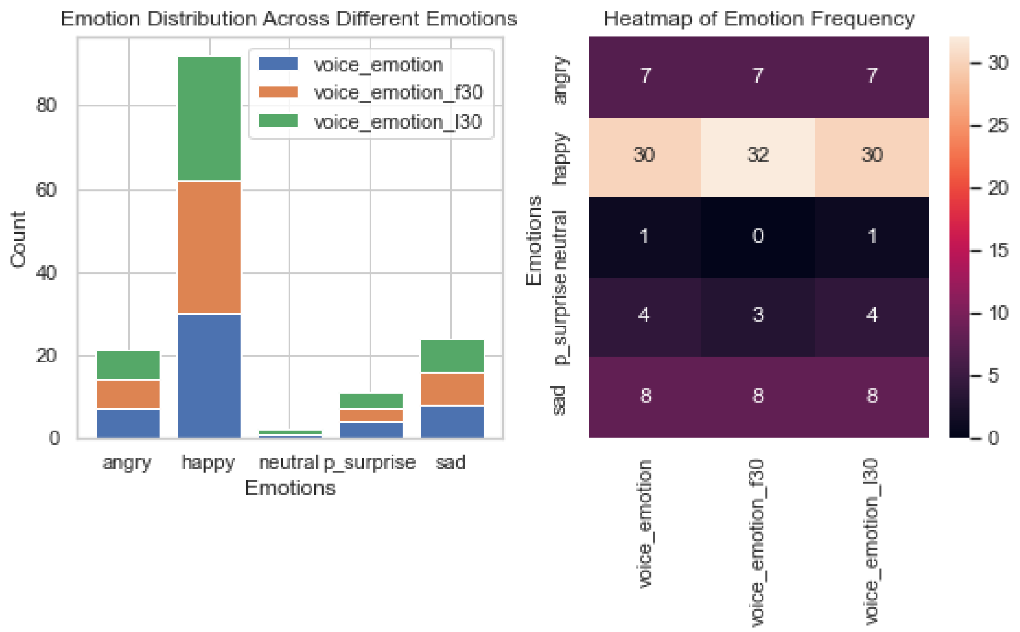


Figure 0-7: Voice Emotion Distribution by Gender

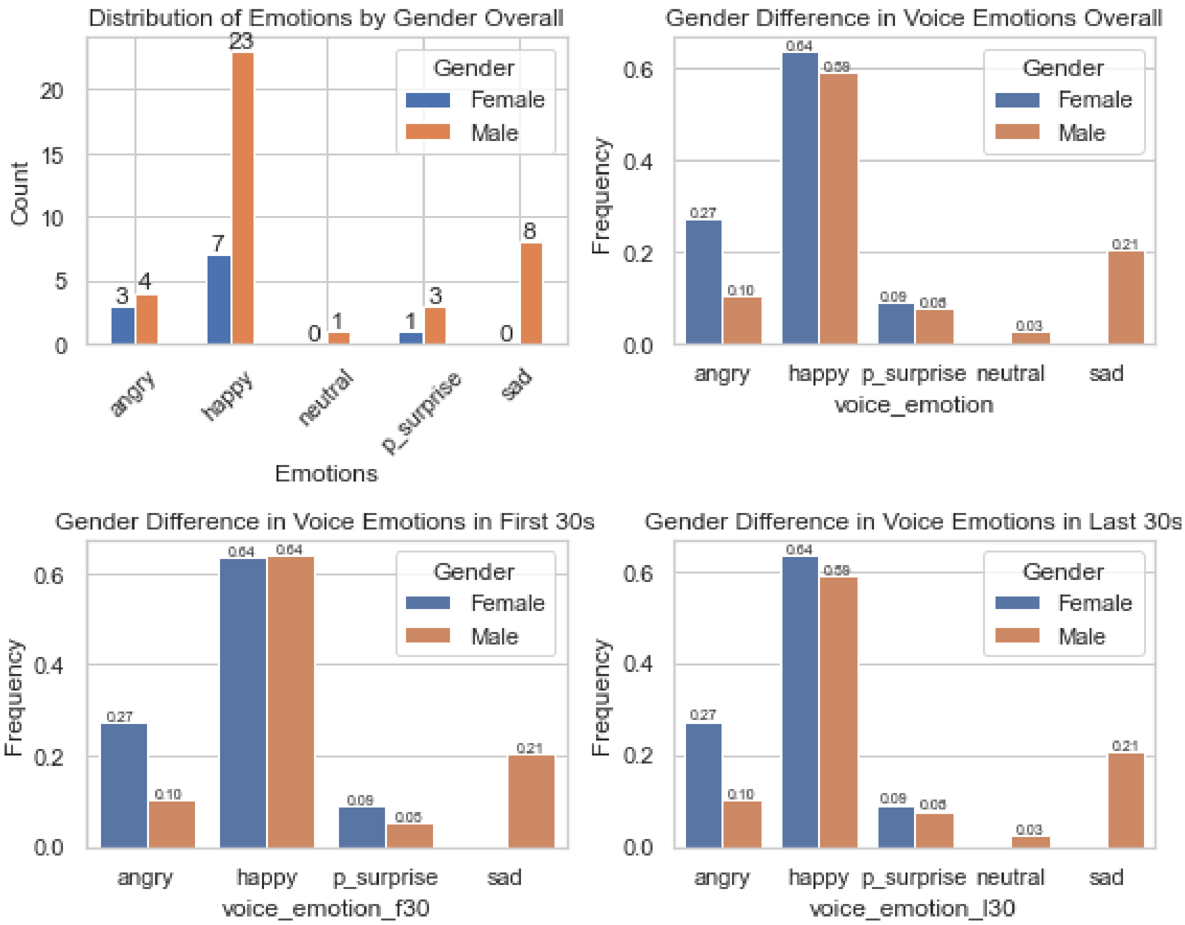


Figure 0-8: Pitch Features by Voice Emotions Using Three Tools – Boxplots

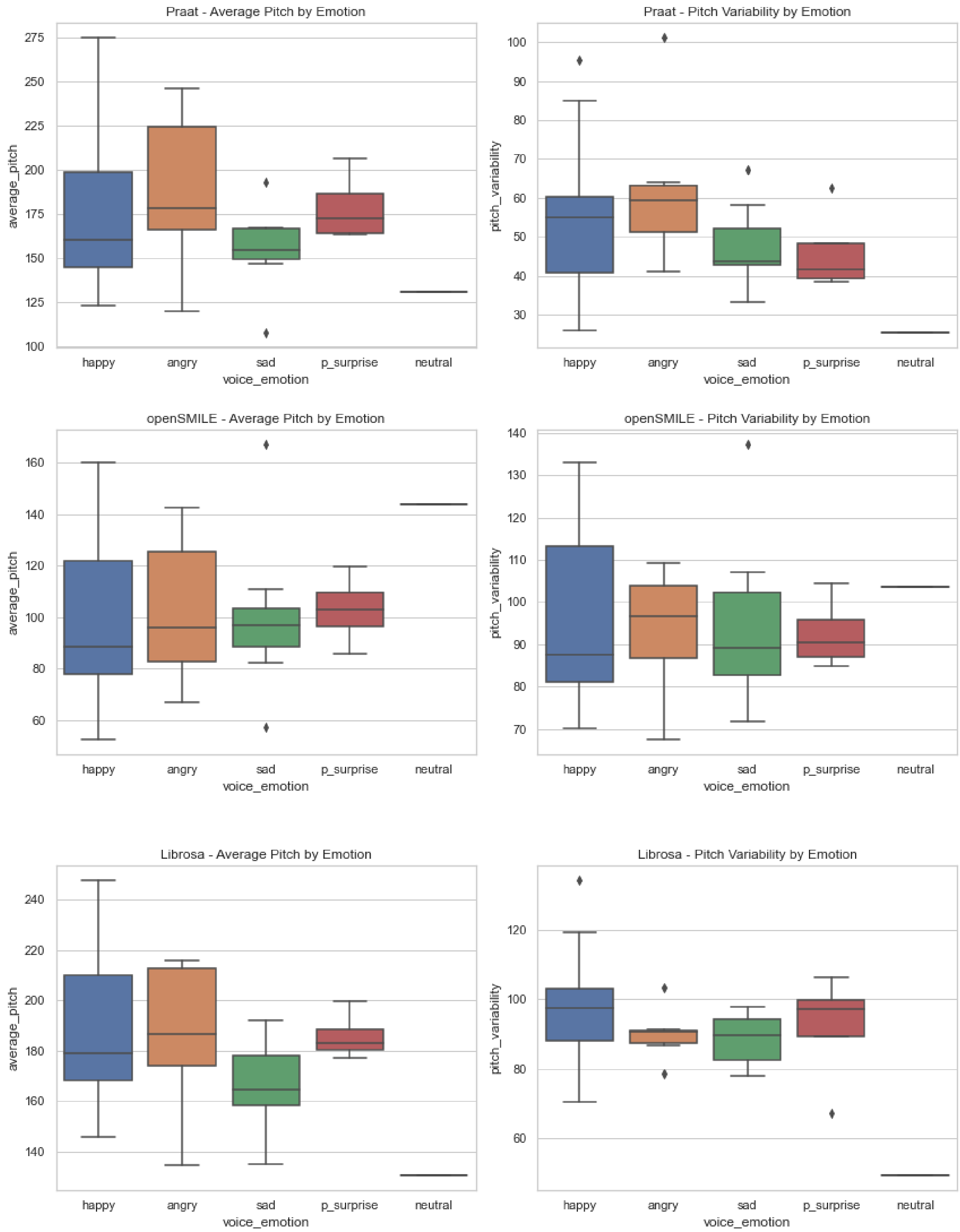


Figure 0-9: Score Comparison for Facial Emotions across Tools

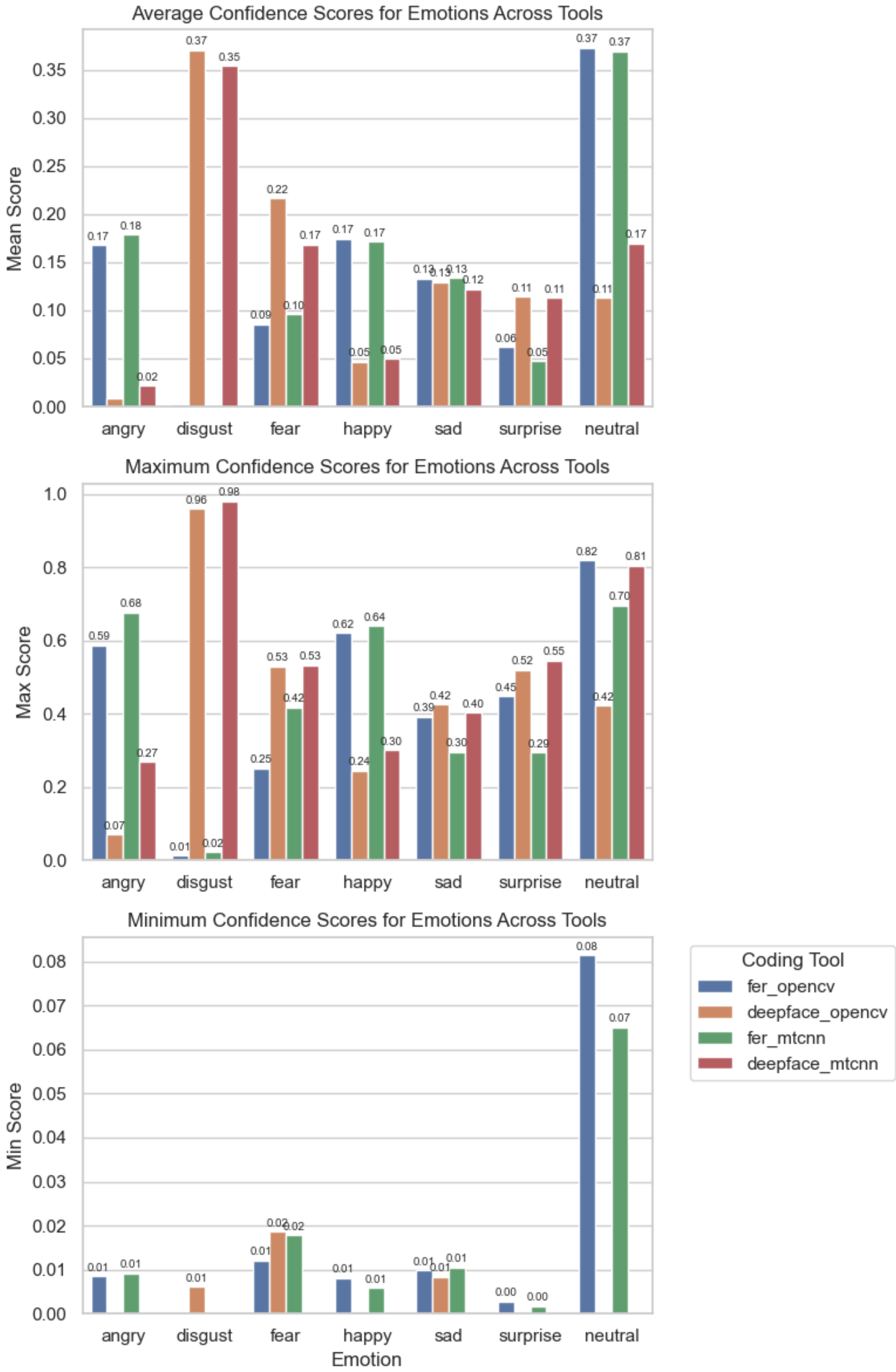


Figure 0-10: Dominant Facial Emotion Frequency Comparison across Tools

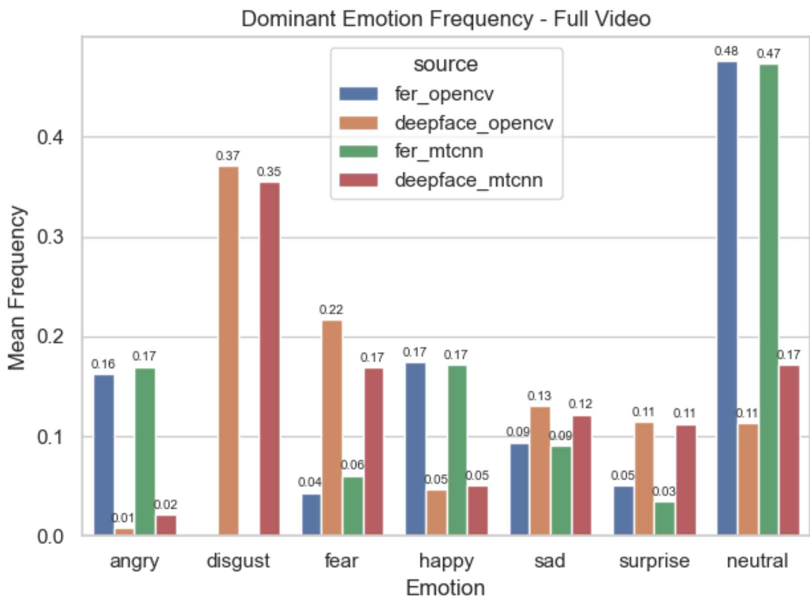


Figure 0-11: Dominant Facial Emotion Frequency Comparison across Tools by Gender

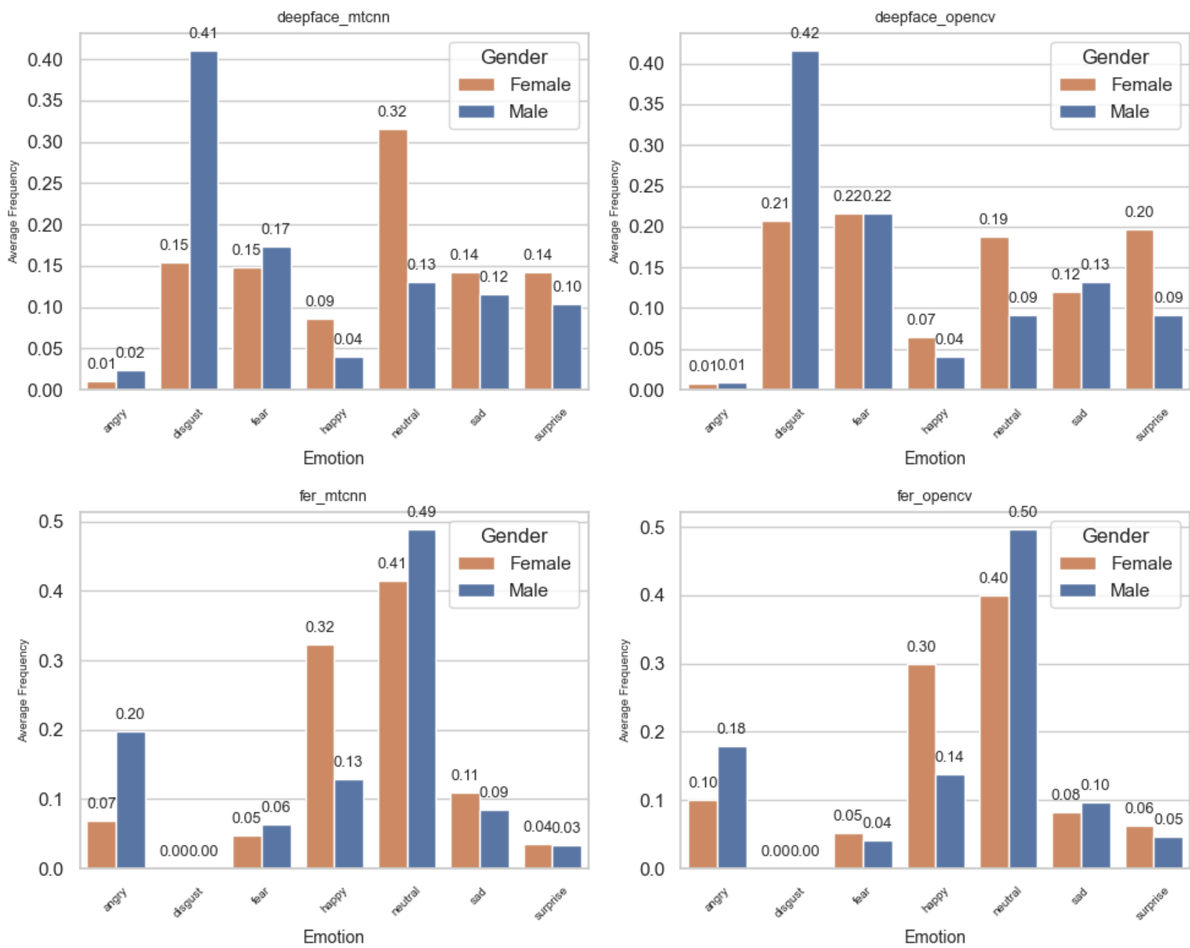


Figure 0-12: Video Level Dominant Facial Emotion Comparison across Tools

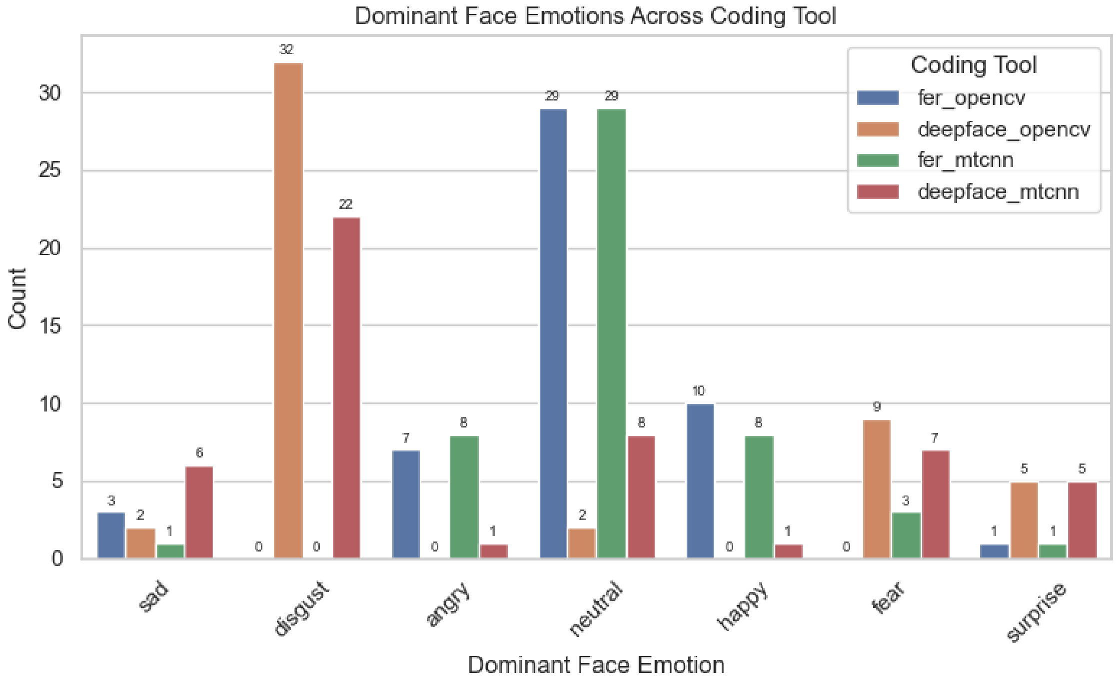
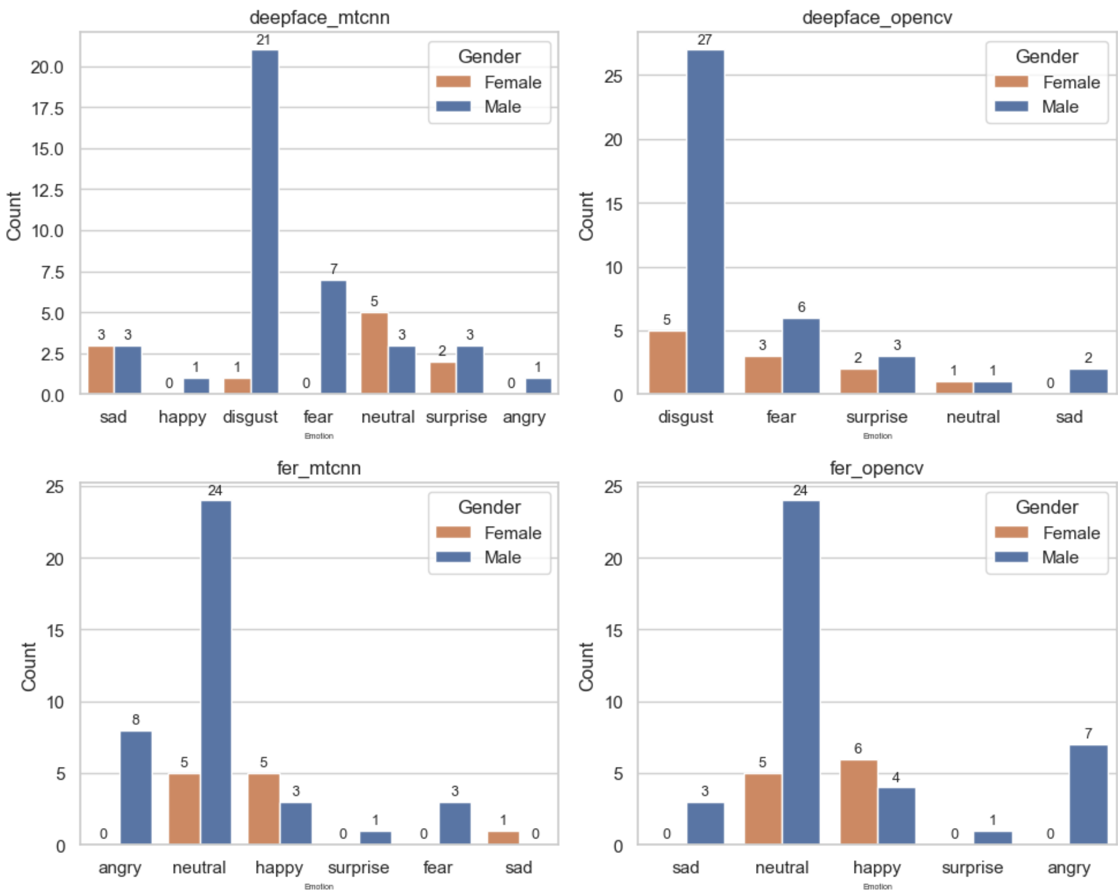


Figure 0-13: Video Level Dominant Facial Emotion Comparison across Tools by Gender



2.7 Tables

Table 0-1: Voice Coding Tool Review and Comparison

Voice Coding Tool	Features	Inferences	Dependent Variables	Studies	Domain
Pre-trained commercial tools[4]					
LVA (Layered Voice Analysis)[5]	Emotional stress level, Cognition level, General stress level, Thinking level	Affective states, Cognitive dissonance, Emotional/cognitive activity level	Stock returns and future profitability, Unexpected future earnings, Daily/Cumulative abnormal return (forward), Financial misreporting(backward)	(Hobson et al., 2012b; Mayew & Venkatachalam, 2012; Price et al., 2016)	Finance Accounting
QA5[6]	Acoustic spectrum	Content (Indicates how pleased or happy the speaker sounds), Excitement (Indicates how positively or negatively excited the speaker sounds), Angry (Indicates how angry the speaker sounds), Imagination activity (Indicates the extent to which the speaker sounds like they are	Persuasion (crowdfunding performance)	(X. Wang et al., 2021)	Marketing

[4] The pricing for the commercial tools listed in this table is provided upon request and typically ranges from the thousands to the ten-thousands USD.
[5] Validated in paper (Elkins & Burgoon, 2010).
[6] QA5 and Ex-Sense Pro-R are both from Nemesysco Ltd (http://nemesysco.com/), an Israeli high-tech firm patented with LVA (US patent No. 6,638,217 B1). Research using LVA Technology: https://www.nemesysco.com/research/. QA7 is the latest version in 2023.

		imagining rather than recalling information)			
Beyond Verbal Emotion AI API	Vocal valence and arousal	Emotion states about sentiment and expressional strength	Crowdfunding performance	(Allison et al., 2022)	Management
Pre-trained opensource tools					
SVM model in PyAudioAnalysis	Vocal valence and arousal	Emotion states about sentiment and expressional strength	Funding performance	(Hu & Ma, 2021b)	Finance
LSTM model in speechemotionrecognition	Vocal valence	Sentiment in the voice	Funding performance	(Hu & Ma, 2021b)	Finance
Praat/Parsemouth	Voice pitch[7] - frequency (Hz)	Emotionality, Masculinity	Election outcomes, Stock price volatility, Audience perception and evaluation	(Boussalis et al., 2021; Dietrich et al., 2019; Klofstad, 2016; Zhang et al., 2022)	Political Science Economics
Librosa	Voice features including Mel, MFCC and chroma coefficients	Input of the deep learning used to represent the voice attributes	Share price	(Gorodnichenko et al., 2023b)	Economics
openSMILE	Voice features including loudness, loudness variability, pitch, and pitch variability	Lowered loudness is associated with trustworthiness	Consumer sentiment	(Hwang et al., 2021)	Marketing
Self-trained machine learning models					
CNN model for voice tone classification trained on Ryson Audio-Visual Database of Emotional	Voice emotions including anger, happiness, pleasant	Positive voice emotion	Share price	(Gorodnichenko et al., 2023b)	Economics

[7] Voice pitch—perceived "highness" or "lowness" as determined by the physiology of the throat

Speech and Song (RAVDESS) and Toronto Emotional Speech Set (TESS)	surprise, sadness, and neutrality				

Table 0-2: Face Coding Tool Review and Comparison

Face Coding Tool	**Features**	**Inferences**	**Dependent Variables**	**Studies**	**Domain**
Pre-trained commercial tools					
iMotions Facial Action Coding System (FACS)[8]	7 facial emotions (happy, sadness, anger, surprise, fear, disgust, and neutrality) Action Unit classification (mouth/eyes open-closed, eyebrows raised-neutral-lowered, head orientation, gaze direction) Subject characteristics (gender, age, and facial hair) Facial emotion valence and arousal	The confidence of each emotional category	Crowdfunding/microlending performance	(Davis et al., 2021; Warnick et al., 2021)	Management
Face Reader[9]		Peak displayed joy, Positive facial emotion, Facial fear	Funding performance, Asset pricing, S&P500 index, Stock market volatility	(Breaban & Noussair, 2018; L. Jiang et al., 2019; Zhang et al., 2022)	Management Economics

[8] https://imotions.com/affectiva-requestdemo/
[9] https://www.noldus.com/facereader. iMotions and Face Reader both from Noldus company.

FACE ++ SDK	7 facial emotions: anger, contempt, disgust, fear, happiness, sadness, and neutrality	Facial emotions	Funding performance	(Hu & Ma, 2021b)	Finance
Microsoft Cognition Service	7 facial emotions: anger, disgust, fear, happiness, sadness, surprise, and neutrality	Facial emotions	Funding performance, Minute-level market responses, S&P500 index, Stock market volatility	(Curti & Kazinnik, 2022; Hu & Ma, 2021b; Zhang et al., 2022)	Finance Economics
Amazon Web Services (AWS) Recognition software	7 facial emotions: anger, calmness, disgust, happiness, sadness, and surprise	Facial anger	Investor response	(Flam et al., 2020)	Accounting
haystack.ai	Facial attractiveness	Facial attractiveness	Crowdfunding performance	(Seigner & Milanov, 2023)	Management
Pre-trained opensource tools					
DeepFace's Emotion Function	7 facial emotions: anger, disgust, fear, happiness, sadness, surprise, and neutrality Age, race, gender	Age, race, and facial emotions	Consumer sentiment	(Hwang et al., 2021)	Marketing
Self-trained machine learning models					
CNN model trained using IAPS Dataset based on ResNet 50 deep neural network	Affective visual expression in frames with and without faces	Peak affective visual expression	Crowdfunding performance	(Y. Huang et al., 2023)	Management
Histogram of Oriented Gradients (HOG) algorithm trained by iBUG face landmark dataset	Eyebrow - the angle of the inner eyebrow ridge Face shape - the roundness of the face Chin angle - the width of the chin	Facial trustworthiness	Audit fee, Crowdfunding performance	(Duan et al., 2020; Hsieh et al., 2020)	Accounting Management

	Philtrum - the lip-to-nose distance scaled by the upper facial height				
Transfer learning using Google Inception (v3) model	Negative sentiment in the news photo	News photo pessimism	Stock market reaction	(Obaid & Pukthuanthong, 2022)	Finance
Transfer learning using Dlib face recognition algorithm (King 2009)	dynamic HFAsy	CEOs' Dynamic Hemifacial Asymmetry of Expressions	Stock market reaction	(Banker et al., 2021)	Accounting
Transfer learning using VGG16 network	Predictions of forward-looking operational information, existing products or services	the nature of information conveyed by corporate images	Short-term abnormal returns	(Cao et al., 2022)	Accounting

Table 0-3: Other Nonverbal Coding Tool Review and Comparison

Pre-trained opensource tools					
OpenPose	Body expansiveness	Body expansiveness	Funding performance	(Dávila & Guasch, 2022)	Accounting
laughter- detection package in python	Assign humor if the laughter occurred between two sentences spoken by the same individual	CEO's use of humor	Stock market returns and analyst forecast revisions	(Call et al., 2023)	Accounting

Table 0-4: Descriptive Statistics Comparison of Voice Coding Tool Output

Tool	Features	Count	Mean	Std	Min	Median	Max
Praat	Average Pitch (Hz)	50	174.66	42.81	107.79	163.58	274.82
	Pitch Variability	50	52.55	16.13	25.59	51.81	101.16
	Average Intensity (dB)	50	54.68	8.79	25.62	57.31	67.81
	Intensity Variability	50	23.88	16.11	9.45	17.68	77.69
Librosa	Average Pitch (Hz)	50	183.93	28.27	130.68	177.83	247.60
	Pitch Variability	50	93.43	13.49	49.51	93.41	134.17
	Average Intensity (dB)	50	0.04	0.02	0.01	0.05	0.10
	Intensity Variability	50	0.05	0.02	0.01	0.05	0.09
openSMILE	Average Pitch (Hz)	50	100.67	28.98	52.75	95.78	167.07
	Pitch Variability	50	94.86	17.42	67.60	90.28	137.30
	Average Intensity (dB)	50	0.0000014	0.0000011	0.0000000	0.0000013	0.0000046
	Intensity Variability	50	0.0000035	0.0000026	0.0000001	0.0000031	0.0000108

Table 0-5: Correlation of Voice Coding Tool Output

		Praat	Librosa	openSMILE
Average Pitch	Praat	1.000***	0.886***	0.082
	Librosa	0.886***	1.000***	-0.003
	openSMILE	0.082	-0.003	1.000***
Pitch Variability	Praat	1.000***	0.819***	-0.128
	Librosa	0.819***	1.000***	-0.044
	openSMILE	-0.128	-0.044	1.000***
Average Intensity	Praat	1.000***	0.559***	-0.091
	Librosa	0.559***	1.000***	-0.186
	openSMILE	-0.091	-0.186	1.000***
Intensity Variability	Praat	1.000***	-0.382**	-0.022
	Librosa	-0.382**	1.000***	-0.021
	openSMILE	-0.022	-0.021	1.000***

Notes: The asterisks (*) indicate the level of statistical significance, with three asterisks (***) denoting a significance level of 0.001, which means there is less than a 0.1% chance that the observed correlation is due to random variation in the sample. Two asterisks (**) denote a significance level of 0.01, and one asterisk (*) denotes denote a significance level of 0.05. This applies to all tables below.

Table 0-6: Descriptive Statistics Comparison across Voice Coding Tool Output by Gender

Tool	Features	Count	Mean	Std	Min	Median	Max
Praat	Female Average Pitch (Hz)	11	244.30	22.55	206.50	230.35	246.05
	Female Pitch Variability	11	56.69	12.80	36.79	51.81	56.35
	Male Average Pitch (Hz)	39	155.01	20.71	107.79	142.76	157.61
	Male Pitch Variability	39	51.38	16.91	25.59	40.76	47.28
openSMILE	Female Average Pitch (Hz)	11	136.15	15.82	109.31	125.42	134.55
	Female Pitch Variability	11	115.15	10.61	96.75	108.74	114.70
	Male Average Pitch (Hz)	39	90.67	23.45	52.75	77.16	87.53
	Male Pitch Variability	39	89.14	14.46	67.60	80.89	85.31
Librosa	Female Average Pitch (Hz)	11	223.95	20.05	181.15	212.82	229.10
	Female Pitch Variability	11	92.91	11.10	67.30	88.61	91.19
	Male Average Pitch (Hz)	39	172.65	18.18	130.68	163.89	172.92
	Male Pitch Variability	39	93.57	14.22	49.51	86.44	93.68

Table 0-7: Gender Difference in Average Pitch and Pitch Variability – t test

		Men	Women	Diff
Average Pitch	Praat	155.01	244.30	-89.29***
	openSMILE	90.67	136.15	-45.48***
	Librosa	172.65	223.95	-51.30***
Pitch Variability	Praat	51.38	56.69	-5.31
	openSMILE	89.14	115.15	-26.01***
	Librosa	93.57	92.91	0.66

Table 0-8: Temporal Difference in Average Pitch and Pitch Variability – t test

		Full Avergae	First 30s Average	Diff to full average	Last 30s Average	Diff to full average
Average Pitch	Praat	174.66	173.05	-1.61	174.30	-0.356
	openSMILE	100.67	97.44	-3.23	99.49	2.045
	Librosa	183.93	187.56	3.63	187.86	3.928
Pitch Variability	Praat	52.55	54.19	1.64	51.93	-0.62
	openSMILE	94.86	96.07	1.21	95.63	0.77
	Librosa	93.43	100.10	6.67*	96.64	3.21

Table 0-9: Correlation of Average Pitch, Pitch Variability and Voice Emotions

Tool	Features	Average Pitch	Pitch Variability	Vocal Anger	Vocal Happiness	Vocal Neutrality	Vocal Surprise	Vocal Sadness
Praat	Average Pitch	1.000***	0.203	0.138	0.082	-0.148	0.026	-0.203
	Pitch Variability	0.203	1.000***	0.226	0.072	-0.241	-0.118	-0.131
	Vocal Anger	0.138	0.226	1.000***	-0.494***	-0.058	-0.119	-0.176
	Vocal Happiness	0.082	0.072	-0.494***	1.000***	-0.175	-0.361**	-0.535***
	Vocal Neutrality	-0.148	-0.241	-0.058	-0.175	1.000***	-0.042	-0.062
	Vocal Surprise	0.026	-0.118	-0.119	-0.361**	-0.042	1.000***	-0.129
	Vocal Sadness	-0.203	-0.131	-0.176	-0.535***	-0.062	-0.129	1.000***
openSMILE	Average Pitch	1.000***	0.879***	0.034	-0.095	0.216	0.022	-0.004
	Pitch Variability	0.879***	1.000***	-0.032	0.023	0.072	-0.039	0.001
	Vocal Anger	0.034	-0.032	1.000***	-0.494***	-0.058	-0.119	-0.176
	Vocal Happiness	-0.095	0.023	-0.494***	1.000***	-0.175	-0.361**	-0.535***
	Vocal Neutrality	0.216	0.072	-0.058	-0.175	1.000***	-0.042	-0.062
	Vocal Surprise	0.022	-0.039	-0.119	-0.361**	-0.042	1.000***	-0.129
	Vocal Sadness	-0.004	0.001	-0.176	-0.535***	-0.062	-0.129	1.000***
Librosa	Average Pitch	1.000***	0.442**	0.047	0.240	-0.272	0.018	-0.275
	Pitch Variability	0.442**	1.000***	-0.107	0.347*	-0.470***	-0.032	-0.159
	Vocal Anger	0.047	-0.107	1.000***	-0.494***	-0.058	-0.119	-0.176
	Vocal Happiness	0.240	0.347*	-0.494***	1.000***	-0.175	-0.361**	-0.535***
	Vocal Neutrality	-0.272	-0.470***	-0.058	-0.175	1.000***	-0.042	-0.062
	Vocal Surprise	0.018	-0.032	-0.119	-0.361**	-0.042	1.000***	-0.129
	Vocal Sadness	-0.275	-0.159	-0.176	-0.535***	-0.062	-0.129	1.000***

Table 0-10: Raw Confidence Score Comparison of Face Coding Tools

Coding Tool	Average Score	Mean	Std	Min	Median	Max
DeepFace_mtcnn	Anger	0.022	0.043	0.000	0.008	0.269
DeepFace_opencv		0.009	0.014	0.000	0.002	0.069
FER_mtcnn		0.179	0.137	0.009	0.130	0.676
FER_opencv		0.168	0.124	0.008	0.132	0.586
DeepFace_mtcnn	Disgust	0.355	0.278	0.000	0.246	0.980
DeepFace_opencv		0.371	0.213	0.006	0.325	0.959
FER_mtcnn		0.001	0.003	0.000	0.000	0.022
FER_opencv		0.002	0.003	0.000	0.001	0.012
DeepFace_mtcnn	Fear	0.168	0.135	0.000	0.136	0.532
DeepFace_opencv		0.217	0.137	0.019	0.194	0.530
FER_mtcnn		0.096	0.077	0.018	0.072	0.418
FER_opencv		0.085	0.056	0.012	0.070	0.251
DeepFace_mtcnn	Happiness	0.050	0.062	0.000	0.024	0.301
DeepFace_opencv		0.047	0.047	0.001	0.035	0.244
FER_mtcnn		0.172	0.144	0.006	0.132	0.639
FER_opencv		0.175	0.142	0.008	0.128	0.621
DeepFace_mtcnn	Sadness	0.122	0.106	0.000	0.100	0.404
DeepFace_opencv		0.130	0.105	0.008	0.093	0.425
FER_mtcnn		0.134	0.074	0.011	0.125	0.296
FER_opencv		0.133	0.079	0.010	0.124	0.391

DeepFace_mtcnn	Surprise	0.113	0.136	0.000	0.059	0.545
DeepFace_opencv		0.115	0.132	0.000	0.057	0.520
FER_mtcnn		0.047	0.054	0.002	0.024	0.293
FER_opencv		0.062	0.074	0.003	0.034	0.448
DeepFace_mtcnn	Neutrality	0.170	0.173	0.000	0.127	0.805
DeepFace_opencv		0.113	0.111	0.000	0.097	0.421
FER_mtcnn		0.370	0.163	0.065	0.348	0.695
FER_opencv		0.373	0.172	0.082	0.321	0.819

Table 0-11: Correlation of Raw Confidence Score across Facial Analysis Coding Tool

		DeepFace_mtcnn	DeepFace_opencv	FER_mtcnn	FER_opencv
Average Confidence Score					
Anger	DeepFace_mtcnn	1.000***	0.15	0.138	0.07
	DeepFace_opencv	0.15	1.000***	0.095	0.162
	FER_mtcnn	0.138	0.095	1.000***	0.946***
	FER_opencv	0.07	0.162	0.946***	1.000***
Disgust	DeepFace_mtcnn	1.000***	0.770***	-0.026	-0.044
	DeepFace_opencv	0.770***	1.000***	-0.07	-0.026
	FER_mtcnn	-0.026	-0.07	1.000***	0.674***
	FER_opencv	-0.044	-0.026	0.674***	1.000***
Fear	DeepFace_mtcnn	1.000***	0.561***	0.162	0.16
	DeepFace_opencv	0.561***	1.000***	0.327	0.312
	FER_mtcnn	0.162	0.327	1.000***	0.856***
	FER_opencv	0.16	0.312	0.856***	1.000***
Happiness	DeepFace_mtcnn	1.000***	0.570***	0.585***	0.577***
	DeepFace_opencv	0.570***	1.000***	0.297*	0.267
	FER_mtcnn	0.585***	0.297*	1.000***	0.931***
	FER_opencv	0.577***	0.267	0.931***	1.000***
Sadness	DeepFace_mtcnn	1.000***	0.610***	0.416**	0.420**
	DeepFace_opencv	0.610***	1.000***	0.430**	0.317*
	FER_mtcnn	0.416**	0.430**	1.000***	0.864***
	FER_opencv	0.420**	0.317*	0.864***	1.000***
Surprise	DeepFace_mtcnn	1.000***	0.640***	0.477***	0.467***
	DeepFace_opencv	0.640***	1.000***	0.04	0.058
	FER_mtcnn	0.477***	0.04	1.000***	0.918***
	FER_opencv	0.467***	0.058	0.918***	1.000***
Neutrality	DeepFace_mtcnn	1.000***	0.492***	0.353*	0.346*
	DeepFace_opencv	0.492***	1.000***	0.233	0.275
	FER_mtcnn	0.353*	0.233	1.000***	0.920***
	FER_opencv	0.346*	0.275	0.920***	1.000***

Table 0-12: Correlation of Opposite Emotion Raw Confidence Score across Facial Analysis Coding Tool

Coding Tool	Anger vs. Non-anger	Disgust vs. Non-disgust	Fear vs. Non-fear	Happy vs. Non-happy	Sad vs. Non-sad	Surprise vs. Non-surprise
DeepFace_mtcnn	0.567***	0.861***	0.824***	0.802***	0.457***	0.734***
DeepFace_opencv	0.473***	0.795***	0.860***	0.656***	0.601***	0.532***
FER_mtcnn	-0.513***	-0.025	-0.131	-0.777***	-0.225	-0.212
FER_opencv	-0.401**	0.156	0.189	-0.790***	-0.056	-0.262
	Positive vs. Negative			Neutral vs. Non-neutral		
DeepFace_mtcnn	0.715***			0.896***		
DeepFace_opencv	0.577***			0.784***		
FER_mtcnn	-0.668***			-0.716***		
FER_opencv	-0.586***			-0.739***		

Table 0-13: Dominant Facial Emotion Frequency Comparison across Face Coding Tools

Coding Tool	Mean Frequency	Mean	Std	Min	Median	Max
DeepFace_mtcnn	Anger	0.021	0.044	0.000	0.008	0.281
DeepFace_opencv		0.008	0.013	0.000	0.002	0.069
FER_mtcnn		0.170	0.203	0.000	0.091	0.871
FER_opencv		0.162	0.177	0.000	0.087	0.701
DeepFace_mtcnn	Disgust	0.355	0.278	0.000	0.246	0.979
DeepFace_opencv		0.370	0.213	0.006	0.327	0.959
FER_mtcnn		0.000	0.000	0.000	0.000	0.003
FER_opencv		0.000	0.001	0.000	0.000	0.006
DeepFace_mtcnn	Fear	0.169	0.135	0.000	0.137	0.532
DeepFace_opencv		0.217	0.138	0.019	0.194	0.531
FER_mtcnn		0.060	0.110	0.000	0.016	0.567
FER_opencv		0.043	0.061	0.000	0.016	0.243
DeepFace_mtcnn	Happiness	0.050	0.063	0.000	0.024	0.316
DeepFace_opencv		0.047	0.047	0.001	0.035	0.245
FER_mtcnn		0.172	0.176	0.001	0.102	0.727
FER_opencv		0.174	0.171	0.000	0.114	0.700
DeepFace_mtcnn	Sadness	0.122	0.106	0.000	0.100	0.403
DeepFace_opencv		0.130	0.106	0.009	0.093	0.425
FER_mtcnn		0.091	0.097	0.000	0.059	0.342
FER_opencv		0.094	0.112	0.000	0.065	0.554
DeepFace_mtcnn	Surprise	0.113	0.136	0.000	0.059	0.546
DeepFace_opencv		0.115	0.132	0.000	0.057	0.520
FER_mtcnn		0.034	0.060	0.000	0.011	0.354
FER_opencv		0.050	0.087	0.000	0.014	0.550
DeepFace_mtcnn	Neutrality	0.171	0.175	0.000	0.127	0.805
DeepFace_opencv		0.113	0.111	0.000	0.096	0.421
FER_mtcnn		0.473	0.248	0.018	0.472	0.927
FER_opencv		0.476	0.244	0.081	0.390	0.977

Table 0-14: Dominant Facial Emotion Frequency Correlation across Face Coding Tools

Coding Tool	DeepFace_mtcnn	DeepFace_opencv	FER_mtcnn	FER_opencv
DeepFace_mtcnn	1.00 ***	0.97 ***	-0.236	-0.237
DeepFace_opencv	0.97 ***	1.00 ***	-0.445	-0.452
FER_mtcnn	-0.236	-0.445	1.00 ***	1.00 ***
FER_opencv	-0.237	-0.452	1.00 ***	1.00 ***

Table 2-15: Gender Difference in Dominant Facial Emotion Frequency – t test

Coding Tool	Average Frequency	Women	Men	Diff
DeepFace_mtcnn	Anger	0.010	0.024	-0.014
DeepFace_opencv		0.007	0.009	-0.002
FER_mtcnn		0.069	0.198	-0.129**
FER_opencv		0.101	0.179	-0.078
DeepFace_mtcnn	Disgust	0.155	0.411	-0.256***
DeepFace_opencv		0.208	0.416	-0.209**
FER_mtcnn		0.000	0.000	0.000
FER_opencv		0.001	0.000	0.001
DeepFace_mtcnn	Fear	0.149	0.174	-0.025
DeepFace_opencv		0.216	0.217	-0.001
FER_mtcnn		0.048	0.064	-0.016
FER_opencv		0.053	0.041	0.012
DeepFace_mtcnn	Happiness	0.086	0.040	0.046
DeepFace_opencv		0.065	0.041	0.024
FER_mtcnn		0.324	0.129	0.195*
FER_opencv		0.300	0.139	0.161*
DeepFace_mtcnn	Sadness	0.142	0.116	0.026
DeepFace_opencv		0.121	0.133	-0.012
FER_mtcnn		0.109	0.085	0.024
FER_opencv		0.083	0.097	-0.014
DeepFace_mtcnn	Surprise	0.142	0.104	0.038
DeepFace_opencv		0.196	0.092	0.104*
FER_mtcnn		0.036	0.034	0.002
FER_opencv		0.063	0.047	0.016
DeepFace_mtcnn	Neutrality	0.316	0.130	0.185*
DeepFace_opencv		0.187	0.092	0.095*
FER_mtcnn		0.414	0.490	-0.075
FER_opencv		0.399	0.497	-0.098

Table 0-16: Temporal Difference in Image Level Dominant Faical Emotions – t test

Coding Tool	Average Score	Full Avergae	First 30s Average	Diff to full average	Last 30s Average	Diff to full average
DeepFace_mtcnn	Anger	0.021	0.022	0.001	0.020	-0.001
DeepFace_opencv		0.008	0.011	0.002	0.007	-0.001
FER_mtcnn		0.170	0.178	0.008	0.167	-0.002
FER_opencv		0.162	0.157	-0.005	0.151	-0.011
DeepFace_mtcnn	Disgust	0.355	0.368	0.013	0.374	0.019
DeepFace_opencv		0.370	0.347	-0.024	0.389	0.018
FER_mtcnn		0.000	0.000	0.000	0.000	0.000
FER_opencv		0.000	0.000	0.000	0.000	0.000
DeepFace_mtcnn	Fear	0.169	0.169	0.000	0.166	-0.003
DeepFace_opencv		0.217	0.225	0.009	0.219	0.003
FER_mtcnn		0.060	0.051	-0.009	0.066	0.005
FER_opencv		0.043	0.038	-0.006	0.047	0.004
DeepFace_mtcnn	Happiness	0.050	0.063	0.013	0.054	0.004
DeepFace_opencv		0.047	0.061	0.014	0.042	-0.005
FER_mtcnn		0.172	0.198	0.026	0.176	0.004
FER_opencv		0.174	0.187	0.013	0.179	0.005
DeepFace_mtcnn	Sadness	0.122	0.098	-0.023	0.127	0.005
DeepFace_opencv		0.130	0.134	0.004	0.129	-0.002
FER_mtcnn		0.091	0.079	-0.011	0.088	-0.002
FER_opencv		0.094	0.088	-0.006	0.095	0.001
DeepFace_mtcnn	Surprise	0.113	0.093	-0.020	0.099	-0.014
DeepFace_opencv		0.115	0.100	-0.014	0.103	-0.012
FER_mtcnn		0.034	0.030	-0.005	0.035	0.001
FER_opencv		0.050	0.044	-0.006	0.055	0.005
DeepFace_mtcnn	Neutrality	0.171	0.187	0.016	0.161	-0.011
DeepFace_opencv		0.113	0.122	0.009	0.112	-0.002
FER_mtcnn		0.473	0.464	-0.010	0.467	-0.006
FER_opencv		0.476	0.486	0.010	0.472	-0.003

Table 0-17: Correlation of Voice Emotions and Face Emotions

Face Coding Tool		Facial Anger	Facial Disgust	Facial Fear	Facial Happiness	Facial Surprise	Facial Sadness	Facial Neutrality
DeepFace_ mtcnn	Vocal Anger	-0.058	-0.125	0.003	-0.058	0.250	0.028	-0.019
	Vocal Happiness	0.117	0.066	-0.024	-0.175	-0.136	0.176	-0.089
	Vocal Neutrality	-0.020	-0.127	-0.058	-0.020	0.429**	-0.053	-0.062
	Vocal Surprise	-0.042	0.036	-0.119	-0.042	-0.098	-0.109	0.273
	Vocal Sadness	-0.062	0.053	0.138	0.327*	-0.145	-0.161	-0.042
DeepFace_ opencv	Vocal Anger	NA	-0.298*	0.111	NA	0.250	0.212	-0.082
	Vocal Happiness	NA	0.323*	-0.255	NA	-0.272	-0.042	0.167
	Vocal Neutrality	NA	-0.190	-0.067	NA	0.429**	-0.029	-0.029
	Vocal Surprise	NA	-0.086	0.246	NA	-0.098	-0.060	-0.060
	Vocal Sadness	NA	-0.014	0.080	NA	0.036	-0.089	-0.089
FER_ mtcnn	Vocal Anger	-0.019	NA	-0.102	-0.019	0.354*	0.354*	-0.124
	Vocal Happiness	-0.089	NA	0.206	0.022	-0.175	-0.175	0.050
	Vocal Neutrality	-0.062	NA	-0.036	-0.062	-0.020	-0.020	0.122
	Vocal Surprise	0.273	NA	-0.075	-0.129	-0.042	-0.042	-0.048
	Vocal Sadness	-0.042	NA	-0.110	0.107	-0.062	-0.062	0.040
FER_ opencv	Vocal Anger	0.003	NA	NA	0.086	0.354*	-0.102	-0.124
	Vocal Happiness	-0.259	NA	NA	0.000	-0.175	0.034	0.215
	Vocal Neutrality	-0.058	NA	NA	-0.071	-0.020	-0.036	0.122
	Vocal Surprise	0.093	NA	NA	-0.147	-0.042	0.236	-0.048
	Vocal Sadness	0.296*	NA	NA	0.055	-0.062	-0.110	-0.181

Table 2-18: Correlation of Voice Features and Face Emotions

Voice Coding Tool		Facial Anger	Facial Disgust	Facial Fear	Facial Happiness	Facial Surprise	Facial Sadness	Facial Neutrality
DeepFace_mtcnn								
Praat	Average Pitch	-0.047	-0.327*	-0.161	-0.095	0.150	0.239	0.314*
	Pitch Variability	-0.150	0.136	-0.270	-0.085	0.221	-0.073	0.046
Open SMILE	Average Pitch	-0.025	-0.255	-0.214	-0.031	0.122	0.034	0.439**
	Pitch Variability	-0.057	-0.278	-0.163	-0.117	0.153	0.204	0.291*
Librosa	Average Pitch	-0.102	-0.308*	-0.057	-0.143	0.085	0.287*	0.241
	Pitch Variability	-0.198	0.082	0.045	-0.166	-0.074	0.138	-0.077
DeepFace_opencv								
Praat	Average Pitch	NA	-0.005	0.033	NA	-0.044	-0.114	0.129
	Pitch Variability	NA	-0.054	0.052	NA	-0.092	-0.059	0.229
Open SMILE	Average Pitch	NA	0.019	-0.078	NA	0.186	-0.123	-0.054
	Pitch Variability	NA	0.053	-0.038	NA	-0.032	-0.116	0.111
Librosa	Average Pitch	NA	-0.006	0.067	NA	-0.124	-0.090	0.162
	Pitch Variability	NA	0.064	0.061	NA	-0.290*	-0.018	0.185
FER_mtcnn								
Praat	Average Pitch	-0.258	NA	-0.065	0.381**	0.010	0.241	-0.132
	Pitch Variability	-0.249	NA	-0.034	0.061	0.435**	0.061	0.016
Open SMILE	Average Pitch	-0.252	NA	-0.018	0.294*	-0.023	0.208	-0.074
	Pitch Variability	-0.356*	NA	0.109	0.312*	0.035	0.112	-0.061
Librosa	Average Pitch	-0.240	NA	-0.016	0.389**	-0.053	0.161	-0.133
	Pitch Variability	-0.010	NA	0.037	0.003	0.105	-0.024	-0.035
FER_opencv								
Praat	Average Pitch	-0.245	NA	NA	0.441**	0.010	-0.075	-0.152
	Pitch Variability	-0.259	NA	NA	0.114	0.435**	-0.201	0.063
Open SMILE	Average Pitch	-0.147	NA	NA	0.360*	-0.023	-0.177	-0.097
	Pitch Variability	-0.303*	NA	NA	0.364**	0.035	-0.126	-0.032
Librosa	Average Pitch	-0.225	NA	NA	0.388**	-0.053	0.048	-0.164
	Pitch Variability	-0.057	NA	NA	-0.035	0.105	0.184	-0.050

Chapter 3

3 Poker Face and Steady Voice: Nonverbal Emotional Neutrality and Gender in Crowdfunding Pitches

3.1 Introduction

Entrepreneurship is an intensely emotional journey. The process of founding and growing a new business is characterized by substantial levels of uncertainty (Packard et al., 2017; Wu & Knott, 2006) accompanied by frequent setbacks and rejection (De Cock et al., 2020; Funken et al., 2020). In communicating with stakeholders and potential resource providers, however, the expression of emotions can be tricky for early-stage entrepreneurs since emotions also regulate social interactions (Van Kleef, 2009). On the one hand, emotions can serve as signals of passion and enthusiasm that enhance empathy and understanding from the audience amidst the uncertainties of early-stage evaluations (Chen et al., 2009; L. Huang & Pearce, 2015). On the other hand, the expression of emotions raises concerns and caution from audiences, particularly when it violates social norms that govern appropriate expression (Ekman, 1993). In the end, not all types of emotional expression lead to successful funding outcomes (see van Kleef & Côté, 2022). For example, Jiang et al. (2019) have shown an inverted U-shaped pattern between facial expressions of happiness and crowdfunding success. Warnick et al. (2021) found evidence that in addition to extremely frequent displays of happiness, anger, or fear, expressing sadness generally decreases funding outcomes in crowdfunding.

However, current research has searched for clues to the nonverbal inference by resource providers mostly in the importance of expressing positive emotions at the appropriate level of intensity in public entrepreneurial pitches, which runs the risk of overemphasizing the role of affective engagement with resource providers, especially in situations with high uncertainty and noise. It is plausible that the affectively charged judgment serves as a means under conditions of unknowable risk for entrepreneurial evaluation, but the core is to identify the cues that fit the professional prototype in entrepreneurship based on experience (Danbold & Bendersky, 2020; L. Huang & Pearce, 2015). Expressing emotions can enhance engagement but may cause misinterpretations and distract from the substantive aspects of the entrepreneurial endeavor. Therefore, it is crucial to balance the consideration of emotional expressiveness with other nonverbal indicators that signal entrepreneurial potential and competence.

Furthermore, the predominance of emotions in decision-making is traditionally seen as irrational, with a significant body of research advocating for the merits of rational capabilities in managerial decisions (Camuffo et al., 2020; Helfat & Peteraf, 2015; Kirtley & O'Mahony, 2023). As a result, emotional neutrality – the observed controlled and neutral emotional state – could be interpreted as an indication of rationality and resilience by resource providers in early-stage entrepreneurial evaluation, which is considered beneficial in the negotiations (Cohen-Chen et al., 2022; Kopelman et al., 2006).[10] This, on the other hand, violates the prevailing gender norm that expects women to be more emotionally expressive and to display

[10] Note that this is a statement about potential inferences by the audience, not a statement that this inference is necessarily true. It is quite possible that emotional expression in presentation is not correlated with emotional influence in decision-making. But in the low-information environment of early-stage entrepreneurship, audiences are likely to use nonverbal cues to infer internal states and mental predilections.

a higher level of emotional disclosure. Previous research highlights the disparity in funding access between female and male entrepreneurs, emphasizing professional investors' bias against stereotypical feminine characteristics (e.g., Balachandra, 2020; Balachandra et al., 2019, 2021; Malmström et al., 2017). These studies suggest women project counter-stereotypical characteristics in facial or verbal communication (Davis et al., 2021; Seigner et al., 2022). Notably, reward-based crowdfunding has emerged as an area where stereotypical perceptions of women can provide an advantage (Johnson et al., 2018; Li et al., 2022; Seigner & Milanov, 2023). Building on studies about the role of emotional expression in early-stage financing and gender bias in pitch evaluation, the effectiveness of showing emotional neutrality and the potential sex differences in the context of rewards-based crowdfunding remain unclear.

In this study of entrepreneur-generated videos for rewards-based crowdfunding pitches, we argue that the key to success lies in aligning specific emotional cues with the pre-existing expectations of resource providers, which are shaped by prevailing social norms (Shields, 2005). As a baseline, we propose that exercising emotional neutrality on the face and in the voice will be interpreted as a professional behavior that aligns with societal expectations of a typical entrepreneur who is emotionally resilient and unbiased in decision-making (De Cock et al., 2020). Given the presence of distinct social norms of emotional expression for men and women, our study further considers how gender norms interact with the assessment of nonverbal emotional neutrality in context of rewards-based crowdfunding. For women, who are expected to be more emotionally expressive and whose audiences appreciate stereotypically feminine traits like expressiveness and emotivity in rewards-based crowdfunding, showing emotional neutrality will be negatively associated with funding success. The data shows that male entrepreneurs with neutral expressions and steady voice pitch are more successful in reaching their crowdfunding goals, while female entrepreneurs with similar neutrality tend to have lower fundraising success rates, suggesting potential biases in evaluating emotional expression by gender.

Our study, then, makes several contributions to the entrepreneurship literature and research. In contrast to most studies that emphasize the expression of positive emotions or focuses exclusively on a single channel (e.g., Allison et al., 2022; Anglin, Short, et al., 2018; Y. Huang et al., 2023; Jiang et al., 2019), our study focuses on facial expressions and vocal pitches as conduits for emotional expression and explores the role of emotional neutrality in entrepreneurial evaluation. This paper reveals a positive correlation between the presence of emotional neutrality in facial and vocal expressions and the success of crowdfunding initiatives. Although not inferring causality, the finding is consistent with the idea that potential resource providers are interpreting nonverbal cues to proxy for unobservable capabilities of entrepreneurs (Chen et al., 2009; L. Huang & Pearce, 2015). Secondly, this study adds to the growing body of evidence about funding gap between male and female entrepreneurs. Different from the mainstream theoretical insights that suggest female entrepreneurs present counter-stereotypical or less feminine characteristics to raise funding (e.g., Balachandra et al., 2019, 2021; Danbold & Bendersky, 2020; Davis et al., 2021), the results show that at least in crowdfunding audiences the inference of emotional regulation is based on very different factors for men and women. Our findings in the context of crowdfunding also raise a question around an empirical regularity in entrepreneurial finance: women tend to be more successful in crowdfunding than in raising funds from later-stage professional investors (Greenberg & Mollick, 2017; Johnson et al., 2018; Wesemann & Wincent, 2021). It will be important for future studies to determine whether professional investors are, in fact, less accepting of gender typical modes of emotional expression for women in entrepreneurial pitches. This potential difference, which would be consistent with other findings that professional investors punish female entrepreneurs for gender typical behavior, could account for some of the higher success rates of women with crowdfunding over later-stage, professional investment. Additionally, although our findings provide additional evidence of female advantage in rewards-based crowdfunding, where stereotypically feminine characteristics like expressiveness and emotivity are appreciated, not fitting gender expectations of emotional expression seems to penalize women. Finally, capturing the nuanced expression of emotions through verbal and nonverbal channels presents empirical challenges. This study offer a methodological contribution to research about entrepreneurial pitch analysis, particularly in the crowdfunding context through employing machine learning tools for the coding, capture, and interpretation of emotional expressions.

3.2 Theoretical Background

3.2.1 Why nonverbal emotional neutrality matters in crowdfunding pitches

Entrepreneurs who excel in emotional regulation often demonstrate a logical, analytical, and objective approach in their decision-making processes (Ivanova et al., 2023; Kosmynin & Ljunggren, 2022). This ability makes them more likely to successfully navigate the emotional rollercoaster ride inherent in encountering unpredictable challenges as they establish and expand their businesses (De Cock et al., 2020). Failure in regulating emotions has been found to corrode entrepreneurial motivation (Doern & Goss, 2014), reduce engagement in learning and innovation (Shepherd et al., 2013), and impair opportunity recognition (Mitchell & Shepherd, 2011). As a result, skill at regulating emotions is a crucial component of entrepreneurial potential.

But how are audiences to look for evidence of this capability? The emotions as social information (EASI) model highlights that emotional expressions affect observers' behavior through both cognitive and affective processes (Van Kleef, 2009). In social settings, individuals communicate their emotions through various behavioral patterns across multiple modalities, including facial muscle movements, vocal cues, bodily movements, gestures, postures, and so on (Keltner et al., 2019), all of which help observers to infer their emotional state and behavioral intentions (e.g., Ekman & Davidson, 1994; Shariff & Tracy, 2011). Facial expressions, in particular, play a prominent role in the nonverbal communication of emotions due to high visibility and universality across cultures (Horstmann, 2003). Emotions expressed by the face are easily recognizable and often spontaneous, providing immediate cues about individuals' emotional display (Matsumoto et al., 2008). Furthermore, vocal cues are particularly potent in capturing attention and conveying emotions when visual input is not available (Guilford & Dawkins, 1991; Hawk et al., 2009). People can discern distinct emotions with a high degree of accuracy through facial expressions and the prosodic elements embedded in speech at a level of accuracy that significantly surpasses random chance (Banse & Scherer, 1996; Rosenberg & Ekman, 1995).

In entrepreneurial pitches, outward displays of nonverbal emotional expressions have been portrayed as indicators of entrepreneurs' emotional intelligence and their ability to regulate cognitive biases (e.g., Cardon et al., 2012; Choudhury et al., 2019). Research has also shown that frequent changes in facial expressions can increase the likelihood of securing funding by capturing observer attention (Warnick et al., 2021). Another study found that vocal expressions with valence-arousal congruence enhance funding through perceived preparedness, while high-arousal vocal expressions increase funding through perceived passion (Allison et al., 2022). Overall, facial and vocal expressions of emotions during the funding pitch process serve interpersonal functions and influence the interaction between entrepreneurs and potential resource providers (Russell et al., 2003).

Audiences that recognize and value emotional regulation in the entrepreneurial process, then, will be looking for nonverbal indicators of this quality in pitches by early-stage entrepreneurs. Showing a neutral face and talking with a steady voice are the keyways that entrepreneurs can communicate emotional control and regulation to an audience. In several other economic and organizational domains, emotional neutrality has been shown to confer advantage. In negotiations, research has established the effectiveness of strategic display of neutral faces at the bargaining table (Kopelman et al., 2006; Van Kleef et al., 2010). Leadership research has also documented the potency of emotional neutrality for task-oriented statements and emotional intelligence signaling (Humphrey, 2002; Sy & van Knippenberg, 2021). These cues may initiate an inferential process within potential resource providers (van Kleef & Côté, 2022), wherein they deduce the capacity to prevent emotions from clouding objective reasoning, based on the observable ability to regulate outward displays of emotions (Brescoll, 2016; Shields, 2002). However, it remains to be investigated whether crowdfunding audiences favor professionalism and rationality projected through facial and vocal emotional neutrality in entrepreneurial pitches.

By focusing exclusively on the valence (positive or negative) and quantity of emotional expression in entrepreneurial pitches, the burgeoning literature on nonverbal expression in entrepreneurship may have overemphasized the role of emotional expression in affective engagement in entrepreneurial potential evaluation (L. Huang & Pearce, 2015). Upon reflecting on the social functions of emotions, this paper posits that showing emotional neutrality helps avoid some of the pitfalls of emotional expression in social settings. Nonverbal emotional expression introduces the risk of creating negative impressions such as being overly emotional or deviating from other display norms (Ekman, 1993; Ekman & Davidson, 1994). Research has addressed the concern that being overly dramatic in emotional expression during crowdfunding pitches can turn potential backers away. For example, one study found that the positive impact of the frequency of entrepreneurs' facial expressions of happiness, anger, and fear diminishes once they surpass a threshold, beyond which the expressions are more likely to be perceived as inappropriate (Warnick et al., 2021). Excessive expression of emotions in campaign has also been shown to reduce support from backers (Raab et al., 2020). Facial emotional neutrality is particularly useful, then, in that it can help mitigate potential misunderstandings arising from emotional expression, especially if there exists an appropriate threshold for the amount of emotion expressed (L. Jiang et al., 2019). Although research on the vocal expression of emotions within entrepreneurial finance is scarce, studies in political science have demonstrated that vocal pitch affects perceptions of leadership ability in both men and women (Anderson & Klofstad, 2012b; Klofstad, 2016; Klofstad et al., 2012, 2015). Research in finance and accounting also have suggested that affective states reflected in the voice of key stakeholders are effective predictors for future firm performance and stock price fluctuations (Gorodnichenko et al., 2023a; Hobson et al., 2012a; Mayew & Venkatachalam, 2012). In this study, we focus on the lack of emotional expressiveness, as observed from the maintenance of a neutral face and minimal variations in vocal pitch.

While expressing emotion triggers engagement and conveys passionate dedication, it may also lead to misinterpretations or confusion about the true motivations of the entrepreneur. Adopting emotional neutrality aids in promoting an objective and reasoned evaluation process among potential resource providers. This, in turn, reduces the likelihood of evoking intense emotional responses and enables the audience to focus on the substantive aspects of the entrepreneurial endeavor, influencing their perceptions of enthusiasm, preparedness and commitment. Although emotional expression can be effective when it increase positive affective reactions among potential funders due to emotional contagion, balancing this approach through showing neutral faces and talking in steady voices can help mitigate misunderstandings and ensure that the evaluation remains focused on the entrepreneur's capabilities and business potential. As such, we propose that entrepreneurs who exhibit emotional neutrality in the face and in the voice are more likely to get funded successfully in rewards-based crowdfunding. Stated formally:

Hypothesis 1(H1). *Showing emotional neutrality in facial and vocal communication during pitches is positively associated with success in rewards-based crowdfunding.*

3.2.2 How gender interacts with evaluation of nonverbal emotional neutrality

Since emotional expression and its interpretation is inherently a social process, the effect of nonverbal expression may well depend on other social norms, as well. In particular, the meaning of emotional neutrality for potential resource providers may be gender specific. In many cultures, the prevailing belief is that women are more emotional than men (Shields, 2002). This leads to strong normative expectations for how men and women express or regulate emotions in social settings (Heilman et al., 2024; Van Boven & Robinson, 2012). Women are expected to be more emotionally expressive compared to men, particularly in emotionally-charged situations like a wedding or memorial service (e.g., Kring & Gordon, 1998). These gendered norms for emotional expression can be quite consequential for female entrepreneurs as others often believe they should express their emotions more openly and immediately than male entrepreneurs.

This belief stems from the role theory that individual behavior is shaped by prevailing social roles with specific behavioral expectations, which serve as social standards to evaluate and condition appropriate behavior (Anglin, Kincaid, et al., 2022; Biddle, 1979, 1986). The belief that women are more emotional than men is rooted in the longstanding gender role norm dictating how men and women should behave, known as the “display rule” (Eagly et al., 2000; Eagly & Karau, 2002). Research consistently demonstrates that men are perceived as more emotionally competent and intelligent when they display emotional neutrality, whereas women are perceived as more emotionally competent and intelligent when they react immediately instead of exhibiting emotional neutrality (Hess et al., 2016). For instance, when observing leaders express negative emotions, the audience responds more favorably to male leaders with neutrality on face and female leaders expressing sadness or anger, thus aligning with gender norms (Lewis, 2000). As such, the lack of nonverbal emotions is a good fit for male entrepreneurs because it is typically associated with men's competence (Hess et al., 2016; Lewis, 2000).

In the context of professional investing, such as pitches to venture capital investors, research has highlighted that female entrepreneurs are better off avoiding gender typical behavior. For instance, feminine behaviors during the pitch (Balachandra et al., 2019) and feminine style in the language of their pitches (Balachandra et al., 2021; Malmström et al., 2017) are negatively associated with fundraising from venture capitalists. Notably, investor gender can significantly impact the success of female entrepreneurs (Snellman & Solal, 2023; Solal, 2021), suggesting that female professional investors are more accepting of female modes of behavior and communication. Increased representation of women in traditionally male-dominated fields can benefit other women, as trust-building and effective communication are fostered through gender matching in mentoring (Blau et al., 2010; Gaule & Piacentini, 2018).

This overall rejection of stereotypically feminine behavior by professional investors is quite noteworthy in the comparison with entrepreneurial crowdfunding, since extensive research has demonstrated that rewards-based crowdfunding has improved the funding chances of female entrepreneurs. This may arise because, as some scholars have argued, female entrepreneurs tend to receive recognition and backing from other women who face similar structural barriers (Greenberg & Mollick, 2017; Wesemann & Wincent, 2021) or share community-minded values (Josefy et al., 2017; Seigner et al., 2022). But it is also likely that the different goals and composition of crowdfunding audiences lead different norms to dominate.

The knowledgeability and motivations of crowdfunding supporters are very different than those of professional investors. First of all, members of "the crowd" (i.e. potential supporters on a crowdfunding platform) typically lack the information, the experience, and the tools to evaluate the financial prospects of a project. Instead, crowdfunding support is motivated 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 & Zhang, 2019). As a result, the enthusiasts and consumers who make up the crowdfunding audience may be less likely to impose norms of rationality for public speech since they are not evaluating the long-term economic prospects of an entrepreneur.

With a lack of expertise and diverse motivation to support, the crowdfunding backers tend to seek information that aligns with social norms. In other words, an audience of amateur, more consumer-oriented, and less experienced potential backers is more susceptible to normative expectations of emotional expression in their evaluations than looking for clues of rationality and impartiality. If female entrepreneurs appear less emotionally expressive, it may not align with the audience's expectations, creating potential challenges in their perception and evaluation (Brescoll, 2016; Van Kleef et al., 2015). Therefore, female entrepreneurs who exhibit a high degree of nonverbal emotional neutrality may be perceived as emotionally incompetent, more likely to "lose control" of their emotions or behave unpredictably in the future (Shields, 2013). Neutral facial expressions and steady voice intonations of female entrepreneurs may be viewed as inappropriate when there is prescriptive norm about emotional expression (Biddle, 1986; Brescoll, 2016).

Thus, defying gender typical emotional expressions may evoke unfavorable responses from an audience adhering to gender norms. In particular, nonverbal emotional neutrality may be perceived as inappropriate when the display fails to align with prevailing norms and expectations (Ekman, 1993; Shields, 2005). Consequently, facial and vocal emotion expressions considered inappropriate by the audience tend to evoke unfavorable responses (Shields, 2002; Van Kleef et al., 2015), which means that women may actually be penalized by crowdfunding audiences when they increase their emotional neutrality. Stated formally:

Hypothesis 2(H2). *The positive relationship between facial and vocal emotional neutrality in pitches and success in rewards-based crowdfunding is attenuated for female entrepreneurs.*

3.3 Research Design

3.3.1 Data Source and Sample

To examine how variation in emotional neutrality affects entrepreneurial fundraising, we gathered videos from the world's largest rewards-based crowdfunding platforms for creative projects, Kickstarter (https://www.kickstarter.com/). On the platform project creators seek to fund an innovative idea, a social event, or life plans by launching a project in the form of a "crowdfunding pitch," in which there is information about a general introduction of the project, the profile of the project creator and the types of rewards that will be offered once the project successfully gets funded (Dushnitsky et al., 2022). This study focuses on the technology and design category of crowdfunding, where projects often resemble those seeking traditional entrepreneurial financing through venture capital or bank loans, allowing us to separate for-profit entrepreneurs from hobbyists (Mollick, 2014). For instance, a small and multifunctional clip holder was successfully funded with the creator's innovative offering to provide one simple solution to multiple tasks that can make life much easier[11].

The rewards-based crowdfunding platform transfers the gatekeeping role for funding professional investors to individual backers with more of a consumer orientation (Ordanini et

[11] https://www.kickstarter.com/projects/norlen/handy-the-multipurpose-clip-holder

al., 2011). These backers contribute small amounts of money in exchange for rewards, such as early access to a product, with their money pooled together to fund an entrepreneur if the pre-set funding goal is reached (Dushnitsky et al., 2022; Mollick, 2014). Entrepreneurs can use an introductory video to communicate their innovative idea and business plans, as well as to present their personality and passion. While professional investors evaluate and support new ventures with high-growth potential, actively participating in the ownership process (Tyebjee & Bruno, 1984), crowdfunding backers do not share in the financial returns but are motivated more by an interest in gaining first access to a novel or innovative product (Schwienbacher & Larralde, 2012) or in helping a nascent entrepreneur in a favored space. In this case, emotional expressiveness might help entrepreneurs establish a personal connection with potential resource providers, and video pitches offer the opportunity to create great emotional engagement and generate high levels of sympathy through narratives and emotion as the first step (Yadav et al., 2011).

The data are collected from 1280 projects launched in the US from January 2020 to May 2021 (17 months) in the technology and design category with customized Python codes, obtaining detailed information about project characteristics, creator profile, pitch media, and campaign results. All projects are in English. We manually screened the video content to ensure the presenters are individual project creators showing their full face[12]. In our sample videos, most entrepreneurs talk with their upper bodies visible, faces toward the screen and voices recognizable. Therefore, facial expressions and vocal intonations are salient nonverbal cues that may influence crowdfunding backers.

The final sample is composed of 183 projects that met these criteria. Because it does not include some large campaigns, the final sample differs on a couple of key dimensions from

[12] 253 projects are with videos in the scraped 1280 projects, of which 42 videos are commercial advertisement with no entrepreneurs in presence and 28 videos have unclear faces.

the underlying sample: the success rate is 36% compared to 41% in the original sample and the final pledged amount is about $40,000 compared to $60,000 in the original sample. But on most dimensions the two are quite similar: campaign duration, prior launch counts, and staff pick incidence are comparable across the samples.

3.3.2 Measures and Processing Procedure

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 the creator receives nothing. *Success* is coded as a binary variable, 1 when the goal was met and 0 otherwise (Josefy et al., 2017; Seigner et al., 2022).

Independent and Interaction Variables

To measure nonverbal emotional neutrality, we follow the video analysis approach proposed in the study by Hu & Ma (2021). We decompose video data into facial, voice and textual dimensions, then apply pretrained machine learning algorithms and software libraries to quantify non-verbal features and conduct dictionary-based textual analysis to construct verbal metrics. Using machine learning algorithms offers advantages over manually coded measures that may lack sensitivity and are error-prone, laborious, and difficult in highly frequent and continuous motion in videos (Hu & Ma, 2021b).

Specifically, we extract the audio files from the video using *MoviePy* library[13] and perform the speech-to-text conversion API provided by *Google Cloud*[14] to obtain the complete speech narratives. The textual content is double-checked using speech recognition service

[13] https://pypi.org/project/moviepy/
[14] Google Cloud Speech-to-Text API can be accessed at: https://cloud.google.com/speech-to-text.

offered by *Microsoft Azure*[15]. To obtain textual measures, we conduct sentiment analysis using NRC Lexicon to get six basic emotions (e.g., anger, disgust, fear, happiness, sadness, and surprise) reflected in the speech content (Hatte et al., 2021; S. H. Ho & Oh, 2020). The scores are calculated and normalized to values between zero and one separately for each pitch speech. A value closer to "one" represents a higher percentage of words related to a specific emotion in the whole textual content during the pitch process.

To measure facial expressions, we use *OpenCV* library[16] to capture a frame every 0.1 seconds in a video and detect faces in the captured frames using pre-trained *Haar Cascade*, saving captured frames with faces as JPG files for each video. The pre-trained algorithm in *FER* library[17] recognizes human faces that are shown in the pictures and characterizes their emotional expression using a vector of confidence scores for seven emotional states: anger, disgust, fear, happiness, sadness, surprise, and neutrality. The scores are calculated and normalized to values between zero and one separately for each face, of which the accuracy reaches around 75% (Khanzada et al., 2020). If at least two individuals are shown in the video, the algorithm returns the average intensity of emotions of everyone (Hu & Ma, 2021b). A value closer to "one" represents a higher degree of emotional expression, by which we can also infer the most dominant emotion among the five categories that is with the highest score. Then, we can measure the average intensity of each emotion in each video by calculating the percentage of frames with this emotion as the most dominant emotion. That said, we divide the number of frames with identified faces with the number of frames with the dominant emotion to generate the video level emotion intensity.

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[15] Microsoft Azure Speech-to-text Services can be accessed at: https://azure.microsoft.com/en-us/products/cognitive-services/speech-to-text/#overview.
[16] https://opencv.org/author/opencv/
[17] https://pypi.org/project/fer/

To process audio files for voice analysis we used *pydub* library[18] to extract audio and transform the files into a single (mono) channel. After that, we coded a series of voice features by analyzing mono audio in *Praat* software[19] (v. 6.2.23; Klofstad, 2016), including the average voice pitch level (mean fundamental frequency F_0), voice pitch variation (standard deviation of the mean fundamental frequency, also known as pitch contour of intonation), and audio quality (HNR[20]). The audio files are analyzed at a sample rate of 16,000, with all other system settings set to their defaults. In the empirical analysis, *Average pitch* and *Pitch variation* in the voice take the logarithm of the sum of original values and 0.0001.

Furthermore, we trained a convolutional neural network (CNN) deep learning model to classify vocal emotions. We use 80% of Toronto Emotional Speech Set (TESS) and Ryerson Audio-Visual Database of Emotional Speech and Song (RAVDESS) data to train the network and tested the CNN model on the remaining 20%, as suggested by Gorodnichenko et al. (2023). 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 Mel-frequency cepstral coefficients (MFCCs), and 12 chroma coefficients), while the second and third layers build on the outputs of their preceding layers. The network culminates in an output layer with five nodes, each corresponding to one of five emotions: happy, pleasantly surprised, neutral, sad, and angry. The trained model achieved an accuracy rate of 85% in the test set. Specifically, the model demonstrated differential accuracy across various emotion classifications: 92% for "anger," 71% for "happiness," 87% for "neutral," 93% for "pleasantly surprised," and 83% for

[18] https://pypi.org/project/pydub/
[19] https://www.fon.hum.uva.nl/praat/
[20] Harmonics -to- Noise Ratio (HNR) quantifies the ratio of the energy of the harmonic (or periodic) components of the voice signal to the energy of the noise (or aperiodic) components. In simple terms, it is a measure of how much of the sound is made up of clear tone (harmonics) as opposed to breathy or noisy sound (noise).

“sad.” We applied the model to process audio comprehensively and predict, resulting in the generation of vocal emotion dummies at the video level.

The behavioral measures are all aggregated to the video level, with a detailed coding process specified in **Online Appendix**. Following this process, the independent variable in the facial dimension is defined as the percentage of frames with neutrality as the most dominant emotion across all identified frames with faces during the pitch process, representing the average intensity of facial neutrality at the video level (***Neutral face***). This measure captures the expected prominence of neutrality displayed on the faces of the entrepreneurs. As research has shown that neutral faces are closer to the neutral point of the bipolar affective space than were prototypical emotional expressions (Carrera-Levillain & Fernandez-Dols, 1994), capturing neutral faces is appropriate to measure facial emotional neutrality. In the voice channel, the emotion is conveyed by the average pitch level and the contour of intonation according to research in communication and psychology (Bachorowski & Owren, 1995; Rodero, 2011). The most salient feature of emotional neutrality in the voice is the lack of pitch variation (monotone voice), as expressions of emotions like anger, fear, sadness, joy, and disgust are often associated with the increase or decrease in mean F0 and F0 range (Banse & Scherer, 1996; Johnstone & Scherer, 2000). Therefore, we use ***Pitch variation*** to measure the average intensity of emotion in the voice.

To identify the entrepreneur’s observable sex (*Female*), we used genderize.io and assigned a value of 1 for entrepreneurs identified by the algorithm as female (Kuppuswamy & Mollick, 2016). We manually validated the assessment by double-checking all the videos in our sample. The algorithm did not differ in its evaluation from the human coders in any cases.

Control variables

First, we include a series of variables showing the frequency of facial and verbal emotion separated by valence. *Positive verbal emotion* represents the average frequency of words related to happiness in the speech content, and *negative verbal emotion* is the average frequency of words related to anger, disgust, fear, and sadness in the speech content. We also include *positive facial emotion* (the percentage of frames with happiness as the most dominant emotion), and *negative facial emotion* (the average percentage of frames with sadness, anger, fear and disgust as the most dominant emotion), as well as *positive vocal emotion* (the dummy showing whether the whole audio is classified as happiness), and *negative vocal emotion* (the dummy showing whether the whole audio is classified as sadness).We also control variation in related video pitch attributes. *Face ratio*, measured by the total number of images where an entrepreneur's face appeared scaled by the sum of captured images in a video, reflects the chance of the audience to see the face. Similarly, we control *speech ratio* which is speech time as a percentage of video (Yang et al., 2022).

In our analysis, we also control for project attributes that can influence outcomes following previous studies (e.g., Anglin et al., 2022; Josefy et al., 2017; Kleinert et al., 2022; Seigner et al., 2022; Taeuscher et al., 2021). *Duration* refers to the predetermined fundraising period established by the project creator upon launching the project. *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. *Staff pick* is a dummy variable that indicates whether the project is featured as a "project we love" on the campaign page (coded as 1 for campaigns that had "project we love" badge, 0 otherwise). This pre-evaluation from the staff serves as a quality signal that potentially impacts fundraising. *Backing experience* is the number of other projects on Kickstarter supported by the creator before this campaign. The previous backing behavior of the project creator might increase the trust of potential backers. *Launch experience* is the number of creators' previously created campaigns on Kickstarter, which signal proficiency in community-based entrepreneurship and potential social resource from previous backers. *Rewards number* is the number of rewards each project offers that can attract crowd funders in different ways. *Facebook followers* is the natural log of the number of followers (plus .0001) the project creator has on Facebook. *Update* is the number of updates posted by the project creator to communicate the addictive information about the project, the funding status, and the delivery info, etc. *Comment* is the number of comments written by the crowds to raise questions and express concerns. These three variables are important signals about social resources gained by the project creator, which might influence project visibility. *Length of project description* is the count of words in the project description. Similarly, *Length of creator biography* is the count of words in the creator's biography. These two measures reflect the project quality. In order to control for the influence of entry time, we incorporate *Start date*, which represents the month in which each project is launched on Kickstarter. Video quality measures like *BGM*, a dummy coded as 1, if the video is with background music, 0 otherwise, and *Audio quality* (indicated by NHR), are also controlled.

3.3.3 Summary Statistics

As shown in descriptive statistics summarized in Table 3-1, 29.5% of our final sample are female entrepreneurs, fitting the conventional wisdom that the design and technology categories are more similar to traditional entrepreneurship with continued underrepresentation of women. The overall success rate of campaigns in our sample was 35.5%. The average extent of facial neutrality in the videos is 0.278, or 27.8%. Entrepreneurs are also more likely to manifest positive emotions in facial expressions and speech content, consistent with previous literature (Anglin, Short, et al., 2018). The average probability of happiness in the face and words is about 0.195 and 0.018, respectively, compared to the average probability of negative emotions (anger, fear, sadness, and disgust) in the face and words at 0.072 and 0.017. On average, faces are shown in 54% of the captured frames, and entrepreneurs spend approximately 90% of the time talking in our sample videos.

***** INSERT TABLE 3-1ABOUT HERE *****

As for the within gender descriptive statistics (cross tabs), Table 3-2 shows that female entrepreneurs are less likely to manifest neutrality compared to their male counterparts (mean difference = -0.102, p-value = 0.000). Additionally, female entrepreneurs (are more likely to show positive emotions on their faces than male entrepreneurs (mean difference = 0.143, p-value = 0.000) and express fewer negative emotions than male entrepreneurs (mean difference = -0.020, p-value = 0.002). These descriptive differences are consistent with previous research on emotion expression variations between women and men in terms of intensity and valence (Davis et al., 2021; Plant et al., 2000). Furthermore, observed differences in voice attributes, such as average pitch, correspond with known biological differences between men and women (Anderson & Klofstad, 2012b; Klofstad, 2016). On average, female entrepreneurs have higher pitch levels in their voices than male entrepreneurs, while male entrepreneurs have higher variation in pitch than their female peers. However, we did not find any gender differences in the likelihood of success.

***** INSERT TABLE 3-2 ABOUT HERE *****

In the Correlation Table in Table 3-3, we display the pairwise correlations for all variables. Interestingly, we found no significant correlation between the extent of facial neutrality and the odds of success, while we did observe a significant and positive correlation between the display of positive facial emotions and crowdfunding success ($r = 0.170$, $p < .05$). This finding aligns with previous research that underscores the role of positive emotions in influencing fundraising performance (L. Jiang et al., 2019; Warnick et al., 2021). We also found that the presence of faces in the crowdfunding pitch videos was negatively correlated with the success of crowdfunding; probably, backers in technology and design generally expect more substantial information about project quality compared to people-related disclosure.

***** INSERT TABLE 3-3 ABOUT HERE *****

3.3.4 Statistical Methods

As encompassed in this specification, we present regression results for Probit specifications in Table 3-4. The variable Y (*Success*) was defined as a function of the nonverbal metrics and other covariates of entrepreneurs (X). We tested the impact of nonverbal emotional neutrality (*Neutral face, Pitch variation*) in base models. XG denoted the interaction of nonverbal emotion neutrality and *Female*, introduced in interaction models. The control variables were denoted by vector F. All models estimated robust standard errors.

After including all the control variables, we added *Neutral face, Pitch variation* as independent variables in the base model (model 1) and then included their interaction terms with *Female* (*Neutral face* x *Female, Pitch variation* x *Female*) in the interaction models (models 2-5) in Table 3-4. To investigate the sex differences comprehensively in how facial and vocal emotions influence crowdfunding success, we incorporated the interaction between emotional valence and sex into our analysis. This addition aims to determine if the observed effects can be attributed solely to the extent of emotional neutrality. As shown in Table 3-3, model 2 includes the interaction terms of facial valence and *Female*, model 3 includes the interaction terms of verbal valence and *Female*, and model 4 includes the interaction terms of vocal valence and *Female*. Model 5 includes the interaction terms of emotional valence across all three dimensions—facial, verbal, and vocal—and *Female*. Overall, there are significant sex differences in how facial neutrality and pitch variation affect crowdfunding success.

***** INSERT TABLE 3-4 HERE *****

3.3.5 Results

To test H1, we examined the correlation between facial and vocal neutrality and crowdfunding success. Since emotional neutrality depends on both facial neutrality and vocal stability, we hypothesized that facial neutrality would be positively correlated with crowdfunding success, while voice pitch variability would be negatively correlated. In model 1, the coefficient for *Neutral face* was significant (b = 9.266, p = .009), indicating a positive association with crowdfunding success, which aligns with our expectations. Although the coefficient for *Pitch variation* was negative, it was not statistically significant (b = -0.563, p = .385). Overall, we found consistent evidence supporting H1 in the facial dimension, but we lack confidence in the vocal dimension.

H2 posited that male entrepreneurs are more successful than their female counterparts when exhibiting neutral facial expressions and speaking in a steady voice. This hypothesis was tested using the interaction models (models 2-5). Since the results are consistent across the models, we focus on model 5 to interpret the findings. The significantly positive coefficient of *Neutral face* (b = 22.402, p = .008) and significantly negative coefficient of *Neutral face* x *Female* (b = - 23.729, p = .036) in model 5 suggest that neutral facial expressions are positively associated with crowdfunding success for male entrepreneurs, but this effect is significantly weaker for female entrepreneurs. Figure 3-1 graphically presents the opposite trends of the association between neutral facial expression and crowdfunding success for men and women. As predicted, an increase of one standard deviation (0.139) in neutral face is associated with a 20.8% increase in the probability of crowdfunding success (dy/dx = 1.498, p = .009), while this increase is associated with a 0.83% decrease in the probability of crowdfunding success (dy/dx = -0.060, p = .866). The data demonstrate that male entrepreneurs achieve higher success rates in crowdfunding when they exercise emotional neutrality on face, while female entrepreneurs do not benefit from showing neutral facial expressions as their male counterparts do.

***** INSERT FIGURE 3-1 HERE *****

In the vocal dimension, the significantly negative coefficient of *Pitch variation* (b = - 2.234, p = .033) and significantly positive coefficient of *Pitch variation* x *Female* (b = 8.215, p = .001) in model 5 indicates that talking using a steady voice is negatively associated with crowdfunding success for male entrepreneurs, while the increased pitch variability benefits women in crowdfunding. As predicted in Figure 3-2, an increase of one standard deviation (0.402) in the log of pitch variability is associated with about 6.55% decrease in the probability of crowdfunding success for men (*dy/dx* = -0.163, $p = .017$), while this change brings about approximately 11.6 % increase in the probability of crowdfunding success for women (*dy/dx* = 0.289, $p = .042$). These findings illustrate the significant sex differences in how pitch variation impacts crowdfunding success, with increased pitch variation being detrimental for males but beneficial for females. Therefore, we find consistent evidence that supports H2 in the facial and vocal dimension.

***** INSERT FIGURE 3-2 HERE *****

Interestingly, there emerged some findings that speaks to the previous research about emotional valence of entrepreneurial pitch. For example, negative valenced speech content during the pitch appears to be marginally associated with crowdfunding success for male entrepreneurs in a negative way ($b = -96.380$, $p = .052$). In contrast, this negative association is significantly stronger for female entrepreneurs ($b = -163.897$, $p = .009$), as shown in model 5. We calculated the average marginal effects, and the results indicate that a one standard deviation (0.012) increase in the expression of negative emotions verbally decreases the probability of funding success for men by 7.73% (*dy/dx* = -6.444, $p = .038$). This effect is approximately doubled for women, with a one standard deviation (0.012) increase in the expression of negative emotions verbally decreasing the probability of funding success by 14.04% (*dy/dx* = -11.703, $p = .002$). In Figure 3-3, we graphically present the sex difference in the effects of negative verbal emotional expression on crowdfunding success.

***** INSERT FIGURE 3-3 HERE *****

Besides, we find emotionality, which is often regarded as feminine characteristics (Balachandra et al., 2019), is beneficial in rewards-based crowdfunding. For example, we observe no significant sex difference in the effects of negative facial expression on crowdfunding success (b = 70.11, p = .109), and the significantly positive coefficient of *Negative faces* suggests that both male and female entrepreneurs can benefit from negative emotional expressions (b = 55.37, p = .079). Although the effect is marginal, this observation is intriguing that showing emotions on face is acceptable even if the emotions are negative. Notably, the coefficient of *Average pitch* is positive (b = 11.14, p = .000) and turns significantly negative for *Average pitch* x *Female* (b = -8.619, p = .024). As shown in Figure 3-4, a one standard deviation (0.223) increase in the log of average voice pitch increases the probability of funding success for men by 16.6% (dy/dx = 0.745, p = .000) and for women by 2.53% (dy/dx = 0.113, p = .270). This suggests that increasing the average voice pitch significantly enhances the probability of crowdfunding success for male entrepreneurs, while it has a smaller and statistically insignificant effect for female entrepreneurs.

***** INSERT FIGURE 3-4 HERE *****

It is noteworthy that voice emotional expression works differently by raising the average pitch level and using a changeable tone. This is probably because pitch variation is more decisive than mean pitch in emotional expression, since a high average pitch is associated with the intensive expression of certain valenced emotions (e.g., happiness, surprise, fear) but does not cover the others (e.g., anger, sadness, disgust) (Rodero, 2011). On the other hand, the changes in the pitch level are often driven by expressing a wide range of emotions no matter what kind of emotions they are. Since positive emotional expression is persuasive in the financing contexts (Chen et al., 2009; Hu & Ma, 2021; Jiang et al., 2019; Li et al., 2017), talking with a high pitch in the voice might demonstrate enthusiasm and passion that brings about crowdfunding success. The expectancy violation theory in previous studies provides a valuable framework to explain the potential advantages of men speaking in a higher pitch during crowdfunding presentations, as this unexpected vocal tone that violates the social norm of men might lead to a positive reevaluation of the speaker's credibility and memorability, especially in contexts where expressing positive emotions is valued (Davis et al., 2021; Seigner et al., 2022).

Overall, the analysis provides evidence suggesting that female entrepreneurs gain advantages in the crowdfunding context by expressing emotions with varied pitch in their voice and through emotional facial expressions. Conversely, male entrepreneurs seem to benefit from a more controlled facial and vocal emotional expressions. When expressing specific emotions, showing negative facial emotions or talking with a high voice pitch seem more beneficial for them.

3.4 Discussion

Recent research about entrepreneurial pitch evaluation emphasize the importance of expressing positive emotions at the appropriate level of intensity. Entrepreneurs must carefully manage how much emotion they show and what types of emotions they express to be successful. While emotions can help engage and motivate audiences, potential resource providers may also use emotional expression cues to infer an entrepreneur's emotional regulation capabilities throughout the ups and downs of creating a new venture. Since careful, unbiased decision-making is an essential entrepreneurial capability, audiences will be looking for indicators that fit the traditional serious entrepreneurial image, such as nonverbal emotional neutrality, to gauge an entrepreneur's ability to navigate this process. What represents effective emotional communication in entrepreneurial pitches, however, can vary substantially with the gender of the presenter.

In this paper we predict that audiences will value nonverbal emotional neutrality, in particular neutral facial expressions and steady vocal pitches, as indicators of the capability to navigate the emotionally demanding process in entrepreneurship. But we hypothesize that this effect will be strictly gender segregated: facial neutrality and steady voice will be positively associated with fundraising success for men but not for women. The results of our analysis are consistent with these predictions in different specifications. While *facial neutrality* is generally positively associated with fundraising success for men, it is not beneficial for women pitching crowdfunding audiences. The consistent finding holds for the change in voice pitch. *Pitch variation,* which responds to the presence of emotional expressions in the voice, is generally negative associated with crowdfunding success for male entrepreneurs, while it is highly positive for female entrepreneurs. This suggests that crowdfunding audiences use different baselines as indicators of emotional regulation for men and women. We contribute to scholar conversations about the role of emotional expression in early-stage financing and different entrepreneurial evaluation outcome for men and women in three ways.

First, this study joins the growing literature on nonverbal expression in early-stage entrepreneurship (e.g., Clarke et al., 2019; Dávila & Guasch, 2022; Hsieh et al., 2020; Jiang et al., 2019). Existing research in strategy and entrepreneurship has, for the most part, largely ignored the "softer" channels, including nonverbal communication, while concentrating on the language-based messages that signal valuable resources and capabilities (Kleinert et al., 2022; Lee et al., 2023; Steigenberger & Wilhelm, 2018; Tumasjan et al., 2021). Our study, in contrast, explores how the nonverbal expression in crowdfunding pitches — and particularly variation in facial and vocal emotion neutrality — shapes the effect of a particular motivating message on fundraising performance. By extracting nonverbal cues from the facial and vocal dimension, we also respond to the rising attention to the application of machine learning based methods in management research (e.g., Choudhury et al., 2019; Momtaz, 2021).

Secondly, by contrasting the effects of emotional neutrality for men and women, the study also adds to – and raises question for – the conversation about the effects of gender on entrepreneurial fundraising. Recent research shed light on professional investors' bias against stereotypical feminine characteristics in venture capitalism (e.g., Balachandra, 2020; Balachandra et al., 2019, 2021; Malmström et al., 2017). Built on the gender-role congruity theory, these studies suggest that perceiving incongruity between the female gender role and the entrepreneur role implies that women are perceived less favorably than men as potential entrepreneurs (Eagly and Karau, 2002; Heilman, 2001; Joshi, 2014). Several strategies have been proposed to correct for the inequalities created by the "lack of fit" of women in entrepreneurship, such as suggest female entrepreneurs (1) respond to prevention-focused question using promotion-focused answers based on regulatory focus theory (Kanze et al., 2018), (2) exhibit greater gender role conformity (e.g., Anglin et al., 2022; Anglin, Wolfe, et al., 2018; McSweeney et al., 2022), or (3) project counter-stereotypical characteristics based on expectancy violation theory (Davis et al., 2021; Seigner et al., 2022). This study joins in the discussion and suggests that women may simply benefit in the context of rewards-based crowdfunding when aligning with a more fundamental gender norm of emotional expressiveness for women (Van Boven & Robinson, 2012), even when that expression is negative. Therefore, our findings raise a question around an empirical regularity in entrepreneurial finance: women tend to be more successful in crowdfunding than in raising funds from later-stage professional investors (Greenberg & Mollick, 2017; Wesemann & Wincent, 2021).

Finally, the fact that women do not fare well when they present a more controlled emotional state raises concerns about the "female-friendly" nature of crowdfunding (Johnson et al., 2018; Li et al., 2022; Seigner et al., 2022; Seigner & Milanov, 2023). Women may succeed at higher rates in crowdfunding because the expectations of the crowd align better with observed characteristics that is more typically feminine. However, there seems to be limited flexibility for women to deviate from these gender norms. Conversely, men benefit more from positive emotional expressions compared to their female counterparts, although they can also face challenges when there is a lack of emotional neutrality reflected from their voice pitch variation.

3.5 Limitations and Future Research

As an analysis of observational data, the study cannot establish a strong causal link between emotional neutrality in facial and vocal expression and success or failure in fundraising. Nonetheless, the descriptive findings reveal an intriguing phenomenon for future studies despite the following noticeable limitations. Firstly, the analysis of video pitches requires the creation of a subsample that is much smaller than the full set of projects in the technology and design categories. While we found only a few substantial differences between this video sample and the full dataset, it is possible that there is some unobserved difference between the projects with video and the full set. In terms of measurement, the study relies on new, computational measures of nonverbal expression. While these measures have been validated, they were not specifically validated with human assessments in this setting. So, at a minimum, the measures are likely to have significant measurement error and could display biases in measurement. Most concerningly, it is possible that early-stage machine learning shows bias in measurement that differs between male and female subjects, which could lead to spurious results in this study. In addition, the crowdfunding setting – while a large and growing arena in entrepreneurial fundraising – is quite distinct from traditional fundraising from professional investors, and this study does not offer the data to establish if these results generalize to professional audiences. This remains an interesting and important area for future research. Finally, while the study controlled for many aspects of verbal and nonverbal expression in these video pitches, we may still suffer from omitted variable bias. In fact, it is hard to fully disentangle the micromechanics referring to backer perceptions without an experiment. Future studies might examine the proposed mechanisms in both formal and informal contexts to advance the understanding about nonverbal cue evaluation.

3.6 Conclusion

As research explores the role of emotions and emotional expression in entrepreneurship, we would do well to remember that emotional regulation is a key capability for effective entrepreneurship. Emotional neutrality can project an image of emotional regulation and rationality, which supports more effective decision-making throughout the entrepreneurial process. The effectiveness of emotional neutrality in crowdfunding pitches, however, is gender specific. The crowdfunding audience, made up of consumers and passionate fans, reacts strongly to violations of gender norms for emotional expression by women. That is, only men are rewarded for exhibiting emotional neutrality. The fact that crowdfunding audiences reward gender typical nonverbal expression by women may partly explain why female entrepreneurs see higher success rates in this setting, but it raises questions for whether this success will translate into important gains in later stage fundraising.

In later stage entrepreneurial fundraising with professional investors, deviation from stereotypically feminine behavior and language has been found to be helpful. In pitches to venture capitalists, women have been found to be penalized for language and behaviors that are more stereotypically female (Balachandra et al., 2021; Malmström et al., 2017), which may help explain why women are less successful than men in later-stage fundraising. As a next step, it will be important to study how professional investors react to emotional neutrality in pitches by men and women to see if they make different assessments than the non-professional audience in crowdfunding. If professional investors react differently to stereotypically female modes of nonverbal expression, this may help explain why women fare worse in later stage fundraising.

3.7 Figures

Figure 3-1: Two-way interaction of neutral face × female on probability of goal success (Table 3-4 - model 5)

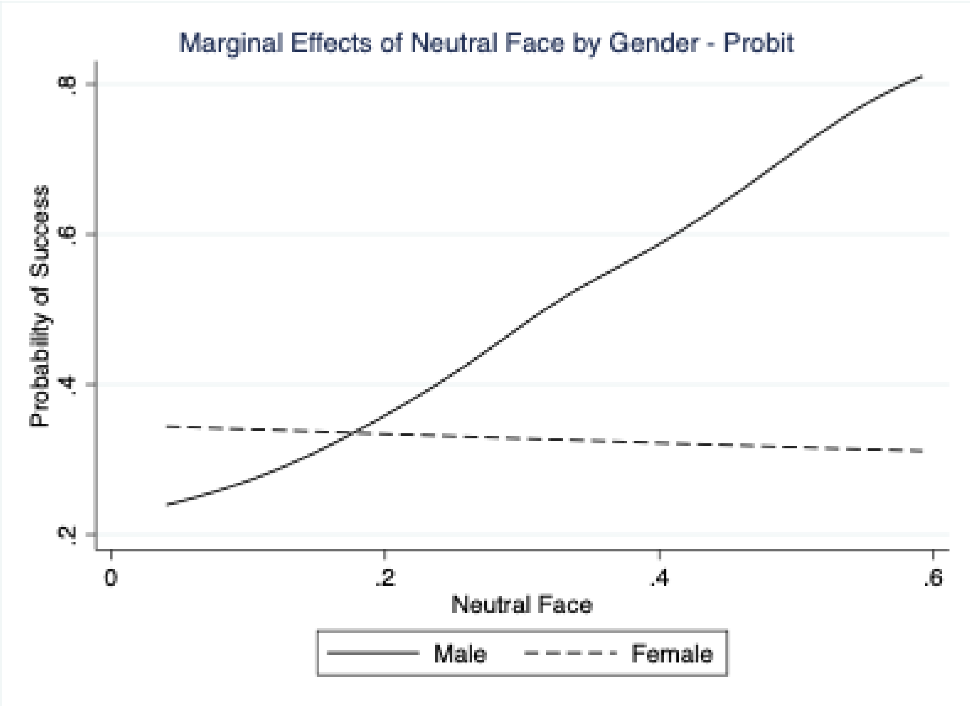


Figure 3-2: Two-way interaction of pitch variation × female on probability of goal success (Table 3-4 - model 5)

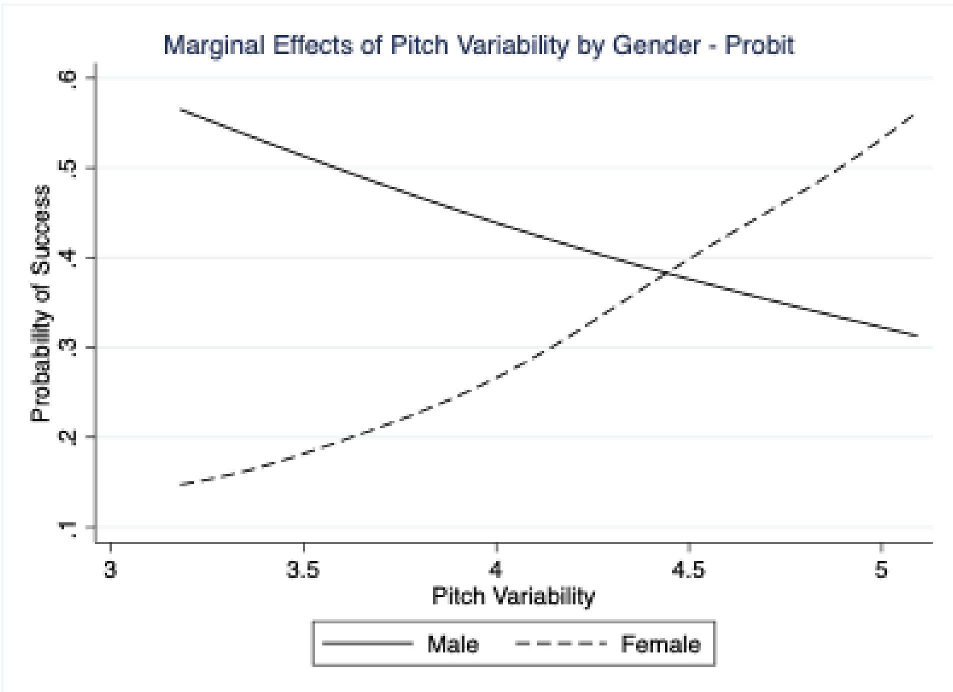


Figure 3-3: Two-way interaction of negative words × female on probability of goal success (Table 3-4 - model 5)

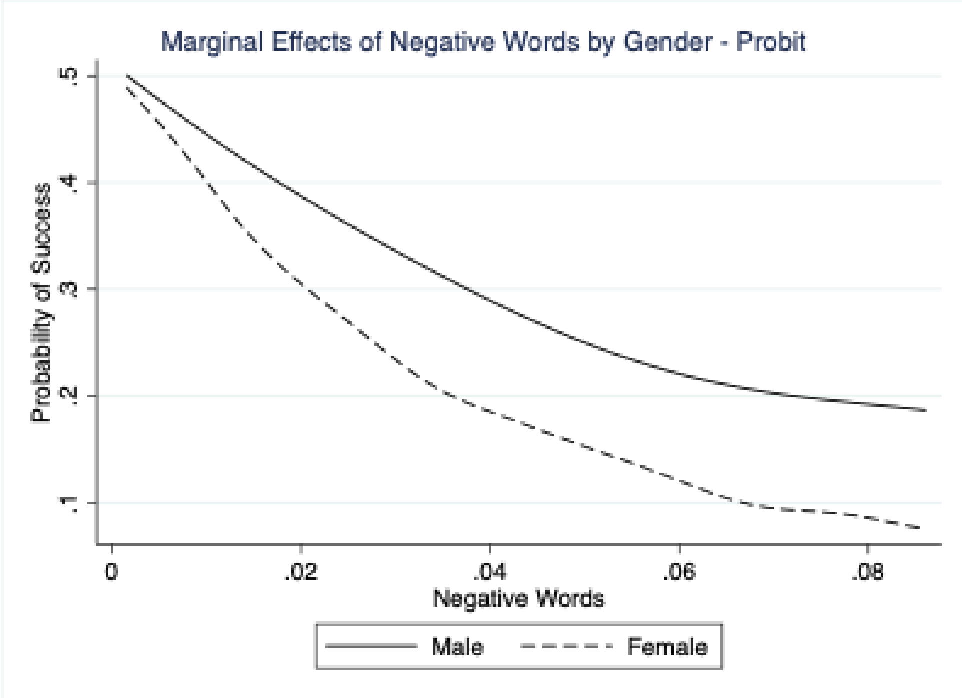
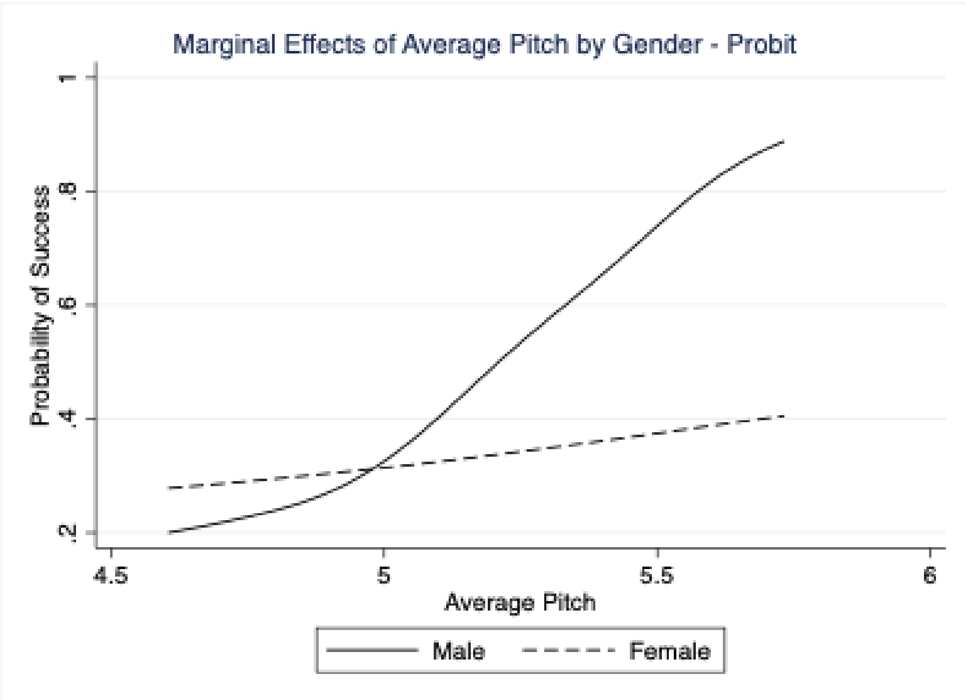


Figure 3-4: Two-way interaction of average pitch × female on probability of goal success (Table 3-3 - model 5)



3.8 Tables

Table 0-1: Descriptive Statistics of Variables

Dependent Variable	N	Mean	SD	Min	Max
Success	183	.355	.480	0	1
Independent Variable					
Neutral face	183	.278	.139	.04	.678
Ln (Average Pitch)	183	5.090	.223	4.604	5.734
Ln (Pitch Variation)	183	4.261	.403	3.181	5.094
Creator-level Controls					
Female	183	.295	.457	0	1
Positive Faces	183	.195	.164	.002	.742
Negative Faces	183	.109	.042	.018	.215
Positive Voices	183	.333	.473	0	1
Negative Voices	183	.290	.455	0	1
Positive Words	183	.018	.016	.001	.125
Negative Words	183	.017	.012	.002	.086
Face Ratio	183	.54	.290	.015	1
Speech Ratio	183	.903	.170	.221	1
Audio Quality	183	.286	.104	.092	.818
BGM	183	.601	.491	0	1
Project-level Controls					
Duration	183	35.142	12.590	9	74
Ln (Funding Goal $)	183	9.564	1.371	4.605	13.017
Staff Pick	183	.115	.320	0	1
Backing Experience	183	3.661	11.442	0	114
Launch Experience	183	2.016	3.339	1	26
Rewards Number	183	7.284	3.808	2	21
Ln (FB Follower)	183	-5.349	6.800	-9.21	8.507
Updates	183	5.273	10.202	0	86
Comments	183	97.033	612.909	0	7674
Length of Description	183	15.372	5.817	3	26
Length of Biography	183	64.984	68.658	2	556
Video length	183	183.554	167.398	25.4	1864.05

Table 0-2: Descriptive Statistics of Main Variables by Gender – t test

	Men Subsample (N =129)		Women Subsample (N =54)		Difference	p-Value
Dependent Variables	Mean	SD	Mean	SD	MeanDiff	
Success	0.341	0.476	0.389	0.492	-0.048	0.730
Independent Variables						
Neutral Face	0.308	0.135	0.207	0.123	0.102***	0.000
Ln(Average Pitch)	5.000	0.176	5.308	0.167	-0.308***	0.000
Ln(Pitch Variation)	4.241	0.422	4.311	0.352	-0.070	0.285
Creator-level Controls						
Positive Faces	0.152	0.126	0.296	0.198	-0.143***	0.000
Negative Faces	0.115	0.042	0.096	0.040	0.020***	0.002
Positive Words	0.018	0.015	0.020	0.017	-0.002	0.168
Negative Words	0.016	0.012	0.018	0.012	-0.002	0.125
Positive Voices	0.372	0.485	0.241	0.432	0.131	0.087
Negative Voices	0.295	0.458	0.278	0.452	0.017	0.821
Face Ratio	0.544	0.300	0.530	0.270	0.013	0.388
Speech Ratio	0.906	0.170	0.897	0.170	0.008	0.381
Project-level Controls						
Audio Quality	0.302	0.093	0.248	0.118	0.054***	0.001
BGM	0.589	0.494	0.630	0.487	-0.040	0.306
Duration	34.209	12.476	37.370	12.697	-3.161	0.061
Funding Goal $	34698.64	59496.31	27128.96	42715.41	-10056.51	0.386
Staff Pick	0.101	0.302	0.148	0.359	-0.047	0.181
Backing Experience	3.891	12.459	3.111	8.617	0.780	0.338
Launch Experience	2.279	3.723	1.389	2.060	0.890	0.050
Rewards Number	7.039	3.671	7.870	4.093	-0.832	0.089
Facebook Follower	265.256	711.448	278.537	824.047	-13.281	0.460
Updates	5.496	11.487	4.741	6.192	0.755	0.325
Comments	119.078	721.434	44.370	170.315	74.707	0.227
Length of Description	15.217	5.871	15.741	5.724	-0.524	0.290
Length of Creator Biography	60.946	61.246	74.630	83.630	-13.684	0.891
Video Length	179.030	122.333	194.361	33.310	-15.331	0.287

*** p<0.01, ** p<0.05, * p<0.10

Table 0-3: Correlation Matrix (Pearson)

Variables	-1	-2	-3	-4	-5	-6	-7	-8	-9	-10	-11	-12	-13
(1) Success	1												
(2) Neutral face	-0.097	1											
(3) Female	0.046	-0.335***	1										
(4) Positive faces	0.170**	-0.433***	0.400***	1									
(5) Negative faces	-0.089	-0.362***	-0.215***	-0.585***	1								
(6) Positive words	-0.039	-0.06	0.072	0.128*	-0.043	1							
(7) Negative words	-0.06	-0.101	0.085	0.142*	-0.059	0.732***	1						
(8) Face ratio	-0.237***	0.033	-0.021	-0.162**	0.142*	0.017	-0.001	1					
(9) Ln(Average pit~)	0.096	-0.301***	0.775***	0.375***	-0.208***	0.057	0.041	-0.065	1				
(10) Ln(Pitch vari~)	0.172**	-0.265***	0.647***	0.357***	-0.197***	-0.006	0.024	-0.184**	0.766***	1			
(11) Speech ratio	-0.037	0.184**	-0.023	-0.106	-0.071	-0.241***	-0.226***	0.291***	-0.106	-0.069	1		
(12) Audio quality	0.013	0.09	-0.240***	0.029	-0.053	0.027	0.018	-0.117	-0.231***	0.043	-0.017	1	
(13) BGM	0.185**	-0.016	0.038	0.086	-0.077	-0.11	-0.043	-0.500***	0.058	0.264***	-0.207***	0.323***	1
(14) Duration	-0.261***	0.102	0.115	-0.054	-0.026	-0.09	-0.058	-0.027	0.037	-0.046	0.023	-0.052	-0.069
(15) Ln(Funding go~)	-0.331***	0.229***	-0.022	-0.098	-0.105	-0.04	-0.169**	0.062	-0.033	-0.141*	0.018	-0.018	-0.139*

(16) Staff pick	0.342***	-0.026	0.068	0.082	-0.07	-0.045	-0.007	-0.155**	0.154**	0.181**	-0.171**	-0.054	0.118
(17) Backing exper~e	0.118	0.048	-0.031	-0.026	-0.022	0.058	0.004	-0.106	0.017	0.048	-0.028	-0.028	0.08
(18) Launch experi~e	0.302***	0.072	-0.122*	-0.141*	0.123*	0.007	0.004	-0.017	-0.073	-0.028	0.098	-0.051	-0.036
(19) Rewards number	0.293***	-0.089	0.1	0.023	0.012	-0.134*	-0.079	-0.193***	0.143*	0.200***	-0.208***	0.029	0.173**
(20) Ln(FB follower)	0.08	0.097	-0.008	-0.162**	0.108	-0.006	0.045	0.066	-0.026	0.013	0.049	-0.146**	-0.044
(21) Updates	0.496***	0.014	-0.034	0.011	-0.077	0.016	0.088	-0.167**	0.061	0.013	-0.049	-0.143*	0.059
(22) Comments	0.210***	-0.088	-0.056	-0.055	0.055	-0.006	-0.031	-0.104	0.033	0.075	-0.004	0.034	0.073
(23) Length of des~n	0.037	-0.087	0.041	0.104	-0.011	-0.033	-0.105	-0.009	0.03	0.003	0.021	-0.064	-0.013
(24) Length of bio~y	-0.11	-0.05	0.091	0.007	0.094	-0.038	-0.089	-0.011	0.052	0.079	-0.01	0.008	0.048
(25) Video length	-0.1	-0.012	0.042	-0.148**	0.123*	-0.341***	-0.392***	0.065	0.047	-0.001	0.058	-0.189**	-0.107
(26) edate	0.079	0.009	-0.112	0.133*	-0.168**	0.037	-0.017	-0.07	-0.107	-0.056	-0.057	0.027	0

	-14	-15	-16	-17	-18	-19	-20	-21	-22	-23	-24	-25	-26
(14) Duration	1												
(15) Ln(Funding go~)	0.279***	1											
(16) Staff pick	0.034	0.001	1										
(17) Backing exper~e	-0.071	-0.062	0.119*	1									
(18) Launch experi~e	-0.171**	-0.246***	0.019	0.296***	1								
(19) Rewards number	-0.118	0.009	0.212***	0.262***	0.106	1							

(20) Ln(FB follower)	-0.051	-0.183**	0.078	0.203***	0.310***	0.059	1						
(21) Updates	0.033	-0.021	0.381***	0.269***	0.184**	0.311***	0.115	1					
(22) Comments	0.011	-0.017	0.08	0.273***	-0.002	0.246***	-0.068	0.292***	1				
(23) Length of des~n	0.077	0.107	-0.079	-0.146**	-0.085	0.04	-0.099	-0.01	-0.007	1			
(24) Length of bio~y	0.153**	0.166**	-0.039	0.04	-0.028	-0.075	-0.079	-0.111	-0.099	0.067	1		
(25) Video length	0.052	0.155**	-0.017	-0.023	-0.022	0.025	-0.105	-0.064	-0.021	0.083	0.143*	1	
(26) edate	-0.03	-0.024	0.03	0.093	-0.039	-0.047	-0.047	-0.031	-0.099	-0.075	-0.08	0.03	1

*** p<0.01, ** p<0.05, * p<0.1

Table 0-4: Probit Regression Results of the Funding Success with Valence-Gender Interactions

VARIABLES	(1) DV:Success Probit regression	(2) DV:Success Probit regression	(3) DV:Success Probit regression	(4) DV:Success Probit regression	(5) DV:Success Probit regression
H1: Neutral face	9.266**	16.09*	18.92**	18.83**	22.40**
	(3.571)	(6.573)	(5.852)	(5.840)	(8.471)
H1: ln(Pitch variation)	-0.563	-1.186	-1.402†	-1.515†	-2.234*
	(0.648)	(0.840)	(0.821)	(0.879)	(1.048)
H2: Neutral face x Female		-11.21	-26.16***	-23.50***	-23.73*
		(8.374)	(7.786)	(5.441)	(11.30)
H2: ln(Pitch variation) x Female		3.514**	3.197*	4.221**	8.215***
		(1.241)	(1.532)	(1.544)	(2.444)
Female	0.0379	-23.63*	-8.017	22.66	3.582
	(0.780)	(10.66)	(5.415)	(14.17)	(20.14)
Positive faces	8.226**	11.59 †	13.82*	12.47*	14.76†
	(3.078)	(6.271)	(5.592)	(5.036)	(8.269)
Negative faces	28.05*	38.92	50.64*	54.10*	55.37†
	(11.87)	(25.35)	(20.84)	(21.52)	(31.55)
Positive words	17.64	33.35 †	42.55	43.13*	61.00
	(16.93)	(18.63)	(32.22)	(20.08)	(38.06)
Negative words	-51.04†	-91.08*	-78.51*	-97.57*	-96.38†
	(27.14)	(36.56)	(40.02)	(38.66)	(49.68)
Positive voices	-0.510	-0.567	-0.754	-0.496	-0.858
	(0.460)	(0.572)	(0.564)	(0.660)	(0.841)
Negative voices	-0.682	-1.449 †	-1.334†	-0.875	-1.119
	(0.528)	(0.764)	(0.767)	(0.660)	(0.874)
ln(Average pitch)	2.752†	6.060***	5.316***	8.487***	11.14***
	(1.509)	(1.681)	(1.570)	(2.256)	(2.981)
Duration	-0.0458*	-0.0434 †	-0.0248	-0.0315	-0.0354
	(0.0207)	(0.0228)	(0.0188)	(0.0195)	(0.0236)
ln(Funding goal)	-1.190***	-1.739***	-1.705***	-1.658***	-2.191***
	(0.245)	(0.290)	(0.349)	(0.276)	(0.444)
Staff pick	1.480**	1.404 †	0.569	0.551	0.695
	(0.565)	(0.820)	(0.779)	(0.665)	(0.814)
Length of biography	0.00532*	0.00974***	0.0100*	0.00929***	0.0118***
	(0.00256)	(0.00257)	(0.00390)	(0.00226)	(0.00355)
ln(FB follower)	-0.0373	-0.0829*	-0.0628†	-0.0843*	-0.109**
	(0.0299)	(0.0392)	(0.0377)	(0.0336)	(0.0366)
Backing counts	-0.122**	-.0124	-.0238		
	(0.0429)	(0.0172)			
Launch counts	0.104	0.161	0.154	0.194	0.315†
	(0.101)	(0.137)	(0.154)	(0.148)	(0.162)
Updates	0.276***	0.421***	0.459***	0.458***	0.671***
	(0.0599)	(0.0720)	(0.0942)	(0.0830)	(0.129)
Comments	0.0682**	0.0859***	0.0728***	0.0795***	0.0746**
	(0.0203)	(0.0237)	(0.0220)	(0.0212)	(0.0253)
Length of description	0.0423	0.0550	0.0530	0.0866*	0.111*
	(0.0415)	(0.0463)	(0.0464)	(0.0419)	(0.0466)
Start date	0.00311*	0.00377 †	0.00482**	0.00496**	0.00475*

	(0.00154)	(0.00193)	(0.00176)	(0.00173)	(0.00189)
Positive face x Female		9.556			14.11
		(9.026)			(9.778)
Negative face x Female		68.04 †			70.11
		(41.09)			(43.80)
Positive words x Female			22.52		28.72
			(36.92)		(38.39)
Negative words x Female			-96.29		-163.9**
			(59.88)		(63.11)
Positive voices x Female				0.890	1.921†
				(0.974)	(1.101)
Negative voices x Female				-0.914	-2.380†
				(1.127)	(1.296)
ln(Average pitch) x Female				-7.031*	-8.619*
				(3.023)	(3.830)
Constant	-79.24*	-109.3*	-130.9**	-152.7***	-155.0**
	(35.84)	(46.00)	(42.30)	(44.74)	(51.15)
Observations		183	183	183	183
Log Pseudolikelihood		-24.882	-25.197	-24.605	-22.130

Robust standard errors in parentheses *** p<0.001, ** p<0.01, * p<0.05, † p<.10
Notes: The following variables were included in the regression analysis but omitted from the table for space limitations: *Face ratio, Speech ratio, BGM, Audio quality, Rewards number, Video length*. None of these variables showed a significant relationship with the outcome variable, fundraising success.

3.9 Online Appendix

3.9.1 Detailed Sampling Process

The full sample spans from April 2009 to May 2021, with 328585 projects of 264312 project creators. As crowdfunding in the technology and design category sharesre attributes of entrepreneurial financing, we start from the latest created projects in this category from 2020 to 2021(17 months) and find there are 759 failed projects. Trying to get a sample consistent with the officially reported success rate of 39.95%, we randomly select 521 successful projects using *.sample* method in python. There are 1280 projects in total in the starting sample.

Then I manually screen the video contents to make sure there are real entrepreneurs showing up and pitching. For example, videos with actors/actresses, or videos like advertisement are screened out. Specifically, 253 projects are with videos in the scraped 1280 projects, of which 42 videos are commercial advertisement with no entrepreneurs in presence and 28 videos have unclear faces.183 projects are kept in the final sample for analysis.

3.9.2 Video Analysis Procedure

(1) Verbal Part

Step 1. Text Extraction

- Transform video (.mp4) to audio (.wav) using *MoviePy* library[21].
- Split each audio file of the project creator where silence is 700 milliseconds or more and get chunks.
- Apply speech recognition on each of these chunks using Google *SpeechRecognition* library[22] (two ways as below, and we refer to the first option that is free).
    - Google Speech Recognition (free; Google Speech Recognition service by default)
    - Google Cloud Speech API[23](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* [24] 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.

[21] https://pypi.org/project/moviepy/
[22] https://pypi.org/project/SpeechRecognition/
[23] https://cloud.google.com/speech-to-text
[24] https://saifmohammad.com/WebPages/NRC-Emotion-Lexicon.htm

- 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[25] to capture frame in each 0.1 second 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 [26]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*.

[25] https://opencv.org/author/opencv/
[26] https://pypi.org/project/fer/

- Calculate the percentage of frames with happiness as the most dominant emotion (number of frames with happiness dominant divided by number of frames with face), which represents an important control variable in our study, *Positive face*.
- Calculate the percentage of frames with sadness, anger, fear and disgust as the most dominant emotion respectively (number of frames with sadness/anger/fear/disgust dominant divided by number of frames with face) and calculate the average of the three percentage scores. The generated average score represents another important control variable in our study, *Negative face*.

(3) Vocal Analysis

Step 1. Process Audio

- Use *pydub* library [27]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*[28] software, the pitch of the female voices was measured within a range of 100–600 Hz, and for male voices within a range of 75–500 Hz. All other system settings were set to their defaults.
- Generate the average voice pitch level (mean fundamental frequency F_0), voice pitch variation (standard deviation of the mean fundamental frequency), and audio quality (NHR) using functions in *Praat*.

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

[27] https://pypi.org/project/pydub/
[28] https://www.fon.hum.uva.nl/praat/

- 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%.
    - 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.
    - 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 2,000 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.
    - 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.

Chapter 4

4 Women Support Women? Public Attention to Fraud Scandal and Gender Homophily in Venture Capital

4.1 Introduction

The increased representation of female investors has been instrumental in mitigating the difficulties female entrepreneurs encounter in accessing funding. Empirical evidence suggests that female investors are more likely than their male counterparts to invest in female-founded startups, a tendency attributable to homophily - the natural gravitation towards individuals who share similar characteristics (Ewens & Townsend, 2020; Greenberg & Mollick, 2017). Yet, the observed gender homophily might raise concerns about the stringency of investment evaluations. Longterm funding for female entrepreneurs could be adversely affected if such concerns led to doubts about their capabilities (Snellman & Solal, 2023). While this long-term implications of skepticism toward VC evaluation is suggested, the short-term consequences of heightened scrutiny on venture capital's evaluation processes remain to be comprehensively explored. The Elizabeth Holmes fraud scandal, for instance, spotlights the discrediting of venture capital (Griffith, 2021b). Following the Holmes scandal, VCs are pressured to demonstrate their competence and safeguard their professional standing. This paper examines how public attention to this scandal may increase skepticism about existing issues in venture capital and highlights shifts in same-gender support in entrepreneurial funding after the crisis.

Existing research has extensively documented the negative consequences of firm misconduct or fraud for various stakeholders. For instance, firms engaged in such activities typically suffer from substantial damage to their reputation (Zavyalova et al., 2012). This reputational fallout can extend to the fraudulent company's directors and CEOs who bear responsibility for monitoring and management roles, often resulting in changes in directorship and executive turnover (Arthaud-Day et al., 2006; Wiersema & Zhang, 2013). The fallout of misconduct extends beyond the corporate echelon to all associated members who may experience a degree of stigmatization, especially in cases where the fraudulent misconduct was unexpected or notably exceptional (Pozner & Harris, 2016; Wiesenfeld et al., 2008). One immediate and measurable impact of such scandals is a decrease in stock prices (Christensen, 2016). Such incidents of fraud precipitate a negative response from investors, with subsequent challenges in securing financing and ensuring firm survival (Mahendiran, 2023). Overall, the extant literature primarily addresses the notoriety engendered by misconduct, centering on the implicated firm and the directly associated individuals.

In the present study, we build upon the recognition that the "failure" label is often transferred from the corporation to the broader social category, a phenomenon that can envelop all individuals associated with the category, commonly referred to as the stigma-by-association (Goffman, 1963). Our specific focus is on examining the spillover effect of high-profile startup misconduct through the shared characteristics of this fraud-tainted firm. The Elizabeth Holmes scandal, which emerged in October 2015 following investigative journalism and regulatory scrutiny, and culminated in a settlement with the SEC over charges of extensive fraud in March 2018 (B. C. Ho, 2018), garnered substantial public attention in the United States, since Holmes' previous success had been celebrated as a beacon of progress for women in the traditionally male-dominated sectors such as technology. We argue that the heightened attention to SEC fraud charge can result in the penalties for startups sharing attributes of Theranos (e.g., stratups with a female founder in biotech industries). This paper aims to explore whether and how female VC partners can support these startups in the face of heightened scrutiny over venture capital's long-standing issues with evaluation rigor and the intensified bias that women are incompetent in traditionally male-dominated professions (Heilman et al., 1997).

Notably, there is persistent skepticism and heightened scrutiny of women who deviate from the conventional prototype of success (Danbold & Bendersky, 2020; Del Carpio & Guadalupe, 2022; Eagly & Karau, 2002b; Heilman, 2001). The successes of women in these fields are often attributed to external factors such as luck, while their failures are seen as indicative of a lack of ability (Alnamlah & Gravert, 2020). For instance, fraud-tainted women in the financial advisory industry face misconduct charges and suffer more severe career repercussions than their male counterparts, despite causing less harm and being less likely to reoffend (Egan et al., 2022). Given the increased caution towards financing risk in the VC industry, the Holmes scandal risks perpetuating the stigma of incompetence associated with women in entrepreneurship. As such, the heightened attention to fraud in financing can undermine investor confidence in female-founded ventures.

It is crucial to recognize that the underrepresentation of women in entrepreneurship renders support from their same-gender peers essential, particularly from those who have successfully navigated the boundary set by traditional "gatekeepers" (Calder-Wang & Gompers, 2021; Germann et al., 2023). The benefit of gender homophily is typically prominent in entrepreneurial financing where female investors tend to express more interest in female-founded ventures (Ewens & Townsend, 2020; Hegde & Tumlinson, 2014; Solal, 2021). However, the reported lower hiring rate, less active investment participation, and lack of professional networks also indicate the challenges faced by female investors (Calder-Wang et al., 2021; Gefen et al., 2022; Harrison et al., 2020). In light of the structural barrier in male-dominant of entrepreneurship and investing, this study discusses how the heightened attention to Holmes scandal might affect gender homophily in the context of female investors and female entrepreneurs. We develop competing hypotheses to explore potential changes in the well-documented phenomenon of same-gender support in early-stage financing (e.g., Greenberg & Mollick, 2017; Snellman & Solal, 2023).

On the one hand, the scandal may exacerbate the stigma of perceived incompetence among female investors, prompting them to adopt a more cautious approach in their associations with female entrepreneurs. In an effort to mitigate the reputational risks linked to backing high-profile failures (Piazza & Perretti, 2015; Wiesenfeld et al., 2008), female investors may strategically diversify their portfolios, thereby reducing reliance on gender-based affinities in investment decisions. This could result in a temporary decline in gender homophily, as relationships become more formalized and less reliant on trust derived from shared gender identity. Conversely, the scandal could also catalyze a strengthening of gender homophily due to identity threat (Petriglieri, 2011). Female investors attempt to decrease the likelihood of potential identity harm derived from the Theranos case of women entrepreneurs and the broader cohort of women in male-dominated fields. In response, they may intensify their support for female-founded startups, actively seeking to counteract these adverse perceptions and reinforce gender homophily in their investment strategies.

To test these predictions, I examine the likelihood of female founders in post-Elizabeth Holmes scandal secured fundings and explore the heterogeneity in the subsamples based on the presence of female VC partners in the funding deal. The analyses utilized Crunchbase data on venture-backed startups in the United States. Using the Google search index for "Elizabeth Holmes" and "Theranos" from 2015 to 2019, I categorized U.S. states into two groups based on their relative attention to the scandal — those with search indices above and those below the median among all states in the sample. This search activity serves as a proxy for investor attention, a measure extensively employed in the finance literature to gauge the public's attentiveness on specific issues, thereby estimating the exposure to particular events (Bennett et al., 2023; Da et al., 2011). Drawing on the approach of Calder-Wang et al. (2021), who investigated the treatment effect of the Ellen Pao trial on women's employment in venture capital, I consider investments in states with heightened attention to the Elizabeth Holmes scandal as the treatment group and those in states with lower attention as the control group. The sample for analysis is observations of 14,741 initial round of funding secured between 2015 to 2019. The preliminary findings show a decrease in female-founded startups in the same industries as Theranos in sates more attantative to the Holmes scandal after 2018 when the fraud was legally charged, while this decrease was mainly driven by the funding deals with female VC partner participation. Moreover, even for the male-founded startups with female cofounders, the penalties for them persist with the presence of female VC partners. The decline in support for startups with any female on the founding team suggests a strategic shift in the investment patterns of female venture capital partners in the initial stage of financing, where gender homophily has traditionally played a significant role.

This paper contributes to the research on startup misconduct and gender homophily in entrepreneurship, as well as female underrepresentation in broader research domains. First of all, this study seeks to provide insights into the change in the already challenging landscape of securing venture capital for female founders by examining whether their same-gender investors deviate from the gender homophily pattern in the face of scandalous negative events. Contrary to the previous research that strengthen an increased inclination to support one another in overcoming gender-specific structural barriers in early stage financing (e.g., Greenberg & Mollick, 2017; Snellman & Solal, 2023), we find that female VC partners tend to support male-founded venture to mitigate the risk post-scandal. Although the scandal may have heightened the collective identity and connections among female VC partners and entrepreneurs, female VC partners may feel compelled to distance themselves from the stigmatized social group of startups sharing characteristics of Theranos. Furthermore, this study explores the indirect consequences of the Holmes scandal, an unexpected failure among VC investors in the US. Although not directly involved in the fraud, these investors are linked to the scandal through their responsibility for due diligence, which failed to prevent the misconduct. The paper theorizes how the heightened scrutiny on evaluation practices affects female VC partners and highlights the broader social implications of the case, providing different insights from discussion about consequences of firm misconduct primarily focusing on directly involved executives and directors , or the unintended impacts on unaffiliated but connected organizations (e.g., Bereskin et al., 2020; Gomulya & Boeker, 2016) and the unintended loss or gain experienced by unaffiliated but associated organizations (e.g., Naumovska & Zajac, 2022; Piazza & Perretti, 2015). Finally, the observed decrease in female founder repesentation in secured funding deals subsequent to the scandal in more attentive states is intriguing. It aligns with prior studies that emphasize the fundamental role of public attention in amplifying the impact of misconduct (e.g., Durand & Vergne, 2015; Han et al., 2023).

4.2 Conceptual Framework

4.2.1 Background

This study examines the period from 2015 to 2019, aiming to assess the impact of the Elizabeth Holmes scandal on the participation of female venture capitalists (VCs). The Elizabeth Holmes scandal centers around Theranos, a biotech company founded in 2003 by Holmes, then a 19-year-old Stanford dropout. The company promised to revolutionize blood testing by using only a few drops of blood. For years, Holmes maintained an illusion of revolutionary innovation, attracting significant investment and striking up partnerships with major corporations. This illusion began to unravel in October 2015 when a series of investigative articles by The Wall Street Journal questioned the legitimacy of Theranos's technology and business practices. The ensuing investigation revealed that the company's blood-testing device, which was claimed to be able to run comprehensive tests with just a few drops of blood, did not work as advertised. In March 2018, the scandal escalated when the U.S. Securities and Exchange Commission (SEC) filed charges against Holmes and Theranos's ex-president Ramesh "Sunny" Balwani, alleging criminal fraud. Theranos ceased operations in June 2018, and Holmes was convicted on four counts of fraud and conspiracy in January 2022, with her prison sentence commencing on May 30, 2023.

From the sociological perspective of Malinowski (1961), organized social action in response to behavior that deviates from social norms is not initiated until there is a public declaration of such deviation. Therefore, this study leverages 2018 Q1 as the inflection point for the DID analysis. This quarter marks the public and legal acknowledgment of the scandal, setting the stage for immediate and significant responses from the VC investment community. By concluding the study at the end of 2019, the analysis avoids the confounding influence of the COVID-19 pandemic, which began to disrupt global investment trends in early 2020 (P. Gompers et al., 2020).

The scandal tarnished the image of Silicon Valley startups and raised serious questions about oversight in venture capital and the extent of due diligence performed by investors. The following extensive media coverage of the Theranos scandal created a narrative of skepticism around Silicon Valley startups, particularly those making bold claims without clear evidence. It led to calls for increased scrutiny of transparency and verifiable proof of concept before large investments and more stringent regulatory measures for startups to reduce the risk of unchecked founder power. Beyond regulatory attention to the startup evaluation, the Holmes scandal could inadvertently render female entrepreneurs face constant comparison to Elizabeth Holmes, especially in biotechnology, life science, and health care. For instance, to counteract any negative associations, female founders have to prove their credibility and differentiate themselves by publishing peer-reviewed studies, partnering with established companies, recruiting reputable advisers, and even dyeing their hair to avoid looking like Holmes (Griffith, 2021a). The selected timeframe is designed to focus precisely on the immediate aftermath of the scandal's public and legal recognition and seeks to delineate the direct effects of the scandal without the interference of later global events.

The following conceptual discussion helps shed light on the potential changes post-Elizabeth Holmes scandal in the representation of female founders in secured funding deals, and female VC investment, which is regarded as the key to improving the situation of female entrepreneurs. This discussion is not intended to be exhaustive about the impacts of the Elizabeth Holmes scandal; rather, it aims to provide insights into the investor response under scrutiny and, more broadly, explore the phenomenon of overcompensation towards women in male-dominated industries following the failure of a prominent female role model. In the following, I propose possible mechanisms based on existing literature findings to motivate my empirical strategy. I first discuss how the official legal announcement of the scandal likely affected gender representation among founders of funded startups, and then explain why this impact is expected to be more pronounced in states that were more closely following the event.

4.2.2 What Changes after the Holmes Scandal?

The Elizabeth Holmes scandal likely intensified public skepticism regarding the investment strategies of Silicon Valley investors, particularly in relation to financing unverified innovative claims and unchecked authority of startup founders. The VC investment activities are thus under heightened scrutiny in a period of introspection and caution. Research on the glass cliff phenomenon suggests that women are more likely to be appointed to leadership positions when an organization faces a period of crisis or downturn, where the chance of failure is higher (Ryan et al., 2016). While such positions can be high-profile and potentially rewarding, they also carry a higher risk of criticism and failure. The post-scandal venture capital landscape, marked by increased caution, can be seen as analogous to the glass cliff scenario. Investors stepping into more active roles during this challenging period may face heightened scrutiny and risk, similar to leaders ascending to prominent positions in times of organizational turmoil. Therefore, the scandal may have been primarily consequential to female VC partners because they may have been called upon to navigate the tumultuous times in the wake of the Holmes scandal. On the other hand, the downfall of a prominent woman in a male-dominant profession could reinforce the stigma of incompetence associated with women in similar roles, thereby intensifying the external pressures faced by female VC investors to mitigate the reputation risk and demonstrate their competence. In the shadow of the scandal, investors may feel compelled to distance themselves from female entrepreneurs who have closer categorical proximity to the scandalized figure. This situation places female VC partners in a delicate position where their efforts to mitigate risks could inadvertently align with a cautious approach that prioritizes distancing from female entrepreneurs over intrinsic motivations to support them.

Scrutiny for female entrepreneurs.

Given this backdrop of increased ethical scrutiny and the recognition of rigrous evaluation, we must consider the situation of female entrepreneurs to manage increased challenges in fundraising. Elizabeth Holmes's previous success is prominent with public recognition and multiple awards. She was widely recognized in the tech and healthcare industries as a pioneering female entrepreneur, often compared to Steve Jobs in her ambition to disrupt a well-established market. Organizational research has consistently shown that misconduct gains prominence due to their status, and high status actors are more likely to receive wide attention (e.g., Dewan & Jensen, 2020; Graffin et al., 2013). As such, her later scandal, which violated social expectancy in a negative way, triggered intense disappointment among various stakeholders (Burgoon, 1993). Violating these expectations not only scandalized Holmes and her company, but also cast a shadow on other industry peers with similar attributes (e.g., Naumovska & Lavie, 2021; Naumovska & Zajac, 2022). Importantly, the social categorical proximity to past transgressors' status of female entrepreneurs is likely to bring about scandalization (Goffman, 1963; Han et al., 2023). As such, Holmes's former status as a role model for women in male-dominated professions could unintentionally result in heightened scrutiny and an intensified obligation for women in comparable roles to validate their competence and integrity.

However, demonstrating such competence proves challenging for women, as studies in male-dominated professions like entrepreneurship and financing reveal that women are subjected to different standards and often receive less favorable evaluations than their male counterparts (Ewens & Townsend, 2020; P. A. Gompers & Wang, 2017; Guzman & Kacperczyk, 2019; Kanze et al., 2018; Malmström et al., 2017; Snellman & Solal, 2023). Various stakeholders are more likely to penalize women for being less capable or skilled than their male peers (Bigelow et al., 2014; Egan et al., 2022; Gu, 2020). Such disparities become more pronounced in the wake of negative events. For instance, evidence has shown that after corporate misconduct, female advisers face a 20% higher likelihood of job loss and a 30% lower probability of securing new employment relative to male advisers in the financial advisory industry (Egan et al., 2022). Moreover, women directors are more likely to leave following financial wrongdoing when the firm has a higher proportion of male directors, a lower proportion of female top managers, and a lower level of gender diversity in the industry (Saeed & Riaz, 2023). These pieces of evidence suggest that gender stereotypes critically influence the assessment of women's competence, potentially pressuring them to overcompensate to prove their abilities. As a result, following an entrepreneurial fraud case involving women, the perceived risks and subsequent costs related to due diligence and reputation management associated with female-founded startups are likely to increase.

Moreover, female-founded startups in health tech or biotech industries are also more likely to be penalized, which can be perceived to share more attributes with Theranos (Goffman, 1963). The penalty of these startups corresponds with the concept of “stigma by association”, originally developed in individual-level studies, where individuals linked to stigmatized others may face negative evaluations regardless of whether they personally exhibit the discrediting attributes (Neuberg et al., 1994; Pryor et al., 2012; Yan & Yam, 2023). The similar spillover effect at the organizational level is supported by a growing body of research, demonstrating how firms respond to large-scale industry scandals or disapproval in an effort to manage categorical stigma (McDonnell et al., 2021; Piazza & Perretti, 2015). Consequently, investors tend to undermine their confidence in female-founded startups in Theranos-associated industries to mtigate the economic risk in the aftermath of the shock. While the support female investors provide for female entrepreneurs is essential, as documented in previous research, how do they balance this support and the importance of safeguarding their professional standing? This study posits that the response of investors depends on the public attention to the scandal.

Attention to the Scandal and the Tradeoff of Female VC.

Although the Elizabeth Holmes scandal is likely to affect the VC industry in general, the impact is expected to be more pronounced in the states where more people are searching for information about Elizabeth Holmes and Theranos, indicating that the scandal is likely more salient in the public consciousness (Bennett et al., 2023; Da et al., 2011; Kearney & Levine, 2015). Public interest and increased awareness in these states are likely linked to intensified media scrutiny, a more robust regulatory response, and heightened caution. This makes the proposed mechanism – scrutiny for female entrepreneurs - more probable in the aftermath of the scandal, as issues receiving frequent and prominent coverage tend to be perceived as more important by the public (Piazza & Perretti, 2015). It is important to recognize that changes in the external environment occur as part of a systematic process, and the entrepreneurial potential of female-founded startups is unlikely to change immediately following the scandal. However, investors are likely to be particularly sensitive to scandal-related risks and may feel compelled to adjust their investment strategies to safeguard their economic returns in the face of increased public scrutiny. This strategic shift represents a direct response to the heightened focus on the scandal's aftermath, with venture capitalists in states where the scandal received more attention likely to be more responsive to these concerns.

However, the motivation of investors to demonstrate their competence appears to conflict with their engagement with female-founded startups. In states with higher attention to the scandal, there is a greater likelihood of caution and scrutiny of female-founded startups. Previous research applying the concept of stigma by association has consistently shown that individuals with even merely associated traits with the stigmatized individual are likely to receive negative inference (e.g., Negro et al., 2021; Yan & Yam, 2023). Aware of this, investors might adopt a more risk-averse approach, preferring to invest in traditionally successful ventures or those led by men. Furthermore, from the perspective of social psychology about stereotype threat (Spencer et al., 2016), stereotype threat arises when a particular social identity (e.g., being a woman in a male-dominated field) becomes salient in a situation where that identity is negatively stereotyped. Female investors might manifest a reluctance to invest in female-founded startups for fear that any failure could be seen as a confirmation of the negative stereotype being representative of their gender. In situations where their gender becomes salient because of a scandal involving a female entrepreneur, female investors might distance themselves from female entrepreneurs to avoid any association with failure that could damage their professional standing. Therefore, the participation of female investors may not guarantee the support for female-founded startups when a high-profile failure is attributed to a female entrepreneur.

Conversely, social identity theory suggests that individuals derive a significant part of their identity from the social groups to which they belong, often leading them to favor their in-group over out-groups (Ashforth & Mael, 1989; Tajfel et al., 1979). When this shared group identity becomes particularly salient in the face of external pressure or attack, members are likely to reinforce their identification with the group to maintain a positive collective identity (Petriglieri, 2011). In the aftermath of the scandal, with heightened public scrutiny, female VC partners may experience a stronger sense of solidarity with other women in the industry, leading to a reinforcement of gender homophily as they seek to support and uplift each other. This heightened sense of obligation among female VC partners to support female entrepreneurs could serve as a counterbalance to negative perceptions, therefore contributing to the resilience and persistence of gender homophily in this context.

This discussion motivates the main empirical strategy to compare the representation of female founders in secured funding deals across states with varying levels of attention to the Elizabeth Holmes scandal. Specifically, the study aims to test the hypothesis that the likelihood of female founder representation in funded biotech startups will be lower in states with higher search index levels related to the scandal compared to those with lower search index levels. To examine the resilience of gender homophily, we examine heterogeneities based on gender representation in VC partner teams.

4.3 Data and Empirical Specification

The core data used in this paper are derived from the Crunchbase platform (https://www.crunchbase.com/), which provides data on startups, founders, investment rounds, and investor details. For each funding round, I possess detailed information about the individuals associated with the financed startup, encompassing its founders, investor firms, and the involved partners, as well as fundamental company details such as age, industry sector, and survival status. In the dataset, investor refers to the investment firm and partner refers to the individual investor that engages in the funding round.

The state-level Google Search Index was downloaded from Google Trends (https://trends.google.com/trends/), a free tool provided by Google that allows users to see how often specific keywords, subjects, and phrases have been queried over a certain period. It works by analyzing a portion of Google web searches to compute how many searches have been done for the terms entered, relative to the total number of searches done on Google over the same time. While Google Trends does not give the exact number of searches, it scales the results on a range of 0 to 100 based on a topic's proportion to all searches on all topics.

The sample starts in January 2015 and ends in December 2019. The Crunchbase database contains 30,321 funding rounds of 22,142 startups made by 13,414 partners during this period, and 676 records with no information on investor gender were dropped. We also drop 1,765 records of informal funding observations such as nonequity assistance, grant, and crowdfunding. Another 16, 539 startup-round-partner records outside the US are dropped. In the dataset, more than half (34.5%) of the funding round observations involve a single partner, while approximately one-third (31.6%) comprises groups of two to three partners. Less than ten percent (9.5%) of the cases include more than three partners. Of the 7,133 unique partners, women represent 10.6%. Furthermore, 16.3% of unique dealt funding records feature at least one female partner.

We aggregated the sample to the startup-round level after these exclusions, including 34,956 secured funding records of 18,013 startups. The final dataset for analysis comprises of 5,998 unique observations of startups that secured the initial VC deal from 2015 to 2019, of which 7.3% has a female founder, and 19.8% has at least one female in the founding team.

The primary variable of interest is *woman founded startup secures funding*, a binary variable coded as 1 when the founder of startups that secured the initial round of funding is female, as 0 otherwise, which changes over the observed announced time of the deal. As explained, the main empirical strategy of this study explores whether the attention to Elizabeth Holmes scandal was associated with a decrease in the likelihood of female founders that secured the deal. To measure attention to the scandal, We look at Google search trends for Elizabeth Holmes, which starts several spikes in interest from 2015, as shown in Figure 4-1. These spikes correspond to key timing points of the scandal related to Elizabeth Holmes or her company, Theranos. In 2015, the first major investigative reports and journalistic inquiries into Theranos' operations and technology were published, notably by The Wall Street Journal. Since a definitive legal position on the allegations against Theranos had not been established, the case had not yet emerged as a clear instance of deviation (Erikson, 2018). In March 2018, the SEC charged Elizabeth Holmes with massive fraud, which serves as a crucial inflection point for public interest and the unfolding of the scandal. We use this particular month as the shock timing and focus on the period from 2015 to 2019 to compare the difference in investor response between the pre-charge and post-charge period. Analyzing the period leading up to and immediately following this charge allows for a focused examination of the impact of this negative event without the distraction of Elizabeth Holmes's earlier success stories or the later complications of the global pandemic.

***** INSERT FIGURE 4-1 HERE *****

The data show that the representation of female founders in securing the initial round of funding increased by 32.8% points after the shock compared with before (from 0.064 to 0.085, *p*-value is 0.000), and increased by 55.4% for those in Theranos-associated industries (from 0.056 to 0.087, *p*-value is 0.000). These substantial increases align with the growing trend in the share of startups founded exclusively by women in VC deals, as observed in the raw data (see Figure 4-1). This trend is further supported by the increasing representation of female partners across the entire VC industry since 2012, as evidenced in Figures 4-1. This observation is consistent with the previous finding that increased representation of female partner benefits fundraising of female founders (e.g., Calder-Wang et al., 2021).

***** INSERT FIGURE 4-2 HERE *****

We use state level Google search trends to identify treatment effects in the difference-in-differences results. We focus on the aggregate Google search index from October 2015 to March 2018, covering the period leading up to the first peak introduced by SEC charge. We take the average of the search indices of the keyword "Elizabeth Holmes" and "Theranos" and divide the states into two group based on the median value of the calculated index. The treatment group comprises the initial VC deals of startups in areas with the search interest above the median value in the sample, corresponding to District of Columbia, California, and Arizona. The state that exhibited the most intense search activity was Arizona, which serves as the benchmark with a Google search index averaged at 73.5. On the opposite end, South Dakota registered the least search interest, scoring 24 on the index. The states with marginally more activity, from lowest to higher, are Mississippi, West Virginia, Kentucky, South Carolina and Alaska.

As shown in Figure 4-3, there is little observable difference in the share of female-founded startups in VC deals between these two groups of states prior to the SEC charge in the raw data. However, following the SEC charge in 2018, a significant divergence emerged in the share of female founders in VC deals. On average, the share change of Theranos-associated startups in securing the initial round significantly increased in nonattentive states (from 0.007 to 0.011, *p*-value is 0.002), whereas this change is not significant for those dealt in attentive states (from 0.060 to 0.082, *p*-value is 0.156).

***** INSERT FIGURE 4-3 HERE *****

We estimate the following difference-in-differences style OLS regressions:

$$Y_{ijt} = \alpha + \delta Attentive\ State_{ij} \times Postshock_t + \beta X_{ijt} + \varepsilon_{ijt} \text{ (1)},$$

where Y_{ijt} is the outcome variable of interest corresponding to the initial VC deal secured by startup i in the state j; $Postshock_t$ equals one for the time period after (and including) the first quarter of 2018, X_i are control variables for funding round i in state j at quarter t. Fixed effects of quarterly time period, states, and industry are also included. The standard errors are clustered at the state level. Under the parallel-trend assumption, δ is the DID coefficient that captures the effect of the attention to scandal on female VC partner representation in the funding rounds in Equation (1).

To test the mechanism behind changes in gender homophily between female VC partners and female entrepreneurs, we examine the heterogeneity in the attention effect between subgroups with and without female partners on VC teams. We repeated the earlier analysis, comparing investments in startups involving female VC partners to those involving only male partners. In the sample of 5,998 initial round VC deals, 11.4% included at least one female partner on the VC teams. Considering the unbalanced sample size in the two subsamples, we estimate the following tripple difference style OLS regressions:

$$Y_{ijt} = \alpha + \beta_1 Attentive\ State_{ij} \times Postshock_t \times Include\ Female\ VC_{ij} + \beta_2 Attentive\ State_{ij} \times Postshock_t + \beta_3 Attentive\ State_{ij} \times Incude\ Female\ VC_{ij} + \beta_4 Include\ Female\ VC_{ij} \times Postshock_t + \beta_5 Include\ Female\ VC_{ij} + \beta_6 X_{ijt} + \varepsilon_{ijt} \text{ (2)},$$

where $Include\ Female\ VC_{ij}$ equals one if at least one female partner participated in the deal i in the state j; β_1 is the parameter of interest, and indicates the extent to which the DID estimate in equation (1) is differentially coming from the participation of at least one female VC partner on the team. The estimation sample, control variables, and clustering are as in Equation (1).

Table 4-1 provides a summary of the variables by attention to the scandal. There are 2,483 observation of startups that secured initial deal in attentive states (treatment group), and 3,515 observations in nonattentive states (control group). On average, the observed deals in states with heightened attention to the Holmes charge had more VC partners involved (p-value is 0.000). These deals were directed more towards startups that were founded 2 years later in the treatment group (p-value is 0.000). Although the investment activities in attentive states and less attentive states can be different in potentially unobservable ways, most observed characteristics of the funding deals in our sample are balanced. Please see the notes in Table 1 for the definitions of other observables.

***** INSERT Table 4-1 ABOUT HERE *****

4.4 Results

Table 4-2 presents the regression results from Equation (1) in column (1), the results from repeated subsample analyses from Equation (1) in columns (2) and (3), and the results from Equation (2) in column (4). Contrary our expectations, the DID coefficient, which was expected to show a larger decrease in the representation of female founders in secured VC deals after the SEC charge in more attentive states, is not significant (δ = 0.0017, p = 0.819). Similarly, the analysis of secured deals involving female VC partners versus those involving only male partners also yields no significant results. However, we do observe a negative coefficient in the subsample with female partner participation (δ = -0.0352, p = 0.267), while the subsample with only male VC partners shows a positive coefficient (δ = 0.0082, p = 0.389). In the triple difference model in column (4), we find the marginally significantly effect of female VC participation that interacts with the treatment effect of attention to the scandal (β_1 = -0.0579, p = 0.068). This suggests that the representation of female founders in secured VC deals decreased when the deal involved at least one female partner. As such, we do not find evidence from the data that supports the proposed mechanisms., implying female founders were not immediately penalized in more attentive states in the aftermath of SEC charge.

***** INSERT Table 4-2 ABOUT HERE *****

Reflecting on the theoretical arguments about stigma by association, we decided to focus on startups founded by women in industries closely related to Theranos, such as biotechnology, life sciences, and healthcare, as these sectors are more likely to be affected by the scandal (Luo & Zhang, 2022). To identify the treatment effect of attention and industry association, we estimate the following triple differences style OLS regressions:

$$Y_{ijt} = \alpha + \beta_1 Attentive\ State_{ij} \times Postshock_t \times Biotech_{ij} + \beta_2 Attentive\ State_{ij} \times Postshock_t + \beta_3 Attentive\ State_{ij} \times Biotech_{ij} + \beta_4 Biotech_{ij} \times Postshock_t + \beta_5 Biotech_{ij} + \beta_6 X_{ijt} + \varepsilon_{ijt} \text{ (3)},$$

where $Biotech_{ij}$ is an indicator for startups belonging to the Theranos-associated industries secured the deal i in the state j; the main parameter of interest is β_1, testing the treatment effect by Theranos-associated industry. The estimation sample, control variables, and clustering are as in Equations (1) and (2).

We repeated the mechanism testing to examine the heterogeneity in the attention effect between subgroups with and without female partners on VC teams, comparing investments in startups involving female VC partners to those involving only male partners. Considering the unbalanced sample size in the two subsamples, we estimate the following quadruple difference style OLS regressions (Muralidharan & Prakash, 2017):

$$Y_{ijt} = \alpha + \beta_1 Attentive\ State_{ij} \times Postshock_t \times Biotech_{ij} \times Include\ Female\ VC_{ij} + \sum_{i=2}^{5} \beta_i \times (4\ Triple\ Interactions) + \sum_{i=6}^{11} \beta_i \times (6\ Double\ Interactions) + \beta_{12} Biotech_{ij} + \beta_{13} X_{ijt} + \varepsilon_{ijt} \text{ (4)},$$

where β_1 is the parameter of interest, reflecting how much the triple difference estimate from equation (3) is specifically driven by the participation of at least one female VC partner on the team. The estimation sample, control variables, and clustering are as in previous Equations.

Table 4-3 presents the results from Equation (3) with the full sample analysis in column (1). The split-sample analysis is shown in columns (2) and (3), contrasting funded startups that include at least one female partner in the deal (column 2) with those that have exclusively male partners (column 3). Column (4) displays the results from Equation (4). In the full sample, the likelihood of female-founded startups in Theranos-associated industries to secure the initial funding decreased around 4.5% points in attentive states post SEC charge (β_1 = -0.0446, p = 0.005). In states where the scandal received more attention, the likelihood of female-founded startups in industries associated with Theranos securing initial funding decreased by 17.3 percentage points post scandal in the subsample of VC deals that involved at least one female partner (β_1 = -0.1735, p = 0.000), even in a small sample of 666 observations. In contract, this likelihood decreased only 3.18 percentage points in the subsample of VC deals that involved exclusively male partners (β_1 = -0.0318, p = 0.047). The significant negative quadruple difference coefficient in column (4) further indicates that the attention to the Holmes scandal led to a 10.5 percentage point decrease in the likelihood of female-founded startups in industries associated with Theranos securing initial funding when a female partner was involved (β_1 = -0.1050, p = 0.007). Across the models, the negative coefficients for the key interaction terms suggest that being in the biotech industry, having female VC involvement, and operating in the post-SEC charge period are associated with a decreased likelihood of women-founded startups securing their initial round of funding. The penalty for female founded startups in Theranos associated industries is not alleviated but rather intensified when female VC partners are involved.

***** INSERT Table 4-3 ABOUT HERE *****

Table 4-4 presents a more focused analysis of the attention-to-Holmes scandal effect on women-founded startups securing funding in split-samples following Equation (1). The analysis is split by industry (biotech vs. non-biotech) and further divided by the presence of female venture capital (VC) partners. The deals secured by biotech startup subsample analysis is shown in column (1), while column (2) presents the results for the non-biotech startup subsample. The further split-sample analysis for the biotech sector is shown in columns (3) and (4), contrasting funded startups that include at least one female partner in the deal (column 3) with those that have exclusively male partners (column 4). Similarly, columns (5) and (6) display the split-sample analysis for the non-biotech sector, with column (5) focusing on deals involving at least one female partner and column (6) on deals without female partners.

In the biotech subsample, there is a statistically significant negative effect of the attention received post-scandal on the likelihood of women-founded startups securing initial funding (β_1 = -0.1050, p = 0.093). Specifically, for every unit increase in attention post-scandal, the likelihood of securing funding decreases by 1.79 percentage points, indicating that biotech startups founded by women were negatively impacted by the increased attention following the Holmes scandal. In contrast to the biotech sector, in the non-biotech subsample, the attention received post-scandal is associated with a statistically significant increase in the likelihood of women-founded startups securing initial funding, by 2.04 percentage points (β_1 = -0.0204, p = 0.044). This suggests that the Holmes scandal may possibly benefit women-founded startups outside the biotech sector. Most interestingly, for biotech startups with female VC involvement, the post-scandal attention is associated with a substantial decrease in the likelihood of securing funding, by 11.3 percentage points, indicating a strong negative effect in scenarios where female VCs are involved in the biotech industry post-scandal (β_1 = -0.1125, p = 0.005), consistent with the previous findings about how female-founded startups in Theranos associated industries may have been particularly penalized in the wake of the Holmes scandal with female partner involvement.

Overall, these results suggest that the immediate response to the Holmes scandal was primarily driven by categorical stigma associated with the biotech industry, rather than by individual characteristics. The significant negative impact observed in the biotech sector, particularly for deals involving female VCs, indicates that the stigma attached to the industry as a whole played a more prominent role in reducing the likelihood of women-founded startups securing funding. In contrast, the more neutral or positive effects observed in non-biotech sectors further support the idea that the stigma was industry-specific rather than targeted at individual founders. Moreover, these findings imply that the phenomenon of gender homophily between female investors and female entrepreneurs in initial stage of fundraising, which is widely discussed in the literature, no longer holds in this context. The negative effects observed, even in cases with female VC involvement, suggest that the usual patterns of gender-based support were disrupted, possibly due to the overarching industry-level stigma.

***** INSERT Table 4-4 ABOUT HERE *****

In summary, the data reveals how the official charge of the fraud case of Holmes had a targeted, negative impact on women-founded startups in associated industries, with the involvement of female VCs exacerbating this effect. Our analysis does not show a significant decrease in the representation of female founders in secured VC deals post-SEC charge in more attentive states, as expected. This negative effect, however, turned significant for female-founded startups in Theranos-associated industries. The negative impact of the Holmes scandal was more pronounced in the biotech and other related sectors, suggesting that the stigma was industry-specific rather than targeted at individual female founders or investors. Additionally, we find persistent decrease in the likelihood of securing initial funding for female-founded startups post-scandal when female VC partners were involved, no matter in Theranos-associated industries or not. Consequently, we find evidence that the usual pattern of gender homophily, where female investors are more likely to support female entrepreneurs, was disrupted post scandal. The negative impact was significant and persistent for female-founded startups in Theranos-associated industries and beyond when female VC partners were involved.

4.5 Discussion and Conclusion

This paper examines whether the public attention to Elizabeth Holmes scandal led to changes in the share of female founders in the VC deals and tests the mechanism of same-gender support in the context of initial fundraising. Our initial DID analysis suggest that in states where public attention was heightened post-scandal, startups securing initial funding rounds are less likely to have female founders when a female VC partner is involved. Using a triple difference approach, with startups from different industries in less attentive states as a comparison group, we find that startups in industries similar to Theranos are 4.5% less likely to have a female founder in attentive states after the scandal. This likelihood further decreases by an additional 10.5% when at least one female VC partner is involved. Contrary to expectations based on gender homophily, female-founded startups faced more significant negative impacts when female investors were involved, particularly in Theranos-associated industries.

Overall, these findings imply that securing funding for female entrepreneurs remains challenging, despite the growing representation of female VC partners in reality. The presumed trust or bond between female investors and female entrepreneurs due to gender homophily appears fragile, particularly in the wake of heightened scrutiny following a high-profile fraud case. This increased attention may lead to greater evaluation rigor across the VC industry and reinforce stigmas around the perceived incompetence of women in male-dominated fields. Investors, concerned about the reputational risks associated with evaluation failures, may view financing startups founded by women as carrying higher risk due to persistent stereotypes of female entrepreneurs as less competent (Heilman et al., 1997; Snellman & Solal, 2023). Consequently, the drive to protect their professional standing conflict with their willingness to support female entrepreneurs. As a result, female VC partners have to strategically diversify their investments and distance themselves from female founders to cope with this trade off.

This study contributes to previous research about the consequence of firm misconduct with a primarily focus on directly associated individuals such as executives and directors (Arthaud-Day et al., 2006; Bereskin et al., 2020; Gomulya & Boeker, 2016; Wiersema & Zhang, 2013) and the unintended loss or gain experienced by unaffiliated but associated organizations (Durand & Vergne, 2015; Jonsson et al., 2009; Naumovska & Zajac, 2022; Piazza & Perretti, 2015). By exploring the impact of a firm misconduct scandal on the attention to the insufficient rigor at the evaluation side, this paper sheds light on wider social implications of corporate scandals. The finding that suggests the stigma was industry-specific rather than targeted at individual female founders or investors requires future research about categorical stigma and its spillover effect. Furthermore, the analysis found that the increase is particularly prominent in states that paid more attention to the scandal, predominantly directed towards male-founded startups. However, the general public attention to the scandal did not significantly affect the likelihood of female-cofounded firms receiving funding. These results underscore the pivotal influence of public attention in the stigmatization process subsequent to the scandal, aligning with prior studies that emphasize the media's fundamental role in amplifying the impact of misconduct through attention attraction (Durand & Vergne, 2015; Han et al., 2023; Piazza & Perretti, 2015).

Most interestingly, the findings pointing to the penalty to female founders and the loss of support for startups with a female founder is intriguing regarding to earlier research on gender homophily in the context of early-stage financing. In contrast to empirical research that show growing representation of female VC partners has played a pivotal role in alleviating the challenges faced by female entrepreneurs in securing funding (Snellman & Solal, 2023; Solal, 2021), the same gender support wavers for female founders in attentive states post scandal. Although the scandal may have heightened the collective identity and connection among female investors and entrepreneurs that can lead to an increased inclination to support one another in overcoming gender-specific barriers (Greenberg & Mollick, 2017), female founders lost the support from female VC partners as they are compelled to mitigate the risk in investment activities in states with heightened scrutiny post-scandal. This is also potentially the strategic response of female VC partners to distance themselves from the gender-related stigma with shared social identity as women. This study focuses on how the stereotype of female founders being seen as less competent leads investors to avoid financing them in order to reduce risk.

From a practical perspective, these findings shed light on the essential role public attention plays in the aftermath of a scandal to shape behaviors of the associated group. Moreover, the importance of same-gender support highlighted by the scandal indicates that networks and mentorship programs among women or other minority groups are beneficial when the supporters gain sufficient status or power.

Although this study carries potentially important theoretical and practical implications, these findings must be viewed in light of their limitations from several concerns about endogeneity. First of all, the use of Google search trends to measure attention to the scandal assumes that increased search activity reflects increased public interest. However, this measure may capture curiosity or other factors unrelated to investors' views or knowledge of the scandal. Also, it is likely that the increased visibility of VC partners after the scandal led to more reporting or discussion about their activities, which in turn could drive search trends. The noise in the treatment identification and the concern about reverse causality may be addressed using an appropriate instrumental variable that is related to Google search interest but exclusive from the investment activities. To follow, the paper shows evidence exclusively related to the Elizabeth Holmes scandal without providing broader context or comparative analysis with other similar scandals. To generalize the findings, it would be ideal to have a robustness check using a similar fraud scandal. Finally, it would be helpful to further validate the proposed theoretical mechanisms in for later empirical testing using experimental methods.

4.6 Figures

Figure 0-1: Google trends for Elizabeth Holmes and Theranos over time of female

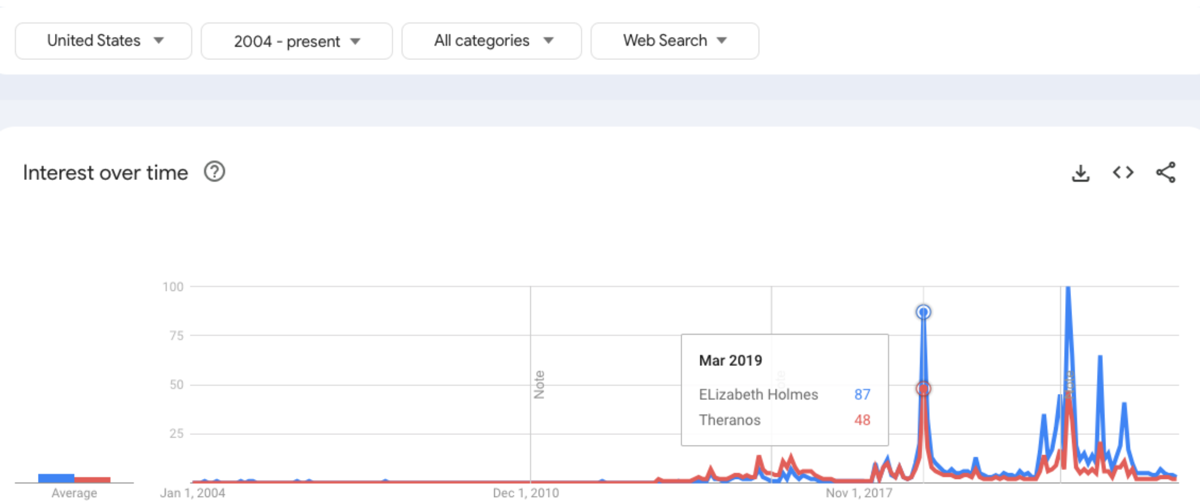


Figure 0-2: Representation partner and female founder in VC deal over time

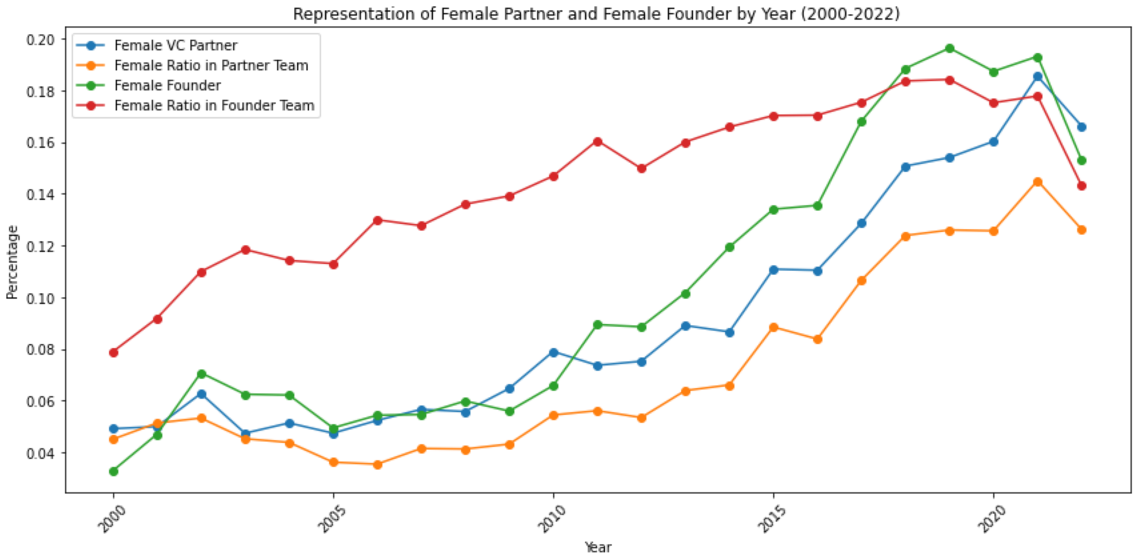
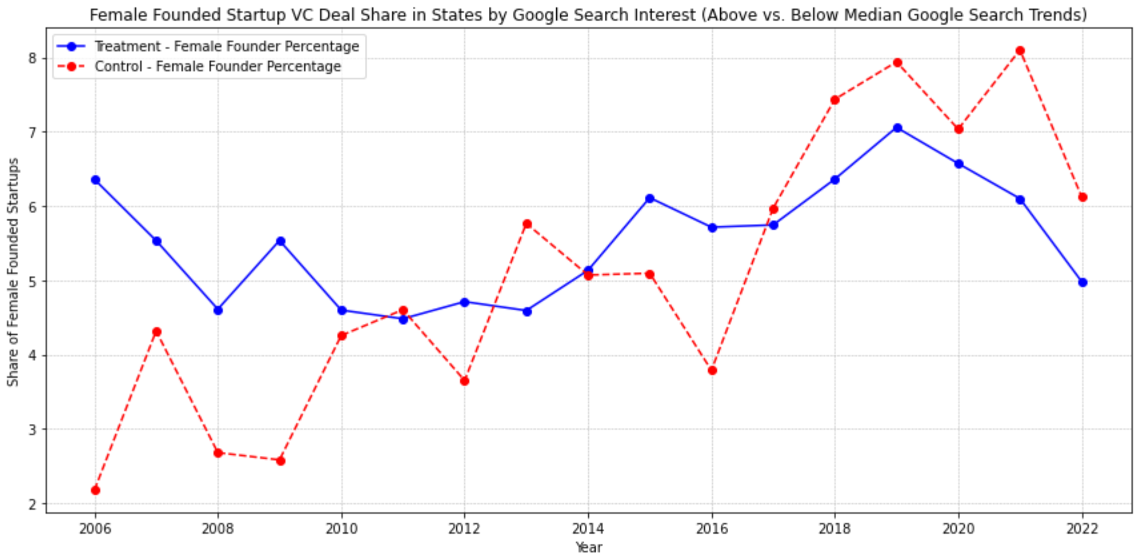


Figure 0-3: Comparison of female-founded startup VC deal share (Raw Data)



4.7 Tables

Table 0-1: Summary Statistics

	Attention to Holmes Scandal = 0			Attention to Holmes Scandal = 1			
	Obs	Mean	SD	Obs	Mean	SD	*p*-values
Female Founder	3515	0.075	0.263	2483	0.069	0.254	(0.414)
Postshock	3515	0.403	0.491	2483	0.383	0.486	(0.119)
Search Index	3515	37.830	27.393	2483	67.169	2.050	(0.000)
Partner Count	3515	1.197	0.571	2483	1.253	0.676	(0.001)
Startup Size	3497	2.419	1.362	2472	2.392	1.281	(0.452)
Funded Year	3506	2012	8.651	2472	2014	4.463	(0.000)
Female Founder Percentage	3515	0.139	0.313	2483	0.146	0.312	(0.413)
Include Female VC	3515	0.113	0.316	2483	0.116	0.321	(0.655)
Female Partner Percentage	3515	0.114	0.309	2483	0.119	0.309	(0.485)

Notes. Table 1 summarizes variables by attention to Holmes scandal for the sample. The last column reports the p-values of two-sample t tests for equal means. Female Founder is a binary variable indicating whether the startup founder that secured the funding is female. Postshock represents a binary indicator indicating whether the initial deal was secured after SEC charge. Search Index measures search activity or trends. Partner Count is the total number of partners involved in the deal. Startup Size is the size of the startup categorized in eight levels based on the number of employees in the startup. Funded Year is the year in which the startup was funded. Female Founder Percentage indicates the percentage of founders that are female within a startup founding team. Include Female VC is a binary variable indicating the presence of a female VC partner. Female VC Percentage indicates the percentage of female VC partners involved in the startup or funding process.The *p*-values show that the two groups of funding deals are well balanced along most of the observed characteristics. Obs, observations. SD, standard deviation.

Table 0-2: Attention-to-Holmes Scandal Effect on Women Founded Startup Securing Funding

DV: Woman founded startup secures funding				
	(1)	(2)	(3)	(4)
VARIABLES	Full sample: Baseline	Subsample: with female VC participation	Subsample: without female VC participation	Full sample: Interaction
Attention x Postshock	0.00170	-0.0352	0.00816	0.00917
	(0.00738)	(0.0309)	(0.00939)	(0.00943)
Attention x Postshock x Include Female VC				**-0.0579†**
				(0.0309)
Attention x Include Female VC				0.0454
				(0.0373)
Postshock x Include Female VC				-0.0205
				(0.0238)
Include Female VC				0.0756*
				(0.0351)
Partner Count	0.00474	0.0694**	-0.000647	0.00518
	(0.00373)	(0.0245)	(0.00361)	(0.00383)
Startup Size	-0.0151***	-0.00572	-0.0142***	-0.0140***
	(0.00248)	(0.00702)	(0.00213)	(0.00216)
Funded Year	-0.00105	-0.00109	-0.00111	-0.00108
	(0.000760)	(0.00163)	(0.000800)	(0.000767)
Constant	2.212	2.298	2.326	2.269
	(1.529)	(3.300)	(1.611)	(1.545)
Quarter FE	YES	YES	YES	YES
State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	5,929	666	5,248	5,929
R-squared	0.049	0.186	0.045	0.058

Notes. OLS regressions testing parallel trends for the difference-in-differences (DD). The dependent variable (DV) of all columns is whether the startup secures the initial funding is founded by a woman. Column (1) analyzes the full sample to check if the Holmes scandal lowers the probability of women-founded startups securing funding. Column (2) uses all secured funds with at least one female VC partner involved and column (3) uses all secured funds with no female VC partner involved. Column (4) uses the full sample with a triple interaction of attention to the scandal, shock time variable, and Include Female VC. We controled Attention x Include Female VC, Postshock x Include Female VC, Include Female VC in this model. Standard errors are clustered at the state level (in parentheses). FE, fixed effect. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Table 0-3: Attention-to-Holmes Scandal Effect on Women Founded Startup Securing Funding

	DV: Women founded startup secures funding			
	(1)	(2)	(3)	(4)
VARIABLES	Full sample: Baseline	Subsample: with female VC	Subsample: without female VC	Full sample: Interaction
Attention x Biotech Postshock	-0.0446**	-0.173***	-0.0318*	-0.0335*
	(0.0150)	(0.0416)	(0.0155)	(0.0157)
Attention x Biotech x Postshock x Include Female VC				**-0.105****
				(0.0368)
Biotech x Attention	0.0248**	0.0432	0.0300**	0.0292**
	(0.00790)	(0.0497)	(0.00879)	(0.00813)
Biotech x Postshock	0.0341*	0.0687	0.0295†	0.0295†
	(0.0147)	(0.0421)	(0.0152)	(0.0157)
Attention x Postshock	0.0227*	0.0499	0.0228†	0.0246*
	(0.00999)	(0.0414)	(0.0113)	(0.0114)
Biotech x Attention x Include Female VC				0.000989
				(0.0338)
Biotech x Postshock x Include Female VC				0.0404
				(0.0342)
Attention x Postshock x Include Female VC				-0.00292
				(0.0440)
Biotech x Include Female VC				-0.0140
				(0.0330)
Attention x Include Female VC				0.0433
				(0.0431)
Postshock x Include Female VC				-0.0434
				(0.0357)
Include Female VC				0.0840†
				(0.0417)
Biotech	-0.0216*	-0.0453	-0.0242*	-0.0217*
	(0.0103)	(0.0570)	(0.0101)	(0.0102)
Partner Count	0.00499	0.0704**	-0.000427	0.00549
	(0.00372)	(0.0240)	(0.00360)	(0.00380)
Startup Size	-0.0151***	-0.00642	-0.0142***	-0.0141***
	(0.00241)	(0.00655)	(0.00209)	(0.00212)
Funded Year	-0.00104	-0.00126	-0.00109	-0.00107
	(0.000765)	(0.00169)	(0.000799)	(0.000766)
Constant	2.198	2.626	2.288	2.247
	(1.539)	(3.421)	(1.610)	(1.542)
Quarter FE	YES	YES	YES	YES

State FE	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES
Observations	5,929	666	5,248	5,929
R-squared	0.050	0.190	0.046	0.060

Notes. OLS regressions testing parallel trends for the triple differences (DDD). The dependent variable (DV) of all columns is whether the startup secures the initial funding is founded by a woman. Column (1) analyzes the full sample to check if the Holmes scandal lowers the probability of women-founded biotech startups securing funding. Column (2) uses all secured funds in the biotech industry with at least one female VC partner involved and column (3) uses all secured funds in the biotech industry with no female VC partner involved. Column (4) uses the full sample with a quadruple interaction of attention to the scandal, biotech industry, shock time variable, and Include Female VC. We controled Attention x Biotech Postshock, Biotech x Attention x Include Female VC, Biotech x Postshock x Include Female VC, Attention x Postshock x Include Female VC, in this model. Standard errors are clustered at the state level (in parentheses). FE, fixed effect. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Table 0-4: Attention-to-Holmes Scandal Effect on Women Founded Startup Securing Funding

	DV: Women founded startup secures funding					
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Biotech subsample	NonBiotech subsample	Biotech subsample: with female VC	Biotech subsample: without female VC	NonBiotech subsample: with female VC	NonBiotech subsample: without female VC
Attention x Postshock	-0.0179*	0.0204**	**-0.112*****	-0.00288	0.0779	0.0192*
	(0.0104)	(0.00983)	(0.0358)	(0.0121)	(0.0498)	(0.0111)
Partner Count	0.0184**	-0.0117*	0.0923***	0.00818	-0.00576	-0.0106*
	(0.00802)	(0.00636)	(0.0223)	(0.00578)	(0.0532)	(0.00581)
Startup Size	-0.0127***	-0.0188***	-0.00510	-0.0120***	-0.0106	-0.0170***
	(0.00269)	(0.00383)	(0.00819)	(0.00318)	(0.00646)	(0.00346)
Funded Year	-0.00157*	-0.000887	0.000522	-0.00178**	-0.00586	-0.000790
	(0.000823)	(0.00109)	(0.00207)	(0.000819)	(0.00357)	(0.00115)
Constant	3.239*	1.919	-0.988	3.652**	11.98	1.706
	(1.659)	(2.197)	(4.171)	(1.651)	(7.142)	(2.308)
Quarter FE	YES	YES	YES	YES	YES	YES
State FE	YES	YES	YES	YES	YES	YES
Industry FE	YES	YES	YES	YES	YES	YES
Observations	2,833	3,091	332	2,492	326	2,751
R-squared	0.062	0.075	0.311	0.052	0.220	0.077

Notes. Subsample OLS regressions testing parallel trends for the difference-in-differences (DD). The dependent variable (DV) of all columns is whether the startup secures the initial funding is founded by a woman. Column (1) analyzes the subsample of startups in the biotech industry to check if the Holmes scandal lowers the probability of women-founded biotech startups securing funding. Column (2) uses the subsample of all secured funds that are not in the biotech industry. Column (3) uses the subsample of all secured funds in the biotech industry with female VC partner involved. Column (4) uses the subsample of all secured funds in the biotech industry with no female VC partner involved. Column (5) uses the subsample of all secured funds that are not in the biotech industry with female VC partner involved. Column (6) uses the subsample of all secured funds that are not in the biotech industry with no female VC partner involved. Standard errors are clustered at the state level (in parentheses). FE, fixed effect. *** p<0.001, ** p<0.01, * p<0.05, † p<0.1.

Chapter 5

5 Conclusion

In this dissertation, I have leveraged advanced coding methodologies to analyze a rich spectrum of unstructured data, including textual, visual, and video content from publicly accessible online platforms, to quantitatively gauge nonverbal emotional cues through computational psychometrics. Using both unstructured and structured archival data, I also stick to econometric methods to conduct rigorous data analyses to provide theoretical insights about gender nuances within entrepreneurship. The findings from the three research chapters not only sheds light on the intricate interplay between nonverbal communication and gender norms in early-stage entrepreneurial evaluation in the informal setting, but also reveals the potential intensification of same-gender support between female investors and female entrepreneurs in the wake of publicized female-led firm misconduct in the formal setting. Additionally, I actively contribute to clarify the complexities associated with emerging research efforts that utilize data-driven analysis and the application of machine learning techniques to develop novel metrics. The support and acknowledgment received from prestigious grants and conferences, underscore the relevance and impact of this scholarly work.

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