Content Analysis in Strategic Management Research

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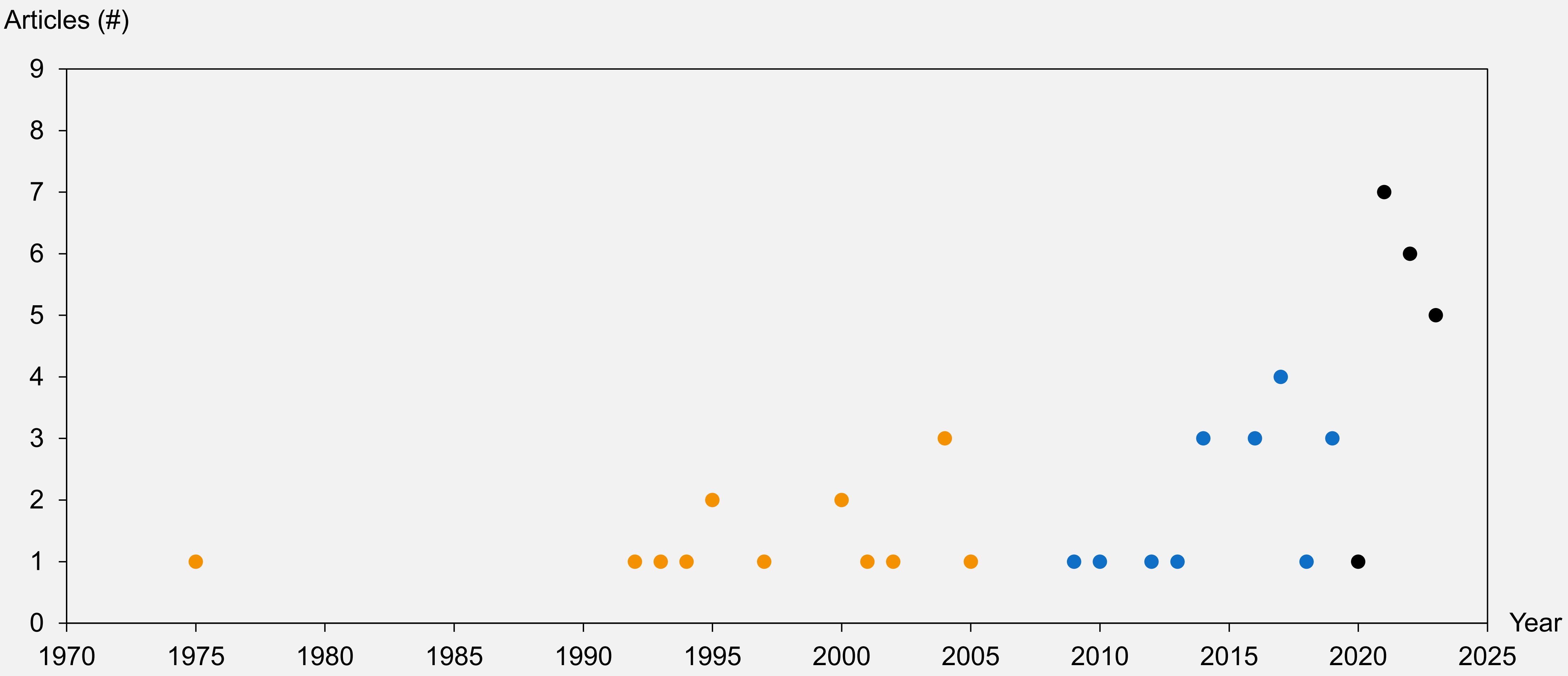

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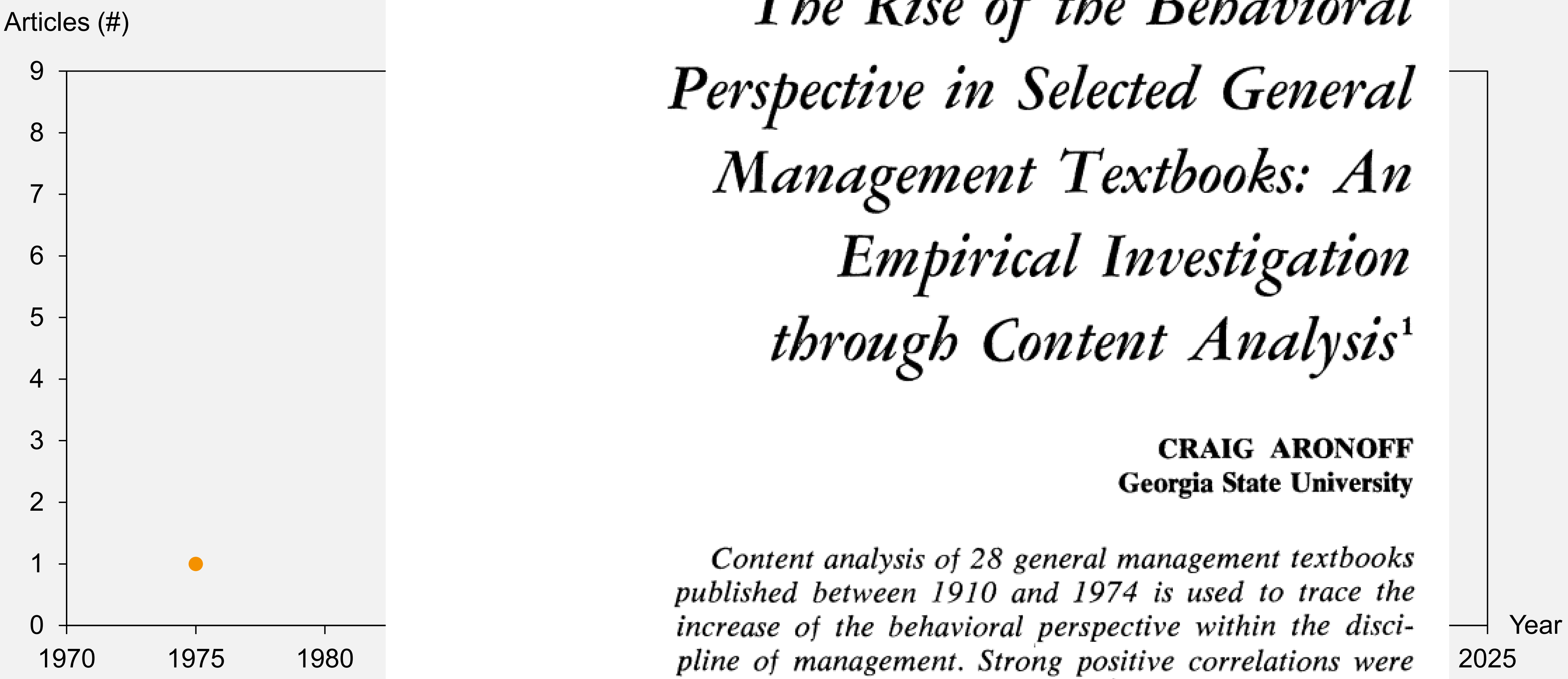
Web of Science search: “content analysis” OR “text analysis” OR “textual analysis” OR “natural language” OR “LIWC” or “NLP” in AMJ, ASQ, OS, SMJ



The Rise of the Behavioral Perspective in Selected General Management Textbooks: An Empirical Investigation through Content Analysis[1]

CRAIG ARONOFF
Georgia State University

Content analysis of 28 general management textbooks published between 1910 and 1974 is used to trace the increase of the behavioral perspective within the discipline of management. Strong positive correlations were found between frequency of terms, indicating the in-influence of the behavioral sciences and time.

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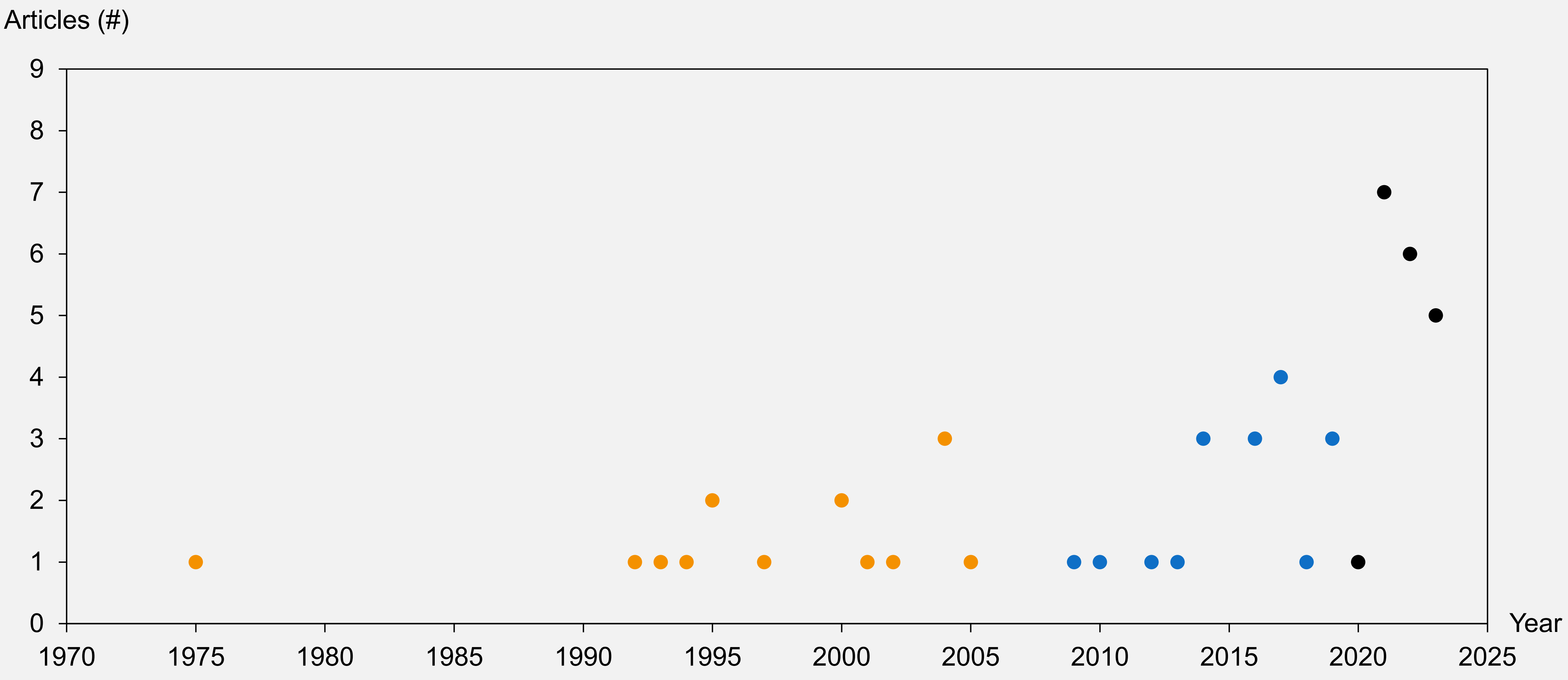

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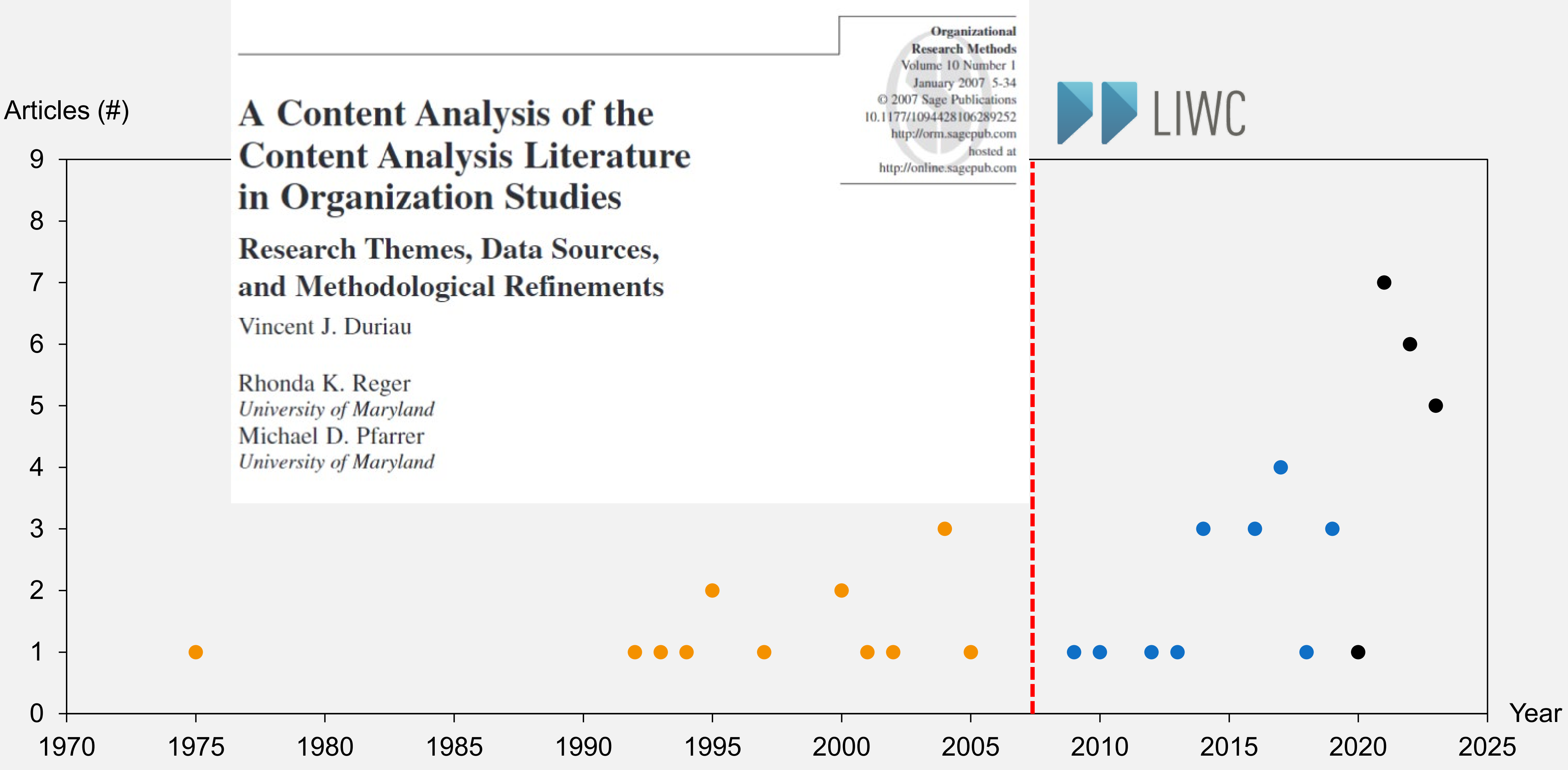
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A Content Analysis of the Content Analysis Literature in Organization Studies

Research Themes, Data Sources, and Methodological Refinements

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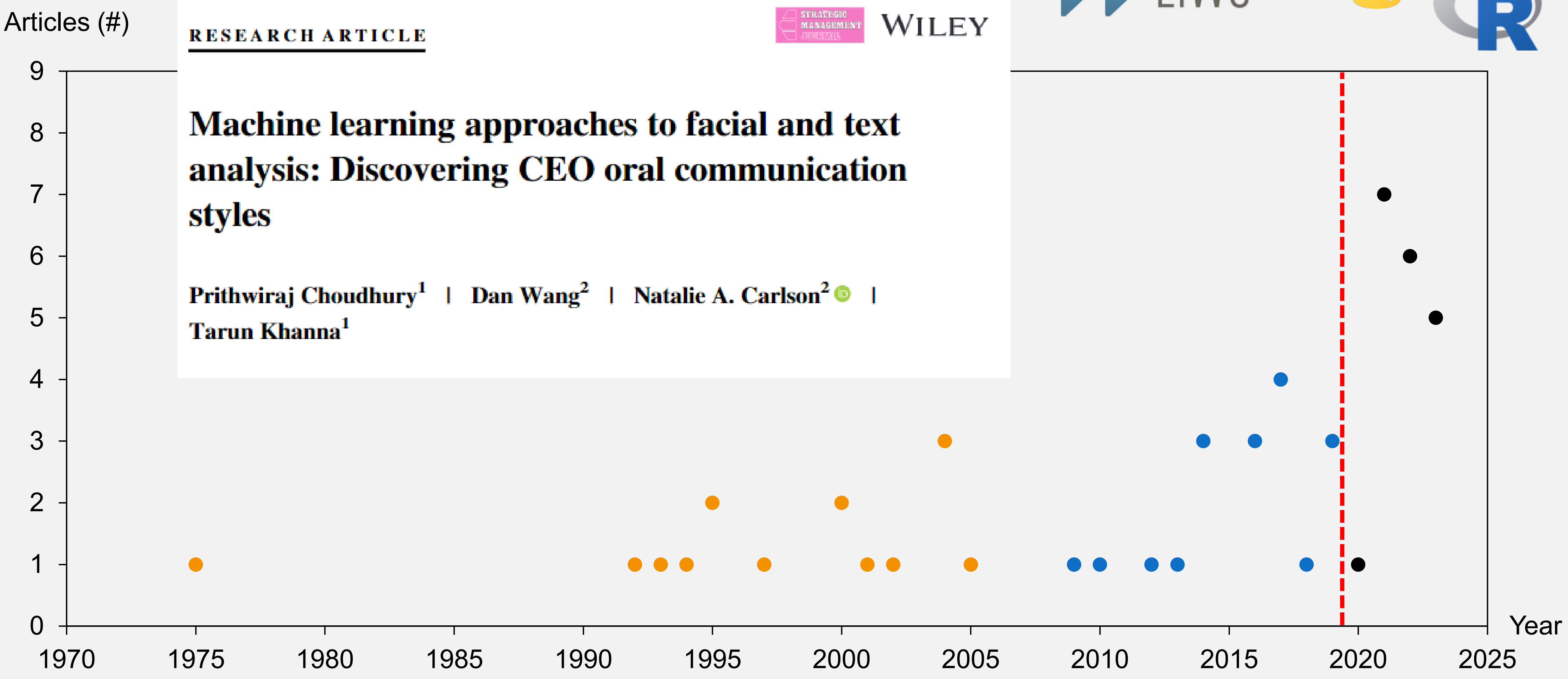
STRATEGIC MANAGEMENT JOURNAL WILEY

RESEARCH ARTICLE

Machine learning approaches to facial and text analysis: Discovering CEO oral communication styles

Prithwiraj Choudhury[1] | Dan Wang[2] | Natalie A. Carlson[2] | Tarun Khanna[1]



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The goal of computer-aided text analysis is to replicate human ratings

Word-based analyses, commonly called "dictionaries," can be very useful proxies for measuring constructs

- Reputation
- Celebrity
- Sentiment
- Regulatory focus
- Temporal focus
- Implicit motives (achievement, power, affiliation)
- Agentic vs. communal
- Cognitive complexity
- Strategic attention
- Concreteness/construal

The Development and Psychometric Properties of LIWC-22

Ryan L. Boyd, Ashwini Ashokkumar, Sarah Seraj, and James W. Pennebaker

The University of Texas at Austin

https://www.liwc.app/static/documents/LIWC-22%20Manual%20-%20Development%20and%20Psychometrics.pdf

Machine learning techniques move away from the need to validate dictionaries as input

1. Word vectors
2. Training
3. Testing
4. Validity checks

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RESEARCH ARTICLE

Measuring CEO personality: Developing, validating, and testing a linguistic tool

Joseph S. Harrison[1] | Gary R. Thurgood[2] | Steven Boivie[3] | Michael D. Pfarrer[4]

STRATEGIC MANAGEMENT JOURNAL WILEY

RESEARCH ARTICLE

Machine learning and human capital complementarities: Experimental evidence on bias mitigation

Prithwiraj Choudhury[1] | Evan Starr[2] | Rajshree Agarwal[2]

https://www.liwc.app/static/documents/LIWC-22%20Manual%20-%20Development%20and%20Psychometrics.pdf

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RESEARCH ARTICLE

Longitudinal analysis of sentiment and emotion in news media headlines using automated labelling with Transformer language models

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Abstract

This work describes a chronological (2000–2019) analysis of sentiment and emotion in 23 million headlines from 47 news media outlets popular in the United States. We use Transformer language models fine-tuned for detection of sentiment (positive, negative) and Ekman's six basic emotions (anger, disgust, fear, joy, sadness, surprise) plus neutral to automatically label the headlines. Results show an increase of sentiment negativity in headlines across written news media since the year 2000. Headlines from right-leaning news media have been, on average, consistently more negative than headlines from left-leaning outlets over the entire studied time period. The chronological analysis of headlines emotionality shows a growing proportion of headlines denoting *anger*, *fear*, *disgust* and *sadness* and a decrease in the prevalence of emotionally *neutral* headlines across the studied outlets over the 2000–2019 interval. The prevalence of headlines denoting *anger* appears to be higher, on average, in right-leaning news outlets than in left-leaning news media.

Natural Language Content Evaluation System For Multiclass Detection of Hate Speech in Tweets Using Transformers

Duván Andres Marrugo-Tobón[†], Juan Carlos. Martinez-Santos and Edwin Puertas

Universidad Tecnológica de Bolívar, Faculty of Engineering, Cartagena de Indias 17013001, Colombia

Abstract

In natural language processing, accurate categorization of tweets, including detecting hate speech, plays a pivotal role in efficient information organization and analysis. This paper presents a Natural Language Contents Evaluation System specifically tailored for multi-class tweet categorization, focusing on hate speech detection. Our system enhances classification accuracy and efficiency by harnessing the power of Transformers, namely BERT and DistilBERT. By leveraging feature extraction techniques, we capture pertinent information from tweets, enabling practical analysis, categorization, and identification of hate speech instances. During training, we also tackle imbalanced corpora by employing techniques to ensure fair representation of different tweet categories, including hate speech. Our system achieves impressive accuracy through extensive training of 95%, showcasing Transformers' effectiveness in comprehending and categorizing tweets, including identifying hate speech. Furthermore, our system maintains a good accuracy during testing of 83%, highlighting the robustness and generalizability of the trained models for hate speech detection. This system contributes to advancing automated tweet categorization, specifically in hate speech detection, providing a reliable and efficient solution for organizing and analyzing diverse tweet datasets.

Keywords

Natural language processing, Hate speech detection, Transformers, DistilBERT, BERT, Feature extraction, Tweet categorization

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Fake News Classification using transformer based enhanced LSTM and BERT

Nishant Rai, Deepika Kumar*, Naman Kaushik, Chandan Raj, Ahad Ali

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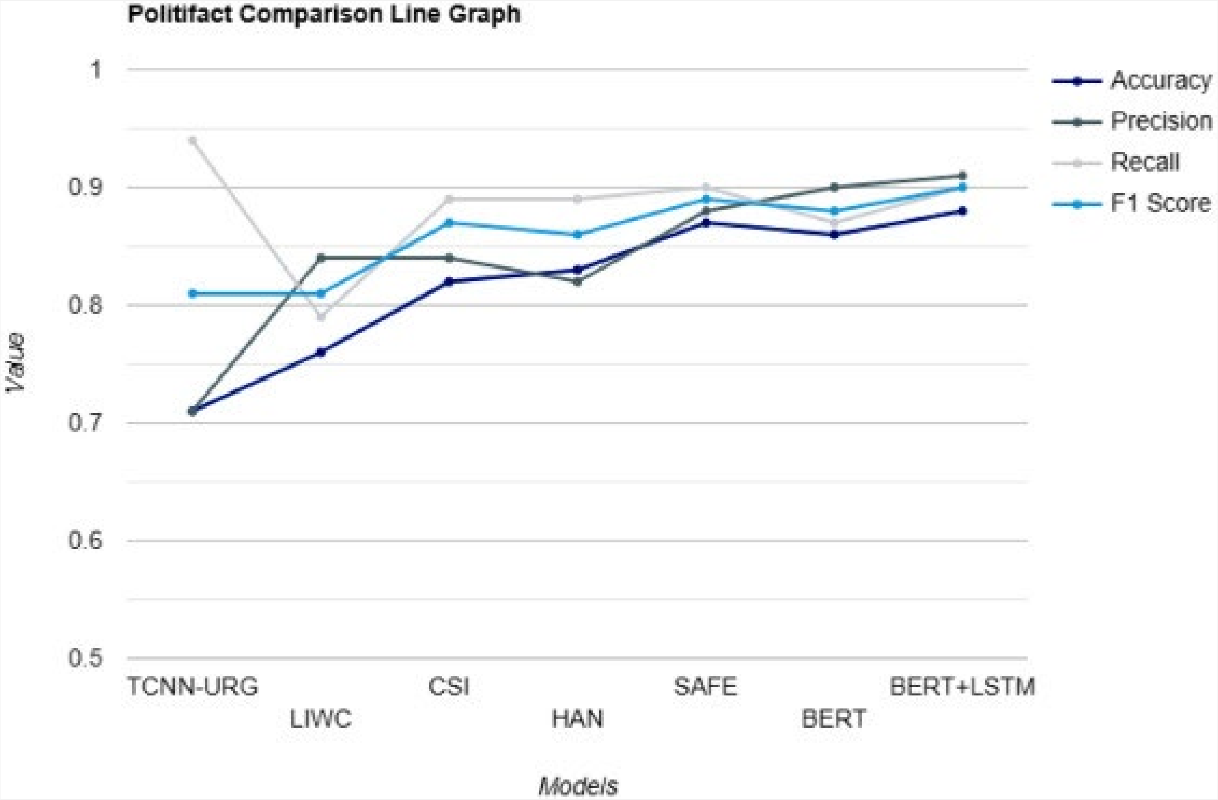

How do you feel? Using natural language processing to automatically rate emotion in psychotherapy

Michael J. Tanana[1] • Christina S. Soma[2] • Patty B. Kuo[2] • Nicolas M. Bertagnolli[3] • Aaron Dembe[2] • Brian T. Pace[4] • Vivek Srikumar[5] • David C. Atkins[6] • Zac E. Imel[2]

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Table 1 Model performance on test set

	Model	F1 Accuracy
BERT		0.66
MaxEnt		
	Unigram	0.60
	Bigram	0.60
	Trigram	0.61
Comparison		
	RNN (Trained on Movie Reviews)	0.49
	LIWC	0.55

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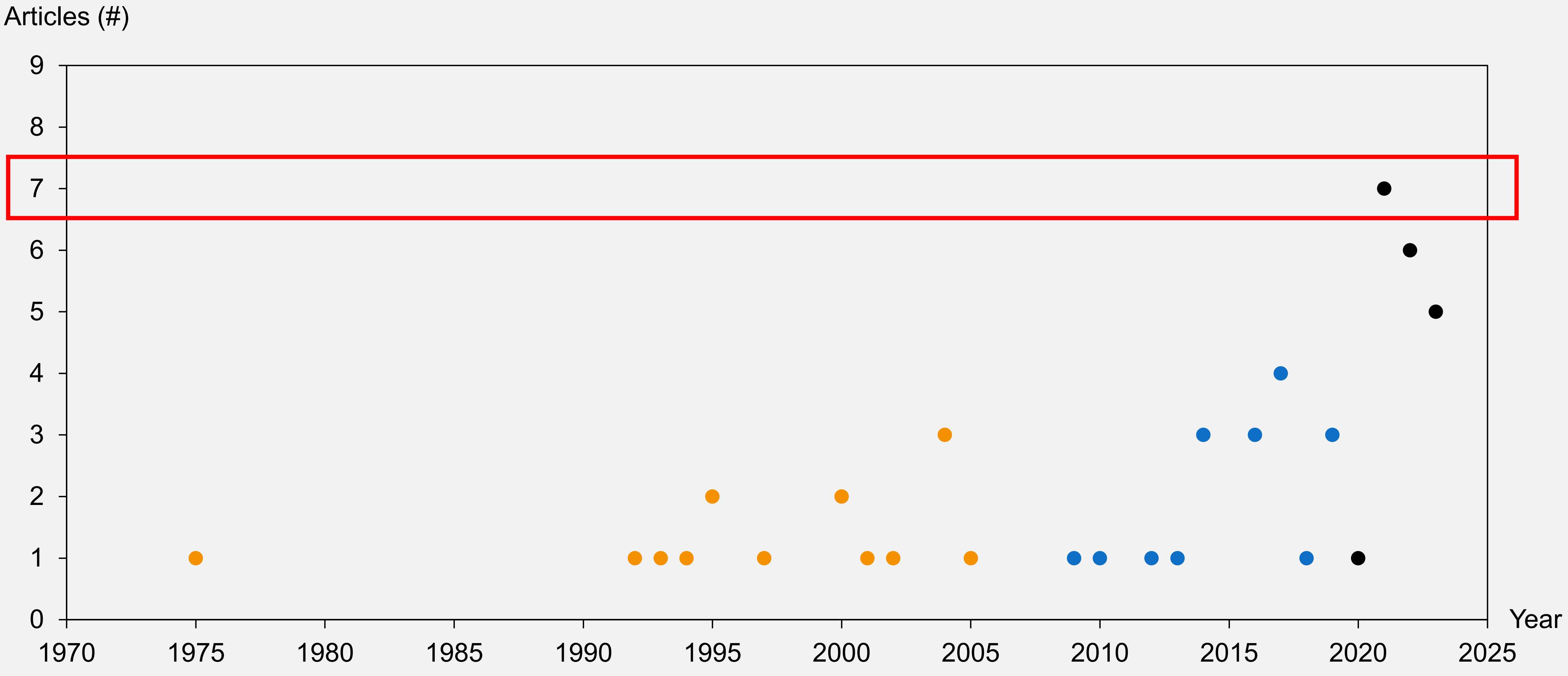
	Input	Reliance on context
LIWC	Validated dictionaries	High
	Labeled training and testing data	High
	Labeled training and testing data	Low

Returning to this chart...



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Making theoretical contributions using content analysis is hard

Thinking theoretically as authors and future reviewers*:

1. Understand the assumptions underlying your data source.
    1. Why is it appropriate to use media coverage to measure firm reputation?
    2. Why is it appropriate to measure public sentiment using Twitter?
    3. Why is it appropriate to measure employee perceptions using Glassdoor?

2. Use the simplest method possible for capturing your construct.
    1. Consider two options for sourcing what people think about the DOJ blocking JetBlue and Spirit's merger:
        1. Hiring 1,000 MTurkers who represent America's population to respond to a survey and write 200 words on it.
        2. Scraping all tweets about the DOJ's action.
    2. Complex methods shrink editors' reviewer pool, such that:
        1. You may not get a reviewer that knows your method.
        2. You might get a review that knows your method better than you do...*and wants to prove it*.

3. Aim for harmony between scale and error.
    1. Computer-aided content analysis is unlikely to ever be "perfect." Having errors does not mean, however, that we should throw away its primary benefit—scalability and reliability.
        1. Computers replace millions of human raters.
        2. Computers do not get fatigued or distracted.
    2. Errors may not always bias your coefficients enough to alter the results.

** regarding publishing in top tier management journals using content analysis to measure constructs*

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