Silent Suffering: Using Machine Learning to Measure CEO Depression

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1 Research questions

Can we/How to use ML methods to analyze speech features of CEOs to measure their level of depression? What's the relationship between CEO depression and career outcomes(resignation/compensation)?

2 Why are the research questions interesting?

• CEO depression is often hidden and difficult to measure through traditional interviews.
• CEOs hold central positions in firms, and their mental health have a huge impact on firms' operations.
• Prior research mainly relied on questionnaires or text analysis, which were difficult to capture depressive states.
• The development of machine learning technology has made speech analysis possible.

3 What is the paper's contribution?

***(1)* Literature on measurement methods for CEO depression**

Prior: Measure an individual's level of depression through questionnaire surveys or interviews.
This: Using ML to analyze speeches and building a depression measuring model (conference calls data).

***(2)* Literature on cross-sectional influencing factors of depression**

Prior: High risk industries/companies with large stock price fluctuations are prone to cause CEO depression.
This: Track changes in depression over time and explore influencing factors (CEO conference call).

***(3)* Literature on the Application of Machine Learning in Depression Detection**

Prior: Machine learning models use speech features to detect depression with an accuracy rate 81 percent.
This: Extracting CEO speech features through Google YAMNet embedding technology and combining ML to predict CEO depression levels.

4 What hypotheses are tested in the paper?

H1: CEO depression can be measured through speech features, and its level is dynamically changing over time.
H2: There are significant differences in the compensation model and career trajectory of depressed CEOs.
H3: Depressed CEOs can directly affect a company's financial performance.

a) Do these hypotheses follow from and answer the research questions?

• Yes, these three hypotheses have been properly validated and answered in the article.

Do these hypotheses follow from theory or are they otherwise adequately developed?

• H1: Affective Computing, speech features can effectively reflect the psychological health status of CEOs.
• H2 comes from the theory of reward and punishment sensitivity and agency theory.

5 Sample: comment on the appropriateness of sample selection procedures.

Sample selection criteria are reasonable (native English speaker; at least 4 minutes; excluding significant noise).

6 Dependent and independent variables: comment on the appropriateness.

This paper strictly defines the core variables (CEO depression, career outcomes, company performance, etc.).

7 Regression model specification: comment on the appropriateness.

The regression design of this study is rigorous, systematic, and scientific.

8 What difficulties arise in drawing inferences from the empirical work?

Machine learning models are trained on the DAIC dataset (which includes speech data from general subjects), and the CEO's speech environment may differ from that of regular subjects, resulting in measurement biases.

9 Describe at least one publishable and feasible extension of this research.

• Using speech features to analyze CEO depression without incorporating other physiological or behavioral data such as facial expressions, heart rate, etc.

- Speech features may be influenced by individual differences, rather than just reflecting depressive states.
- CEOs may deliberately conceal emotions, voice features may not fully reflect true mental status.

Future improvements

• Combining multi-modal data such as facial expression analysis, heart rate monitoring, and text emotion analysis to improve the accuracy of depression measurement.

• Establish a more targeted depression training dataset for CEOs and optimize the applicability of ML models.

10 Summarize the similarities, differences, and correlations between literature.

Generality:

Methodology: Machine learning is used to process unstructured data and verify incremental information value;
Interdisciplinary: Integrating psychology/behavioral science and economics;
Practice oriented: Promote innovation in financial technology or organizational management.

Differences:

Application scenarios: Micro expressions and digital footprints focus on individual financial risks, CEO depression research focuses on organizational decision-making;
Data attributes: The first two are external behavioral data, while the latter are internal physiological data;
Theoretical objective: Optimize the prediction model in the first two articles, and explore the impact mechanism of mental health in the third article.

表 1: 三篇文献的异同点对比

维度	**Chang 2025（视频分析）**	**Berg 2020（数字足迹）**	**Cheng 2024（语音分析）**
研究领域	金融科技（信用评估）	金融科技（信用评估）	组织行为学/心理健康
数据来源	实时视频（微表情）	数字足迹（设备、邮件、浏览行为）	语音数据（财报电话会议）
研究对象	个人借款人	消费者（电商平台用户）	企业 CEO
核心变量	自变量：快乐、恐惧表情 因变量：贷款违约概率	自变量：数字足迹特征） 因变量：消费者违约风险（二分类）	自变量：语音声学特征（音调、语速） 因变量：CEO 抑郁程度、职业影响
预测目标	贷款违约概率（短期信用风险）	消费者违约风险（跨期信用行为）	CEO 抑郁程度及其职业影响
变量类型	自变量：非结构化（视频帧序列） 因变量：二元分类	自变量：半结构化（行为标签） 因变量：二元分类	自变量：非结构化（语音波形） 因变量：连续变量 + 分类变量
测量挑战	微表情瞬时性（≤0.5 秒）与伪装控制	数据噪声（非金融行为多义性）	语音分离与情感特征提取
因果性分析	仅验证相关性	验证预测能力，涉及行为反馈	探索潜在因果关系
社会影响	提升金融包容性	扩大信贷覆盖（无信用记录者）	揭示高管心理健康与企业治理关联