SOCI 40133 Research Appendix

"The Many Frames of Artificial Intelligence"

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Prospective abstract: Algorithms and artificial intelligence (AI) are beginning to overhaul many organizational domains. Management research has largely examined AI as accomplishing a singular frame of economic productivity or a binary coupling with fairness as an ethical constraint on that goal. Using vectorized text models such as word embeddings, I analyze a large novel dataset of millions of AI-related documents published from 1995 to 2020 to reveal a multitude of competing and overlapping frames. I present a grounded theoretical model of AI multiobjectivity: how these goals are constituted, trade off against each other, and co-evolve over time. Disentangling these frames beyond a singular or binary framework can facilitate a deeper understanding of organizations and the development of beneficial AI.

Keywords: artificial intelligence, framing, imaginaries, discourse, values, goals, organizational theory, institutional theory

Alternative titles:

- Clarifying the Goals of AI Systems
- An Event-Based Model of Framing and Sensemaking in Artificial Intelligence
- Changes in Framing Over Time and Between Stakeholders in Artificial Intelligence

Target journals: AMJ, ASQ, SMJ, OS, MS, ASR, AJS, JMS

1. INTRODUCTION

AI is beginning to reshape organizations across a range of industries (Fang et al. 2019; Amabile 2019; von Krogh 2018; Baum and Haveman 2020; Keding 2020; Pachidi et al. 2020; Raisch and Krakowski 2020). It has been labeled a "general purpose technology" with implications for organizations across many sectors, including its use to develop further technology (Cockburn, Henderson, and Stern 2018). Given this cross-context significance, scholars have begun to document the effects of AI on a range of organizational features, such as organizational control (Kellogg, Valentine, and Christin 2020), power asymmetries (Curchod et al. 2020), platforms (Gregory et al. 2020; Clough and Wu 2020), surveillance (Brayne 2017), revenue management (Lobel 2020), and the unequal distribution of organizational resources (Ahmed and Wahed 2020).

The primary goal of AI is, of course, the fulfilment of its intelligent capabilities, such as a predictive algorithm that makes accurate diagnoses based on medical imaging (Lebovitz, Lifshitz-Assaf, and Levina 2019). This does not always happen because of "algorithm aversion," when people avoid incorporating algorithms into their work and decision-making routines (Dietvorst, Simmons, and Massey 2014; 2015; 2018; Kawaguchi 2020). While many studies focus solely on the economic productivity of AI, some computer scientists, ethicists, and social scientists have begun to examine productivity alongside an ethical constraint, such as unbiasedness (Cowgill and Tucker 2019; Cowgill et al. 2020; Sunstein 2019; Schwemmer et al. 2020; Lambrecht and Tucker 2019; Obermeyer et al. 2019), fairness (Cowgill and Tucker 2019; Butterworth 2018; Cowgill, Dell'Acqua, and Matz 2020; Morse et al. 2020; Parkes and Vohra 2019), trustworthiness (Brundage et al. 2020; Marcus and Davis 2019; Kizilcec 2016; Glikson and Woolley 2020), and interpretability (Doshi-Velez and Kim 2017; Yu et al. 2020; Samek, Wiegand, and Müller 2017).

Constraining economic productivity creates a challenge in understanding and implementing beneficial AI systems. For example, computer scientists recognize an inherent fairness-accuracy trade-off: when we impose any constraint on a predictive algorithm, such as requiring equal outcomes across race, the algorithm is necessarily less accurate in its predictions (Corbett-Davies et al. 2017; Kleinberg, Mullainathan, and Raghavan 2016). So how much fairness is worth sacrificing for how much accuracy? In general, how can we align AI systems with our complex, conflicting values (Donaldson and Neesham 2020; T. W. Kim, Donaldson, and Hooker 2019)?

The present work seeks to clarify these goals and their relations as a framing contest, a theory developed by Kaplan (2008) to model "how actors attempt to transform their own cognitive frames into the organization's predominant collective frames through their daily interactions." We use an approach of "computational grounded theory" to inflate this theorization to a macro-level, modeling how frames are put forth and contested throughout the field of AI (Glaser and Strauss 1967; Nelson 2020). Our computational text analysis, particularly vectorizations such as topic models and word embeddings that reveal latent textual features, can garner an understanding similar to human reading of the texts but at much larger scale. This analysis is supplemented throughout with human reading of a small sample of texts and interviews with various AI stakeholders, such as software developers and managers. We show the constitution, trade-offs, and evolution of an overlapping multitude of frames. We argue that a full picture of this framing contest is necessary for beneficial AI.

2. FRAMING CONTESTS

Frames are the “schema of interpretation” in society, as popularized by the sociologist Erving Goffman (1974). Frames “organize experience and guide action, whether individual or collective” (Snow et al. 1986). They have been most extensively utilized in the study of social movements via the interplay of cognition and politics (Benford and Snow 2000). A stream of research has brought frames per se into the organizational and management literature, primarily in connect to nonmarket actors such as social movements (e.g., Lounsbury, Ventresca, and Hirsch 2003).

Many of the social phenomena described as frames, particularly in the domain of emerging technology, can be analyzed with a number of other theoretical lenses, such as “social imaginaries.” Augustine et al. (2019) laid out five social imaginaries of geoengineering technology (e.g., launching particulates or mirrors into the atmosphere to reduce sunlight and cool the earth). The first imaginary was scientists describing the technology as a “technofix”, a logical step in humanity’s increasing control of the Earth, but then environmental critics brought in “human hubris” as a critical imaginary, highlighting humanity’s track record of harming the Earth. Other relevant lenses include “organizational goals” (e.g., Warner and Havens 1968), “organizational identities” (Glynn 2000; Livengood and Reger 2010; Whetten 1989), “issue selling” (Dutton and Ashford 1993), “impression management” (Gardner and Martinko 1988), “values” (e.g., Hitlin and Piliavin 2004), concepts in a “conceptual space” (Hannan 2019), and ideas in a “field ideology” (Hehenberger, Mair, and Metz 2019). Organizational actors need to make sense of these phenomena, intertwining with the theory of “sensemaking,” which refers to “the social psychological and epistemological processes by which actors form an understanding of the situations they find themselves in" (Fiss and Hirsch 2005). All of these theories fit into broader literatures on organizational theory, culture, and cognition.

Kaplan (2008) introduces the term "framing contests" in the context of organizational strategy making. This process includes a variety of techniques for actors within an organization to pitch, defend, and advocate for their preferred frames, such as undermining the legitimacy of alternative frames or realigning the frame with the interests of other actors from whom the proponent seeks to garner support. The context of research is an ethnographic study of a manufacturer of telecommunications immediately after the 2001–2 "bubble" burst, which led to a contentious period of new projects and perspectives. Two more recent studies detail framing contests in the biofuel industry (Hiatt and Carlos 2019) and the emergence of new frames in post-crisis Detroit (S. Kim 2021). These studies provide a theoretical foothold in which to make our primary contribution, integrating frames, imaginaries, and the many other social forces present in the emerging use of AI in organizations.

3. AI AS A MULTIOBJECTIVE PROBLEM

Humans have discussed the idea of artificial entities that have some or all intelligent abilities of humans since antiquity with the Greek myths of Pandora and Talos. AI has been present in some form since the creation of a checkers programs in 1951 and 1951 on the Ferranti Mark 1. After decades of booms and busts (known as "AI winters"), the modern period of booming interest started with Deep Blue's victory over world chess champion Garry Kasparov in 1996. Due to recent advances, particularly the advent of deep learning in 2012 marked by the ImageNet challenge, AI is being rapidly adopted across organizational domains.

Since 2018, there have been numerous calls for further study of algorithms, AI, machine learning, and deep learning in organizations (e.g., Faraj, Pachidi, and Sayegh 2018; Gregory et al. 2020; von Krogh 2018; Murray et al. 2019; Murray, Rhymer, and Sirmon 2020). We use AI as a general term for the various intelligent capabilities of artificial entities, discriminating between different algorithms where relevant. AI has been used to refer to a vast range of technologies, as even among humans, “intelligence” can include a vast range of mental capacities. Naturally AI has been labeled a “general purpose technology,” defined as pervading the economy and facilitating further technical improvement and innovation (Cockburn, Henderson, and Stern 2018; Bresnahan and Trajtenberg 1995). Because AI can have so many effects, and because there are so many people and organizations working towards certain outcomes, means AI is a “multiobjective problem” (Vamplew et al. 2018).

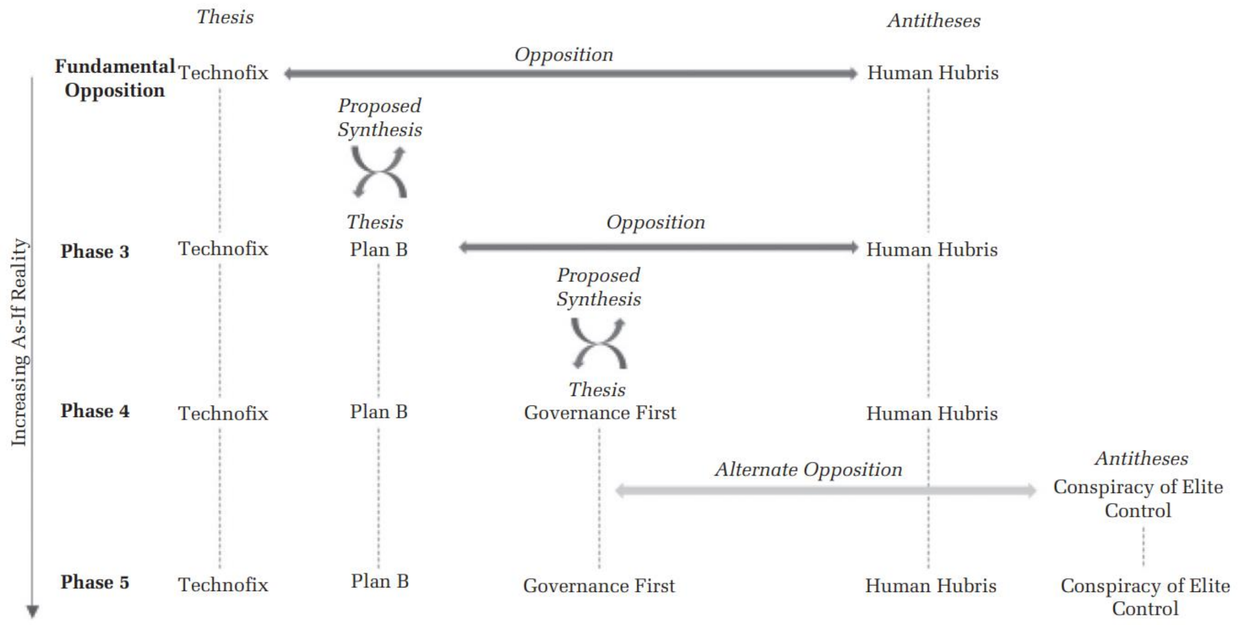
We can reveal and clarify those various frames via the framing contest theory. Moreover, we can contribute a new understanding of framing contests: rather than in previous where framing contests have been short-lived engagements in which a dominant frame typically emerges, AI is an example where the framing contest lasts for decades and may never result in a dominant frame. Instead, different frames are constantly pushing and pulling on the technology in various directions.

4. METHODOLOGICAL APPROACH

For the SOCI 40133 final project, I begin exploring AI discourse via the News on the Web (NOW) Corpus available on the RCC server. I am approaching this as computational grounded theory (Nelson 2020). This project is in the first step of this approach, pattern detection using computational exploratory analysis. After this class, I will continue in this step and then embark on the second step, hypothesis refinement using human-conducted interpretive analysis, and the third step, pattern confirmation.

I envision the final output of this project as similar to the paper Augustine et al. 2019, “Constructing a Distant Future: Imaginaries in Geoengineering”, published in 2019 in *Academy of Management Journal*. That paper laid out five “social imaginaries” of geoengineering (e.g., launching particulates or mirrors into the atmosphere to reduce sunlight and cool the earth). The imaginaries were present since before 1990 up until 2016. For example, the initial framing was scientists treating the technology as a “technofix”, a logical step in humanity’s increasing control of the Earth, but then environmental critics brought in “human hubris” as a critical frame, highlighting humanity’s track record of harming Earth. This was a qualitative paper, but I hope to computationally track analogous frames in artificial intelligence discourse. See, for example, this figure from the paper:

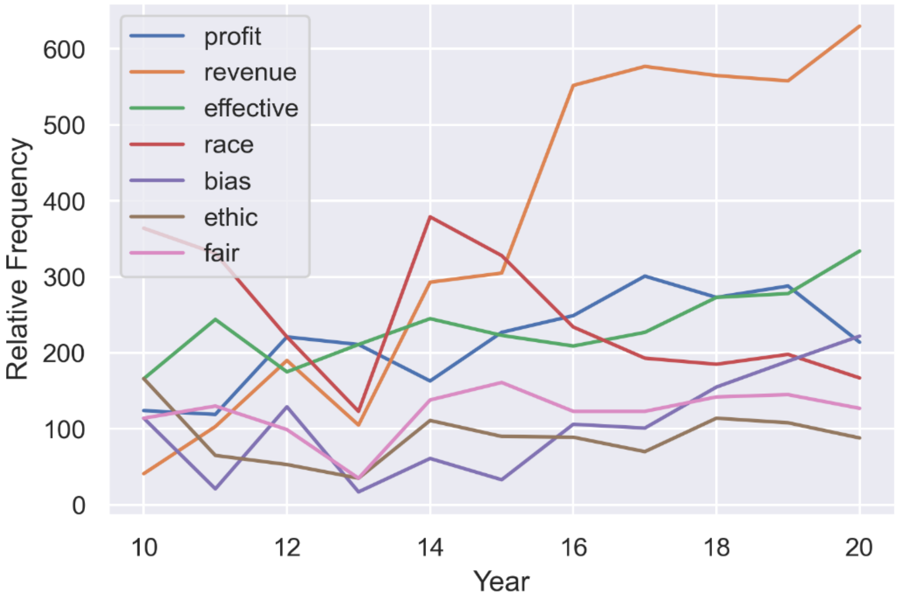
FIGURE 1
Dialectic Process



5. EXPLORING THE CORPUS

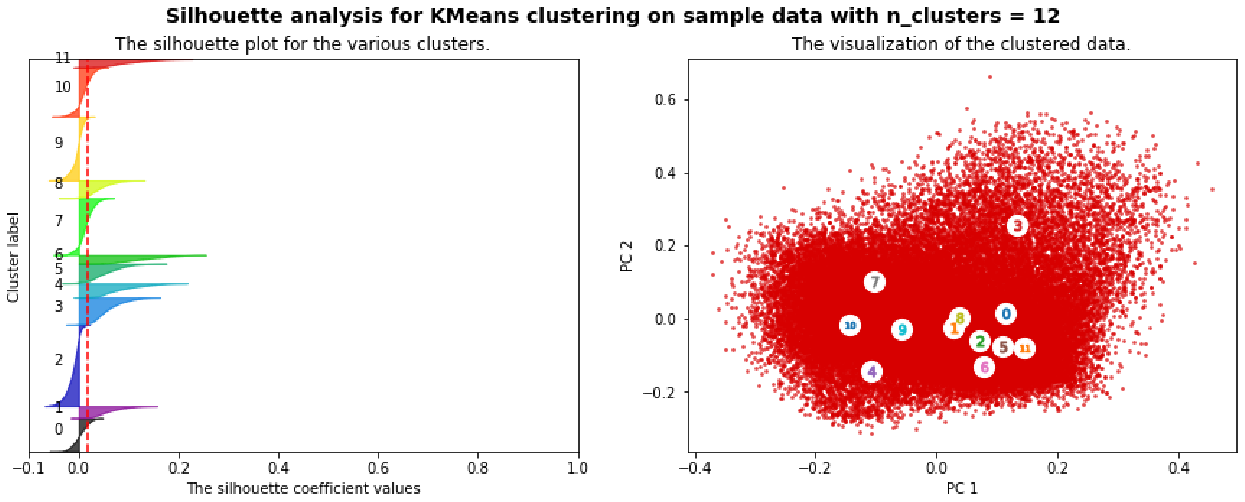
I am fairly convinced that most computational text analysis projects should start with the basics and only use more sophisticated methods where less sophisticated methods fail. So after gathering and cleaning the corpus for SOCI 40133, I was most interested in simple keyword counts. Figure 1 shows relative frequency (count-of-word * 1,000,000 / total-words-in-year) of various keywords related to the economic and social dimensions of AI. I did not see evidence of the main trend I was looking for, an increase in mentions of "bias", "ethic", or "fair" over time or peaks corresponding with major AI events (e.g., AlphaGo defeating the world Go champion in 2016), though "bias" did increase from 2017 to 2020. I was surprised to see a huge increase in mentions of "revenue", at least without a comparable increase in "profit". If the general social trend were an increase in businesses with AI-related revenue or a near-potential for AI-related revenue, then I would expect both keywords to increase in relative frequency.

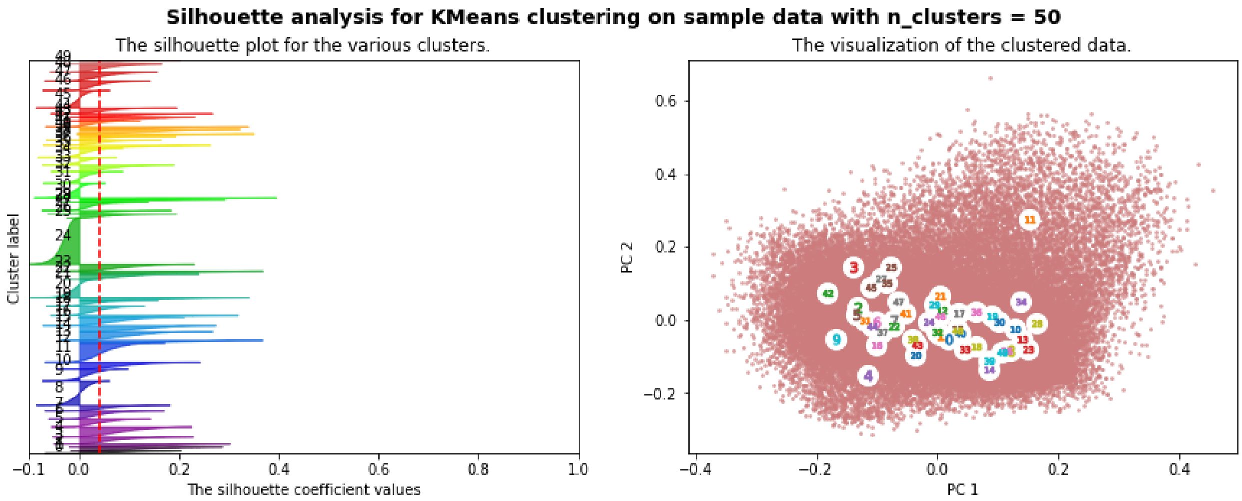
Figure 1. Relative Frequency of AI Keywords Over Time



Several of these keywords may also vary in usage over time, which is not captured by a simple count. For example, a 2012 article that mentions “bias” says, “Coupled with the data, though, we must have a much better understanding of decision making, which means extending knowledge about cognitive biases, about boundary work (scientists, citizens, and policymakers working together to weigh options on the basis not only of empirical evidence but also of values).” (“The Future of Big Data”, Pew Research Center). This refers to the cognitive biases of humans, which affect policy. A 2020 article uses “bias” a different way, “Current implementations of the software also perpetuate racial bias by misidentifying people of color far more frequently than white people.” This is a more machine-centric usage of “bias”.

These disparate trends suggest a need for clustering and topic models to aggregate words into coherent topics and detect connections between words as well as changes in topics over time. First, KMeans clustering using 3–50 clusters does not seem to perform well on the data. Unlike the multidimensional scaling of datasets in class, the AI news articles just look like a blob. The silhouette scores are very low.





The top terms in each cluster had some coherence. For example, we see business, customers, digital, customer, and security in one cluster; another is china, Chinese, trump, trade, Huawei, government, and companies; another is facebook, people, game, just, apple, says, company. This gives me some sense of the frames through which AI are viewed (e.g. a business-oriented frame, a China-oriented frame, and a Silicon Valley-oriented frame), but the others are less interpretable.

I built a vanilla LDA topic model, toying with the parameters and getting the most coherent results with 10 topics. The outputs of the topic model are listed in Table 1.

Table 1. Vanilla LDA Topic Model of AI Corpus

Topic_0	Topic_1	Topic_2	Topic_3	Topic_4	Topic_5	Topic_6	Topic_7	Topic_8	Topic_9
google	market	learn	china	health	model	business	say	say	security
app	company	human	say	patient	learn	company	people	india	say
apple	year	work	company	information	image	customer	work	global	government
device	growth	need	facebook	test	machine	service	year	industry	state
user	financial	people	chinese	study	network	cloud	game	country	law
camera	share	machine	people	disease	high	solution	think	development	public

amazon	stock	change	social	medical	base	platform	know	government	information
feature	investment	way	trump	say	fig	digital	want	year	africa
phone	report	science	coronavirus	research	process	market	come	innovation	national
iphone	increase	job	pandemic	help	algorithm	product	thing	sector	country

In this run, Topic_0 is Google, Amazon (not Apple), phones, devices, etc. Topic_1 is business (e.g. markets, stocks, investments). Topic_2 is less clear, but learning and science seem related. Topic_3 is related to China, Trump, and the coronavirus. Topic_4 is healthcare (e.g. health, patient, disease). Topic_5 is perhaps more technical content (e.g. model, machine, network, algorithm). In another run, Topic_0 has something to do with knowledge, gaming, and design. Topic_1 is China and international trade. Topic_2 and Topic_3 are more generic, then Topic_4 is autonomous cars and energy, and Topic_5 is business and marketing. Again we see that this is in general a very business-oriented corpus.

These are interesting, but notably there is nothing on the “ethics” dimension, such as “bias” or “fairness”. Since this was a primary interest of mine, I looked for a Python package to conduct seeded LDA and found the ‘GuidedLDA’ package. It was a headache to install, and I ended up having to just copy the .py files into the LDA package. I used the following seed topics based on the vanilla LDA:

```
['china','chinese','trump','global','government','state','world','country','president'],
['stock','financial','investment','growth','revenue','profit','company','market'],
['phone','iphone','apple','camera','device','app','facebook','google'],
['health','medical','covid','coronavirus','patient','patients','care','healthcare'],
['car','driving','autonomous','car','cars','vehicle','vehicles'],
```

['algorithm','model','learn','network','process','network','learn'],

and a seventh list of keywords for the topic I wanted to encourage:

['bias','race','fair','ethic','privacy','liberty','surveillance']]

Unfortunately, as shown in Table 2, the topics seemed less coherent than the vanilla LDA, and I did not get a stable “ethics” topic. I tried several parameters and did not get an “ethics” topic, but I may not have properly seeded the LDA. More detail is in the annotated code file.

Table 2. Seeded LDA Topic Model of AI Corpus

Topic_0	Topic_1	Topic_2	Topic_3	Topic_4	Topic_5	Topic_6	Topic_7	Topic_8	Topic_9
said	company	google	health	technology	data	data	said	like	data
china	market	new	patients	new	learning	said	new	people	ai
government	business	apple	medical	ai	model	security	year	just	technology
world	year	app	covid	said	machine	facebook	university	time	business
chinese	growth	like	research	data	using	information	students	think	new
new	million	users	19	systems	used	media	world	world	digital
country	companies	amazon	care	energy	models	use	technology	way	learning
economic	services	company	healthcare	car	based	content	research	human	work
state	financial	phone	data	driving	deep	gt	team	going	need
global	data	video	patient	intelligence	neural	people	science	says	intelligence

I was interested in how the topics evolved over time, which can also help us understand what the stable topics are within the corpus. So I focused on dynamic topic modeling (DTM), as detailed in the SOCI 40133 homework. The DTM took 36 hours to run on a single thread. I modified the vanilla LDA output code to create a series of tables for how each topic changed over the 11 years in the NOW corpus. This is too much output to list here, but Table 3 is an example of the most interesting topic, where—this is reading the tea leaves—the nature of "human"-"computer" interaction has shifted from "robots" (i.e., embodied AIs) to "models" (i.e., disembodied AIs) and from simply "thinking" about AI to actually "working" with AI.

Table 3. Evolution of a Topic in the Dynamic Topic Model

2011	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**
human	human	human	human	human	human	human	human	learn	learn	learn
computer	computer	computer	computer	people	people	work	work	work	work	work
think	think	think	think	computer	work	people	learn	human	human	model
robot	say	say	people	work	learn	learn	say	say	machine	human
say	robot	learn	work	learn	say	say	people	people	say	machine
learn	learn	work	learn	think	think	machine	machine	machine	model	research
work	work	people	say	say	machine	think	need	need	research	science
people	people	robot	robot	robot	robot	robot	robot	research	people	study
science	science	science	machine	machine	computer	computer	think	university	need	patient
know	know	machine	science	way	way	way	way	science	science	people
year	year	know	way	year	year	research	research	way	university	need
machine	machine	year	know	science	research	need	university	think	study	university
way	way	way	year	know	know	university	computer	robot	way	test
university	university	university	university	thing	science	year	future	future	change	health
thing	thing	thing	thing	university	thing	science	science	job	health	image
research	research	research	research	research	university	know	year	change	patient	say
problem	problem	problem	come	need	need	thing	know	model	help	base
brain	brain	brain	need	come	future	future	create	help	job	high
need	need	come	problem	future	come	create	change	create	algorithm	process
come	come	need	brain	problem	create	come	job	computer	process	algorithm

I also built *word2vec* and *doc2vec* embeddings of the AI NOW corpus. Both of these were easier with the multiprocessing capability of *genism.models.word2vec.Word2Vec()*. The embeddings were coherent. For example, similar to the king – man + woman = queen analogy, we can show that google + android – facebook = os/voice/ios. However, some other analogies do not work, and overall it was challenging to find relevant relationships between the word vectors.

Similarly, BERT classifiers and GPT-2 text generation showed coherent results. I trained a BERT classifier to differentiate articles published in 2015 and 2017, which are before and after AlphaGo's victory over Lee Sedol in 2016, which was a big year for AI. Because I had some trouble differentiating the years with traditional machine learning classifiers, I chose a hopefully easy task as a basic check that the texts were in fact different. Ultimately I found a 68.6% accuracy using the Hugging Face BertForSequenceClassification.

For text generation, Tables 4 and 5 show some prompts and associated outputs. We see that, as expected (or at least hoped), the fine-tuned GPT-2 generates more AI-relevant text. I also asked GPT-3 what it thinks the future of artificial intelligence is, to which it gave a trivial or perhaps ingenious response.

Table 4. Pre-Trained and Fine-Tuned GPT-2 Prompts and Output

Prompt	**Pre-trained GPT-2**	**Fine-tuned GPT-2**
My favorite activity is	to play with your friends. I love to play with my friends.	to watch a video of a video game and then play it back to the computer.
The solution to the world's problems is	to create a world where people are free to choose their own path.	to create a new kind of economy that works for everyone.

Table 5. Pre-Trained GPT-3 Prompt and Output

Prompt	**Pre-trained GPT-3**
The future of artificial intelligence is	in question because some people say it is unpredictable and others say it is predictable. This is because right now some things are predictable and some things are unpredictable.

6. FUTURE RESEARCH

Through this qualitative and computational exploration of AI discourse, I have built some hypotheses that I think could be further developed or tested using these methods. These hypotheses can be tested with corpus such as newspaper articles about AI (e.g., NOW AI, NOW AI filtered more narrowly such as paragraphs that mention AI, ProQuest), scholarly papers on AI in computer science, social science, and ethics (e.g., Scopus), analyst reports (e.g., Thomson One Investext), press releases (e.g., LexisNexis), mission statements (e.g., company websites), and earnings conference calls (e.g., Refinitiv). I tried to replicate my code on the ProQuest TDM server with a corpus of 410,915 newspaper articles from all of their news databases (e.g. ProQuest Historical Newspapers) from 1990 to 2021. Unfortunately, almost every step of data processing and analysis on the ProQuest server has to be recoded because their servers cannot handle large computational loads. For example, simply tokenizing 200,000 newspaper articles will cause the kernel to die. I have not yet had time to fully recode my preprocessing or analysis in time for this final project, but I hope to complete that replication in the Spring Quarter.

In addition to the text analysis, I hope to conduct 10-30 interviews with AI stakeholders (for which I am currently working on an IRB application with the University of Chicago).

These are my specific hypotheses and the methods I envision to test them for the second and third steps in Nelson's (2020) three-step framework:

- H1 (Milestone Effects): AI milestones change the constitutions, frequencies, and relationships of frames.
    - H1a: After milestones, ethical frames grow in salience relative to performance frames.
    - H1b: After milestones, critical frames grow in salience relative to positive frames.
    - H1c: After milestones, the existential risk (e.g. Terminator and human extinction) frame grows in salience.
    - H1d: After milestones, there is more exploitation relative to exploration of technical AI strategies (e.g. Lasso, BERT, neural networks).

My sense is that the best specific method for H1 (Milestone Effects) will be structural topic models (STM), which are similar to dynamic topic models but also incorporate metadata other than time, such as publisher and genre. However, it might be best to use a series of vanilla LDA topic models or STMs without a time variable. This would allow a difference-in-differences estimate of stable snapshots in the corpus, such as all scholarly papers published in the 3-12 months[1] after a milestone event compared to those published up to 9 months before a milestone event and more than 12 months after any previous milestone events. For a difference-in-differences estimate, we also need a comparison corpus. In the case of scholarly papers, that could be non-AI papers in the same discipline or papers on a similar but separate topic, such as blockchain.

The biggest challenge with H1 will probably be finding a truly exogenous shock relative to a dependent variable of interest. For example, if my dataset is scholarly papers and my discontinuity is a new AI architecture (e.g. AlphaGo, which defeated world Go champions in 2016), then it may be endogenous within the scholarly discourse. I have spoken with a graduate student who is using the 2012 ImageNet competition as an exogenous shock based on the reasoning that it was only a small group of scholars who developed that approach, such that it was exogenous to the vast majority of scholars. Even in that case, the grad student is having some trouble convincing economics-oriented scholars of the validity of their causal inference—I will see whether their submission is successful. The strongest case for causal inference in my context might be media and corporate analyst coverage of AI milestones because the milestones are exogenous to the journalists and analysts.

[1] Different timelines would make sense for different corpuses because, ideally, we will capture the time of working on a document in which the authors are most influenced by outside events. For scholarly papers in computer science, this may be a few months before presentation at a conference. For scholarly papers in social science and ethics, this may be a year or two before publication in a journal. For newspaper articles, perhaps no adjustment is necessary.

For a closer view of AI firms, it may be best to focus on corporate analysts, for whom AI developments are still exogenous (e.g. Benner and Ranganathan 2012).

- H2 (Stakeholder Effects): The frames used by AI stakeholders vary based on how closely they are involved in AI.
    - H2a: Stakeholders more involved in AI (e.g. computer scientists, AI firms) are less likely to discuss ethics than those less involved (e.g. social scientists, activists).
    - H2b: Stakeholders more involved in AI discuss ethics in a more positive way than those less involved.

For H2 (Stakeholder Effects), a series of topic models, separated by authorship (e.g. AI researchers, AI companies, AI-focused ethicists, AI-focused social scientists, journalists covering AI) seems straightforward. The biggest challenge here may be disentangling genuine differences in frames between the stakeholders and other discursive practices. For example, if I compare newspaper articles to scholarly papers, there will be many non-framing differences, such as the reading level or the formatting of the documents.

- H3 (Trade-Off Avoidance): Some frames are more likely to be discussed in the same document than others.
    - H3a: AI discussants avoid discussion of ethics and performance in the same document (i.e. the topic models have low intersection; the word embeddings have large cosine differences).

  - H3b: AI discussants avoid discussion of security and transparency in the same document.

For H3 (Trade-Off Avoidance), and the more general research goal of mapping out AI frames and their relations, I will use topic models to measure the extent of topic overlap.

Aside from the hypotheses and general cartography of AI frames, I hope to conduct various robustness checks of the AI discourse models. For example, using text, can we see when AI winters happened? Can we see when deep learning became a focus in 2012? While we should not expect the models to verify all of our intuitions about AI discourse, the models should verify the most obvious claims. Similarly, for H1a-H3b, there will inevitably be many different ways to construct the models, such as different inclusion criteria for the documents, and I will try to test many of them (e.g., with bootstrapping) to see if there is convergence.

- H4 (Organizational Outcomes): The use of AI performance frames, meaning a focus on AI that is economically efficient and productive, is associated with better organizational outcomes (e.g. investment, revenue) than the use of AI ethics frames, meaning a focus on AI that is fair and beneficial to society.

The analysis for this would be straightforward with a series of regression models that have the relative proportion of a frame within a corpus (as documented in a topic model, e.g., performance framing being twice as common as ethics framing) as an independent variable and the organizational outcome as the dependent variable.

- H5 (The Power of Early Action): Frames and other textual features (e.g., diction) that are common early in the history of AI have a disproportionate effect on later-stage AI discourse.

I have not yet figured out exactly how to test this final hypothesis. I do not believe topic models are fine-grained enough because they cannot disentangle what frames are present early and late in the discourse because they are fundamental to AI discourse (e.g., it is difficult to discuss AI without discussing its technical aspects: models, algorithms, processes, etc.) and what frames are present late because they were also present early. I may find more traction here in my interviews with AI stakeholders. I plan to ask them, for example, how did different frames emerge in AI discourse, and what led those frames to persist or dissipate?

Most of these hypotheses could also be approached with word embeddings (e.g., the cosine similarity between "artificial intelligence" and various terms) and "discourse atoms," which I have not yet had time to implement for my corpus (Arora et al. 2018).

In addition to developing these hypotheses and providing initial evidence (though again, I'm approaching this as a theory-building exercise, not theory-testing), I hope to lay out 5-10 frames comparable to the 5 social imaginaries laid out by Augustine et al. (2019) as the core contribution of their paper. An example would be the "4th Industrial Revolution" frame, in which AI is discussed not just as a boost to economic productivity, but as an overhaul of humanity's current economic and social systems. One example of this is the rhetoric of Andrew Yang, a Democratic primary candidate in the 2020 U.S. presidential election, who argues that the coming automation of U.S. jobs shows the need for a universal basic income (i.e., "freedom dividend").

Practically speaking, I am applying for a $2,000 Summer Research Grant with the University of Chicago Social Sciences Division to support this research for the summer, though currently I do not have a particular need for the funding. This research has been accepted for presentation at the 2021 July meeting of the European Group for Organizational Studies (EGOS). I hope that it will serve as my Qualifying Paper (i.e., second-year paper) for the sociology PhD program. In terms of feedback, I am most interested in whether this current plan of listing propositions/hypotheses and frames/imaginaries is a sufficient contribution for sufficient contribution for a paper at a journal such as the *Academy of Management Journal, Strategic Management Journal*, or *Administrative Science Quarterly*? Should I focus more on a particular hypothesis? Which are most interesting? Should I center a specific contribution to the literature on framing, such as showing how frames emerge in a “general purpose technology”? Is there some feature of the emerging AI literature that I can more explicitly criticize? Etc.

REFERENCES

Ahmed, Nur, and Muntasir Wahed. 2020. “The De-Democratization of AI: Deep Learning and the Compute Divide in Artificial Intelligence Research.” *ArXiv:2010.15581 [Cs]*, October. http://arxiv.org/abs/2010.15581.

Amabile, Teresa. 2019. “GUIDEPOST: Creativity, Artificial Intelligence, and a World of Surprises Guidepost Letter for Academy of Management Discoveries.” *Academy of Management Discoveries*, February, amd.2019.0075. https://doi.org/10.5465/amd.2019.0075.

Arora, Sanjeev, Yuanzhi Li, Yingyu Liang, Tengyu Ma, and Andrej Risteski. 2018. “Linear Algebraic Structure of Word Senses, with Applications to Polysemy.” *ArXiv:1601.03764 [Cs, Stat],* December. http://arxiv.org/abs/1601.03764.

Augustine, Grace, Sara Soderstrom, Daniel Milner, and Klaus Weber. 2019. “Constructing a Distant Future: Imaginaries in Geoengineering.” *Academy of Management Journal* 62 (6): 1930–60. https://doi.org/10.5465/amj.2018.0059.

Baum, Joel A. C., and Heather A. Haveman. 2020. “Editors’ Comments: The Future of Organizational Theory.” *Academy of Management Review* 45 (2): 268–72. https://doi.org/10.5465/amr.2020.0030.

Benford, Robert D., and David A. Snow. 2000. “Framing Processes and Social Movements: An Overview and Assessment.” *Annual Review of Sociology* 26 (1): 611–39. https://doi.org/10.1146/annurev.soc.26.1.611.

Benner, Mary J., and Ram Ranganathan. 2012. “Offsetting Illegitimacy? How Pressures from Securities Analysts Influence Incumbents in the Face of New Technologies.” *Academy of Management Journal* 55 (1): 213–33. https://doi.org/10.5465/amj.2009.0530.

Brayne, Sarah. 2017. “Big Data Surveillance: The Case of Policing.” *American Sociological Review* 82 (5): 977–1008. https://doi.org/10.1177/0003122417725865.

Bresnahan, Timothy F., and M. Trajtenberg. 1995. “General Purpose Technologies ‘Engines of Growth’?” *Journal of Econometrics* 65 (1): 83–108. https://doi.org/10.1016/0304-4076(94)01598-T.

Brundage, Miles, Shahar Avin, Jasmine Wang, Haydn Belfield, Gretchen Krueger, Gillian Hadfield, Heidy Khlaaf, et al. 2020. “Toward Trustworthy AI Development: Mechanisms for Supporting Verifiable Claims." *ArXiv:2004.07213 [Cs]*, April. http://arxiv.org/abs/2004.07213.

Butterworth, Michael. 2018. "The ICO and Artificial Intelligence: The Role of Fairness in the GDPR Framework." *Computer Law & Security Review* 34 (2): 257–68. https://doi.org/10.1016/j.clsr.2018.01.004.

Clough, David R., and Andy Wu. 2020. "Artificial Intelligence, Data-Driven Learning, and the Decentralized Structure of Platform Ecosystems." *Academy of Management Review*, October, amr.2020.0222. https://doi.org/10.5465/amr.2020.0222.

Cockburn, Iain, Rebecca Henderson, and Scott Stern. 2018. "The Impact of Artificial Intelligence on Innovation." *National Bureau of Economic Research,* March. https://doi.org/10.3386/w24449.

Corbett-Davies, Sam, Emma Pierson, Avi Feller, Sharad Goel, and Aziz Huq. 2017. "Algorithmic Decision Making and the Cost of Fairness." In *Proceedings of the 23rd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, 797–806. Halifax NS Canada: ACM. https://doi.org/10.1145/3097983.3098095.

Cowgill, Bo, Fabrizio Dell'Acqua, Sam Deng, Daniel Hsu, Nakul Verma, and Augustin Chaintreau. 2020. "Biased Programmers? Or Biased Data? A Field Experiment in Operationalizing AI Ethics." *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3615404.

Cowgill, Bo, Fabrizio Dell'Acqua, and Sandra Matz. 2020. "The Managerial Effects of Algorithmic Fairness Activism." *AEA Papers and Proceedings* 110. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3523937.

Cowgill, Bo, and Catherine E. Tucker. 2019. “Economics, Fairness and Algorithmic Bias.” *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3361280.

Curchod, Corentin, Gerardo Patriotta, Laurie Cohen, and Nicolas Neysen. 2020. “Working for an Algorithm: Power Asymmetries and Agency in Online Work Settings.” *Administrative Science Quarterly* 65 (3): 644–76. https://doi.org/10.1177/0001839219867024.

Dietvorst, Berkeley J., Joseph Simmons, and Cade Massey. 2014. “Understanding Algorithm Aversion: Forecasters Erroneously Avoid Algorithms After Seeing Them Err.” *Academy of Management Proceedings* 2014 (1): 12227. https://doi.org/10.5465/ambpp.2014.12227abstract.

Dietvorst, Berkeley J., Joseph P. Simmons, and Cade Massey. 2015. “Algorithm Aversion: People Erroneously Avoid Algorithms after Seeing Them Err.” *Journal of Experimental Psychology: General* 144 (1): 114–26. https://doi.org/10.1037/xge0000033.

———. 2018. “Overcoming Algorithm Aversion: People Will Use Imperfect Algorithms If They Can (Even Slightly) Modify Them.” *Management Science* 64 (3): 1155–70. https://doi.org/10.1287/mnsc.2016.2643.

Donaldson, Thomas J., and Cristina Neesham. 2020. “The Problem of Value Alignment in Business Decision Making: Humans vs. Artificial Intelligence.” *Academy of Management Proceedings* 2020 (1): 14706. https://doi.org/10.5465/AMBPP.2020.14706abstract.

Doshi-Velez, Finale, and Been Kim. 2017. “Towards A Rigorous Science of Interpretable Machine Learning.” *ArXiv:1702.08608 [Cs, Stat]*, March. http://arxiv.org/abs/1702.08608.

Dutton, Jane E., and Susan J. Ashford. 1993. “Selling Issues to Top Management.” *Academy of Management Review* 18 (3): 397–428. https://doi.org/10.5465/amr.1993.9309035145.

Fang, Christina, Chengwei Liu, Bo Cowgill, Jerker C. Denrell, Phanish Puranam, Zur Shapira, and Sidney G. Winter. 2019. "Machines vs Humans: How Can We Adapt Organizations to AI?" *Academy of Management Proceedings* 2019 (1): 12809. https://doi.org/10.5465/AMBPP.2019.12809symposium.

Faraj, Samer, Stella Pachidi, and Karla Sayegh. 2018. "Working and Organizing in the Age of the Learning Algorithm." *Information and Organization* 28 (1): 62–70. https://doi.org/10.1016/j.infoandorg.2018.02.005.

Fiss, Peer C., and Paul M. Hirsch. 2005. "The Discourse of Globalization: Framing and Sensemaking of an Emerging Concept." *American Sociological Review* 70 (1): 29–52. https://doi.org/10.1177/000312240507000103.

Gardner, William L., and Mark J. Martinko. 1988. "Impression Management in Organizations." *Journal of Management* 14 (2): 321–38. https://doi.org/10.1177/014920638801400210.

Glaser, Barney G., and Anselm L. Strauss. 1967. *The Discovery of Grounded Theory: Strategies for Qualitative Research*. 1st edition. Chicago: Aldine Publishing.

Glikson, Ella, and Anita Williams Woolley. 2020. "Human Trust in Artificial Intelligence: Review of Empirical Research." *Academy of Management Annals* 14 (2): 627–60. https://doi.org/10.5465/annals.2018.0057.

Glynn, Mary Ann. 2000. "When Cymbals Become Symbols: Conflict Over Organizational Identity Within a Symphony Orchestra." *Organization Science* 11 (3): 285–98. https://doi.org/10.1287/orsc.11.3.285.12496.

Goffman, Erving. 1974. *Frame Analysis: An Essay on the Organization of Experience*. Boston: Northeastern University Press.

Gregory, Robert Wayne, Ola Henfridsson, Evgeny Kaganer, and Harris Kyriakou. 2020. "The Role of Artificial Intelligence and Data Network Effects for Creating User Value." *Academy of Management Review*, March, amr.2019.0178. https://doi.org/10.5465/amr.2019.0178.

Hannan, Michael T. 2019. *Concepts and Categories: Foundations for Sociological and Cultural Analysis*. New York: Columbia University Press.

Hehenberger, Lisa, Johanna Mair, and Ashley Metz. 2019. "The Assembly of a Field Ideology: An Idea-Centric Perspective on Systemic Power in Impact Investing." *Academy of Management Journal* 62 (6): 1672–1704. https://doi.org/10.5465/amj.2017.1402.

Hiatt, Shon R., and W. Chad Carlos. 2019. "From Farms to Fuel Tanks: Stakeholder Framing Contests and Entrepreneurship in the Emergent U.S. Biodiesel Market." *Strategic Management Journal* 40 (6): 865–93. https://doi.org/10.1002/smj.2989.

Hitlin, Steven, and Jane Allyn Piliavin. 2004. "Values: Reviving a Dormant Concept." *Annual Review of Sociology* 30 (1): 359–93. https://doi.org/10.1146/annurev.soc.30.012703.110640.

Kaplan, Sarah. 2008. "Framing Contests: Strategy Making Under Uncertainty." *Organization Science* 19 (5): 729–52. https://doi.org/10.1287/orsc.1070.0340.

Kawaguchi, Kohei. 2020. "When Will Workers Follow an Algorithm? A Field Experiment with a Retail Business." *Management Science*, June. https://doi.org/10.1287/mnsc.2020.3599.

Keding, Christoph. 2020. "Understanding the Interplay of Artificial Intelligence and Strategic Management: Four Decades of Research in Review." *Management Review Quarterly*, February. https://doi.org/10.1007/s11301-020-00181-x.

Kellogg, Katherine C., Melissa A. Valentine, and Angéle Christin. 2020. “Algorithms at Work: The New Contested Terrain of Control.” *Academy of Management Annals* 14 (1): 366–410. https://doi.org/10.5465/annals.2018.0174.

Kim, Suntae. 2021. “Frame Restructuration: The Making of an Alternative Business Incubator amid Detroit’s Crisis.” *Administrative Science Quarterly*, January, 000183922098646. https://doi.org/10.1177/0001839220986464.

Kim, Tae Wan, Thomas Donaldson, and John Hooker. 2019. “Grounding Value Alignment with Ethical Principles.” *ArXiv:1907.05447 [Cs]*, July. http://arxiv.org/abs/1907.05447.

Kizilcec, René F. 2016. “How Much Information?: Effects of Transparency on Trust in an Algorithmic Interface.” In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, 2390–95. San Jose California USA: ACM. https://doi.org/10.1145/2858036.2858402.

Kleinberg, Jon, Sendhil Mullainathan, and Manish Raghavan. 2016. “Inherent Trade-Offs in the Fair Determination of Risk Scores.” *ArXiv:1609.05807 [Cs, Stat]*, November. http://arxiv.org/abs/1609.05807.

Krogh, Georg von. 2018. “Artificial Intelligence in Organizations: New Opportunities for Phenomenon-Based Theorizing.” *Academy of Management Discoveries* 4 (4): 404–9. https://doi.org/10.5465/amd.2018.0084.

Lambrecht, Anja, and Catherine Tucker. 2019. “Algorithmic Bias? An Empirical Study of Apparent Gender-Based Discrimination in the Display of STEM Career Ads.” *Management Science* 65 (7): 2966–81. https://doi.org/10.1287/mnsc.2018.3093.

Lebovitz, Sarah, Hila Lifshitz-Assaf, and Natalia Levina. 2019. “To Incorporate or Not to Incorporate AI for Critical Judgments: The Importance of Ambiguity in Professionals’

Judgment Process." *SSRN Electronic Journal*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3480593.

Livengood, R. Scott, and Rhonda K. Reger. 2010. "That's Our Turf! Identity Domains and Competitive Dynamics." *Academy of Management Review* 35 (1): 48–66. https://doi.org/10.5465/amr.35.1.zok48.

Lobel, Ilan. 2020. "Revenue Management and the Rise of the Algorithmic Economy." *Management Science*, September, mnsc.2020.3712. https://doi.org/10.1287/mnsc.2020.3712.

Lounsbury, M., M. Ventresca, and P. M. Hirsch. 2003. "Social Movements, Field Frames and Industry Emergence: A Cultural-Political Perspective on US Recycling." *Socio-Economic Review* 1 (1): 71–104. https://doi.org/10.1093/soceco/1.1.71.

Marcus, Gary, and Ernest Davis. 2019. *Rebooting AI: Building Artificial Intelligence We Can Trust*. First edition. New York: Pantheon Books.

Morse, Lily, Mike H. M. Teodorescu, Yazeed Awwad, and Gerald Kane. 2020. "A Framework for Fairer Machine Learning in Organizations." *ArXiv:2009.04661 [Cs]*, September. http://arxiv.org/abs/2009.04661.

Murray, Alex, Scott Kuban, Matthew Josefy, and Jonathan Anderson. 2019. "Contracting in the Smart Era: The Implications of Blockchain and Decentralized Autonomous Organizations for Contracting and Corporate Governance." *Academy of Management Perspectives*, April, amp.2018.0066. https://doi.org/10.5465/amp.2018.0066.

Murray, Alex, Jennifer Rhymer, and David G. Sirmon. 2020. "Humans and Technology: Forms of Conjoined Agency in Organizations." *Academy of Management Review*, March, amr.2019.0186. https://doi.org/10.5465/amr.2019.0186.

Nelson, Laura K. 2020. “Computational Grounded Theory: A Methodological Framework.” *Sociological Methods & Research* 49 (1): 3–42. https://doi.org/10.1177/0049124117729703.

Obermeyer, Ziad, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. 2019. “Dissecting Racial Bias in an Algorithm Used to Manage the Health of Populations.” *Science* 366 (6464): 447–53. https://doi.org/10.1126/science.aax2342.

Pachidi, Stella, Hans Berends, Samer Faraj, and Marleen Huysman. 2020. “Make Way for the Algorithms: Symbolic Actions and Change in a Regime of Knowing.” *Organization Science*, October, orsc.2020.1377. https://doi.org/10.1287/orsc.2020.1377.

Parkes, David C., and Rakesh V. Vohra. 2019. “Algorithmic and Economic Perspectives on Fairness.” *ArXiv:1909.05282 [Cs]*, September. https://arxiv.org/abs/1909.05282.

Raisch, Sebastian, and Sebastian Krakowski. 2020. “Artificial Intelligence and Management: The Automation-Augmentation Paradox.” *Academy of Management Review*, February, 2018.0072. https://doi.org/10.5465/2018.0072.

Samek, Wojciech, Thomas Wiegand, and Klaus-Robert Müller. 2017. “Explainable Artificial Intelligence: Understanding, Visualizing and Interpreting Deep Learning Models.” *ArXiv:1708.08296 [Cs, Stat]*, August. http://arxiv.org/abs/1708.08296.

Schwemmer, Carsten, Carly Knight, Emily D. Bello-Pardo, Stan Oklobdzija, Martijn Schoonvelde, and Jeffrey W. Lockhart. 2020. “Diagnosing Gender Bias in Image Recognition Systems.” *Socius: Sociological Research for a Dynamic World* 6 (January): 237802312096717. https://doi.org/10.1177/2378023120967171.

Snow, David, E Burke Rochford, Steven Worden, and Robert Benford. 1986. “Frame Alignment Processes, Micromobilization, and Movement Participation.” *American Sociological Review* 51 (4): 464–81. https://doi.org/10.2307/2095581.

Sunstein, Cass. 2019. “Algorithms, Correcting Biases.” *Social Research: An International Quarterly* 86 (2): 499–511.

Vamplew, Peter, Richard Dazeley, Cameron Foale, Sally Firmin, and Jane Mummery. 2018. “Human-Aligned Artificial Intelligence Is a Multiobjective Problem.” *Ethics and Information Technology* 20 (1): 27–40. https://doi.org/10.1007/s10676-017-9440-6.

Warner, W. Keith, and A. Eugene Havens. 1968. “Goal Displacement and the Intangibility of Organizational Goals.” *Administrative Science Quarterly* 12 (4): 539. https://doi.org/10.2307/2391532.

Whetten, David A. 1989. “What Constitutes a Theoretical Contribution?” *Academy of Management Review* 14 (4): 490–95. https://doi.org/10.5465/amr.1989.4308371.

Yu, Haizi, Heinrich Taube, James A. Evans, and Lav R. Varshney. 2020. “Human Evaluation of Interpretability: The Case of AI-Generated Music Knowledge.” *ArXiv:2004.06894 [Cs]*, April. http://arxiv.org/abs/2004.06894.