Artificial Concepts of Artificial Intelligence: Institutional Compliance and Resistance in AI Startups

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ABSTRACT

Scholars and industry practitioners have debated how to best develop interventions for ethical artificial intelligence (AI). Such interventions recommend that companies building and using AI tools change their technical practices, but fail to grapple with critical questions about the organizational and institutional context in which AI is developed. In this paper, we contribute descriptive research around the life of "AI" as a discursive concept and organizational practice in an understudied sphere—emerging AI startups—and with a focus on extra-organizational pressures faced by entrepreneurs. Leveraging a theoretical lens for how organizations change, we conducted semi-structured interviews with 23 entrepreneurs working at early-stage AI startups. We find that actors within startups both conform to and resist institutional pressures. Our analysis identifies a central tension for AI entrepreneurs: they often valued scientific integrity and methodological rigor; however, influential external stakeholders either lacked the technical knowledge to appreciate entrepreneurs’ emphasis on rigor or were more focused on business priorities. As a result, entrepreneurs adopted hype marketing messages about AI that diverged from their scientific values, but attempted to preserve their legitimacy internally. Institutional pressures and organizational constraints also influenced entrepreneurs’ modeling practices and their response to actual or impending regulation. We conclude with a discussion for how such pressures could be used as leverage for effective interventions towards building ethical AI.

CCS CONCEPTS

• Social and professional topics → Socio-technical systems; • Applied computing → Sociology.

KEYWORDS

organizational theory, artificial intelligence, industry practice, qualitative methods, ethical systems

1 INTRODUCTION

Academic researchers, advocacy groups, and technology companies have created guidelines and tools for developing ethical artificial intelligence (AI) [15, 37]. This research is intended to ameliorate the considerable negative social impacts produced in AI systems, such as how AI models encode racial and gender biases [6, 7, 40, 46, 58], worsen disordered eating and body dysmorphia [28], and magnify inequality [1, 12, 41]. However, the real-world utility of available interventions for ethical AI remains unclear.

As with any research intended for real-world applications, robust consideration of the context of implementation is critical. An emerging body of research has begun to recognize that effective change demands non-technical strategies to contend with organizational context [45], such as the conditions inside technology firms which might influence, or even prevent, the effectiveness of interventions for ethical AI. Tight development timelines, lack of formal organizational processes, and challenging internal stakeholder dynamics shape how real-world companies can move in the direction of more ethical AI development [22, 24, 31, 32, 45]. Studies of AI ethics in organizational contexts often focus on interventions such as model fairness [22, 31, 32] and model interpretability techniques [4, 23, 29]. However, such studies have largely been constrained to organizations that are mature enough to consider specific AI ethical interventions to begin with.

AI startups constitute a growing portion of the technology sector [63]. As a result, these companies and the ethical practices they embrace are likely to play a significant role in the impact of future technology on society. Only a handful of studies have characterized ethical AI development at smaller firms [24, 64]. This emerging area of research has begun to illuminate the unique challenges nascent firms must address when attempting to adopt responsible, transparent, and accountable AI practices. For example, as with more mature companies, small firms must navigate complex dynamics amongst stakeholders like clients, investors, and regulators but unlike more established organizations, they must do so under significant resource constraints that threaten their very existence [24]. Therefore, the ethical AI practices they are able to adopt are necessarily limited.

While existing research has illustrated the organizational constraints to ethical AI, especially intra-organizational dynamics, less is known about how the inter-organizational or field-level dynamics shape firms’ capacity to develop ethical approaches. The field-level, i.e., “institutional” dynamics and market-based pressures that impact an organization’s chances of survival inevitably alter the structures and practices firms adopt [13, 36, 43, 49]. By behaving in ways that conform with institutional expectations, emerging organizations can improve their social and cultural fitness; however,
institutional expectations sometimes conflict with each other and also with economic pressures. As a result, emerging organizations such as AI startups must skillfully navigate a complex gauntlet of social, cultural, and economic challenges. How these field-level dynamics factor into the ethical choices of startups, such as their decisions around the use of AI, is an under-explored area of research.

Here, we contend that before effective ethical AI practices for startups can be developed, an understanding of the inter-organizational and institutional dynamics these firms face must be developed. Building on recent scholarship that takes a contextual and organizational approach to ethical AI, we engage in descriptive research around the life of “AI” as a discursive concept and organizational practice that is situated within an institutional context. Instead of focusing on ethical practices directly, we take a step back to ask fundamental questions about the forces that shape the very nature of how entrepreneurs define, build, and talk about AI itself.

To that end, we ask two research questions:

RQ1: What institutional pressures influence how startup entrepreneurs define, discuss, and build AI?

RQ2: When do entrepreneurs comply with, avoid, or resist these pressures?

To address these questions, we conducted semi-structured interviews with 23 individuals working at early-stage startups across a range of industry domains. In our interviews, we focused on the financial, regulatory, and normative pressures AI startups encounter. Using abductive analysis, we illustrate how AI entrepreneurs both comply with and resist institutional pressures through the technological and business practices they employ. We find that AI entrepreneurs face a tension between the expectations of technology entrepreneurship, which rewards rapid development and optimistic promises about technology’s potential, and entrepreneurs’ own values of scientific integrity, which prioritize meticulous practices and encourages skepticism. This tension was further heightened by external stakeholders’ unrealistic expectations about the potential of AI, particularly when such stakeholders had limited technical knowledge. We also find that whereas AI entrepreneurs saw privacy regulation as beneficial and aligned with their own values of autonomy, they held less uniformly positive views of other AI regulatory processes such as those employed by the Food and Drug Administration (FDA) in approving AI medical devices. Drawing from our theoretical motivations, we conclude with a discussion of how our results point to both constraints and opportunities for future research on ethical interventions for AI startups.

2 RELATED WORKS

Organizational dynamics are a significant source of influence on the effectiveness of interventions for ethical and responsible AI. Practitioners in well-resourced organizations have expressed aspirations for ethics-supportive structures as such cross-team integration, risk-anticipation frameworks, and firm-level mission and values [45]. Our own research builds on these recent findings by addressing inter-organizational and institutional conditions (i.e., external pressures) that are likely to be sources of change for organizations, especially emerging organizations such as AI startups, which typically lack formal mechanisms for addressing ethical concerns [24, 64]. In this section we provide an overview of the relevant frameworks we draw from in organizational theory to explain how organizations adopt procedures and adapt over time to institutional pressures.

2.1 Resource Dependency and Institutionalism: How Organizations Change

Organizational theory offers different frameworks to understand how organizations change. In the early days of the discipline, the dominant paradigm was of rationality: theorists described organizations as rational systems, machines for achieving a goal in the market, and that all organizational decisions were imbued with this same mechanical, systematic precision. Within this school were early 1900s thinkers like the German sociologist Max Weber, with his focus on bureaucracies as structural realizations of rational authority [70], and American mechanical engineer Frederick Winslow Taylor, with his focus on bringing “scientific” methods to management to wring ever-greater “efficiency” out of a labor force [60].

Starting in the 1970s, however, the field took a relational turn, recognizing that organizations do not operate in a vacuum of rationality but instead within complex ecologies of other actors. Two schools of thought—resource dependency theory and institutionalism—both address how firms seek to mitigate external pressures and uncertainty within their organizational ecosystems. Resource dependency theorists focus on organizations as their unit of analysis, i.e. the “meso” or “middle” level of institutional change (bigger than “micro”, or individual people, but not as large as “macro”, or field-level norms or systems). They examine the interactions between these units, using this perspective to analyze how organizations strategically seek to manage resources and mitigate dependencies on their exchange partners [49]. In doing so, organizations improve their fitness within the market. Resource dependency theory has been recently used to analyze the precarity of firms operating within complex supply chains, as they “require networks to accommodate the interdependencies in product and service flows, resource flows, and information flows” [42].

The theory of institutionalism looks at the “macro” level, foregrounding patterns taking place at the level of entire organizational fields or social orders. Institutionalism focuses on unconscious social and cultural expectations, contending that these influences lead to widespread changes in multiple organizations, shaping fields of industry [13, 36, 65, 72]. A critical component of institutional theory examines how new organizations establish legitimacy, where their actions are perceived as “desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions” [56]. Amidst technological and market uncertainty, new firms improve their odds of survival by accruing legitimacy from an audience of stakeholders in the field including funding entities, regulatory bodies, and competitor companies. In their pursuit of legitimacy, organizations change over time, increasingly reflecting the established norms and practices of the field [13]. Recent scholarship has used this lens to examine organizational changes around
3 METHODS

In this section, we describe our methods for gathering data to answer our research questions. We elected to conduct qualitative interviews, as interviews are an ideal method for better understanding actors’ cognitive interpretations of their social reality, and for accessing their own explanations of their behavioral practices within that social reality.

3.1 Participant Recruitment & Sampling

We recruited participants, which we refer to here as “entrepreneurs,” from US-based, early-stage startups that involve a significant AI, machine learning, or predictive analytics component. Our focus on early-stage startups was driven by theory [44]; because emerging organizations face many threats to their survival, they are heavily dependent on other organizations. As a result, inter-organizational and institutional dynamics are likely to factor significantly into their behavior. We define “early-stage” as companies that had raised less than $50M in funding from any source or who were at or before the Series B stage. As our interviews progressed and patterns related to both regulatory pressures, especially privacy and the FDA, and related to funding, especially VC and crowdfunding, we began targeting our recruitment efforts towards additional startups that would further illuminate these trends. We recruited participants through a variety of methods including: 1) posts to AI and technology related listservs, message boards, social media, and Slack groups; 2) messages to general company contact email addresses or to specific individuals through email or LinkedIn; and 3) through our own direct or indirect professional contacts. In total, we interviewed 23 entrepreneurs from 20 different companies. Our entrepreneurs’ companies came from a variety of industry domains including healthcare (n=7), business analytics (n=6), fitness and wellness (n=5), design and engineering services (n=2), aviation (n=1), social planning (n=1), and agriculture (n=1). A breakdown of the self-described demographic, educational, and professional characteristics of our sample are available in the Supplementary Materials.1 Participants were sent a $25 gift certificate in exchange for their participation.

3.2 Interview Protocol

At the beginning of the interview session, we described to our entrepreneur participants our practices for protecting their privacy and confidentiality, then read them a verbal consent script, and gave them an opportunity to ask any questions. After providing consent, the first author asked questions based on the interview instrument (provided in the Supplementary Materials). In general the interview instrument was designed to surface data relevant to several core areas related to our research questions, including questions about the overarching aims of the company and the entrepreneur’s role within it, followed by questions tailored to entrepreneur’s area of expertise. For example, in cases where entrepreneurs were involved in the company’s AI development, we asked additional technical questions about data collection, choice of models, evaluation criteria, and infrastructure. In most cases, we asked entrepreneurs about their companies’ existing sources of financing and their plans for fundraising. We also asked entrepreneurs for their personal definition of AI. Lastly, we asked entrepreneurs about the social or ethical implications of their company. Audio recordings of the interviews were sent to a third party service for transcription, which were then verified by the first author. Our study design and protocol were approved by the Princeton University Institutional Review Board (IRB).

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1https://arxiv.org/abs/2203.01157
3.3 Data Analysis
We adopted an abductive approach to our analysis [59, 62], which allowed us to iterate between deductive analysis guided by relevant theory and inductive analysis guided by emergent patterns in our data. To facilitate this process, the first author initially selected 11 transcripts that contained discussions of theoretically-meaningful themes or that illustrated common patterns across participants. In a preliminary analysis phase, both authors read each of these transcripts and applied descriptive codes [50]. After discussing these codes in detail, transcripts were re-coded using line-by-line in-vivo codes (i.e., using participants’ own words) in an effort to better preserve entrepreneurs’ perspectives [50]. For example, one participant discussed the drawbacks of venture capital (VC), relating VC financing to rocket fuel: “There are actually very few businesses where rocket fuel is the right thing [P13]:” This excerpt was tagged with the in-vivo code “rocket fuel.” In-vivo codes were then aggregated into groupings of similar topics. For example, codes related to VC funding were grouped with the “rocket fuel” quote. The authors subsequently discussed the in-vivo codes as well as relevant theory and chose to focus the next analysis phase on five core themes: 1) the “AI hype cycle” or how “buzz” surrounding AI drives external stakeholders’ interest in AI companies; 2) practices surrounding the scientific legitimacy of entrepreneurs’ AI approaches; 3) pressures to raise funds or secure clients; 4) the impact of regulations; or 5) entrepreneurs’ own personal beliefs and ethical values that relate to their companies. These themes all appeared in multiple interviews with participants and had direct relevance to the study’s theoretical focus on institutional and organizational theory. All 23 transcripts were then coded according to the five themes. The authors frequently discussed transcripts and code applications to achieve consensus. We did not measure inter-rater reliability. Inter-rater reliability is a methodologically unhelpful tool for interpretive research, when codes come out of the collaborative process between researchers and consultation with literature, and not emergent ground-up from data [34].

4 RESULTS
4.1 Organizational Responses to Financial Pressures
The need to signal legitimacy to sources of financial support (e.g., investors and clients) constituted a significant vector of influence on how entrepreneurs defined, spoke about, and developed practices for AI. A tension that arose repeatedly in our interviews derived from a conflict between institutional values, specifically the values of science as a practice, and the values of technology entrepreneurship. Whereas scientific practice values systematic, methodological approaches paired with conservative interpretations of findings, technology entrepreneurship values rapid innovation and aspirational visions that extend beyond current technological reality, i.e., the “fake it ‘til you make it” Silicon Valley culture. In a variety of ways, AI entrepreneurs attempted to mitigate the conflicts between the values of entrepreneurship and science by decoupling their external rhetoric from their day-to-day practices.

One way this decoupling manifested was through the use of the idea of “AI” itself. Entrepreneurs leveraged the concept of “AI” as a symbol of their technological proficiency even though they personally harbored disdain for the technical ambiguity of the concept. According to our entrepreneurs, “AI” had no precise technical meaning and was instead employed as an operational tool to signal legitimacy to resource-rich external stakeholders [P1, P2, P5, P6, P7, P9, P10, P11, P13, P14, P15, P18, P21] rather than as an accurate descriptor of what their companies actually do. In other words, “It’s just a buzz word [P6]” for primarily marketing benefit.

Entrepreneurs described a widespread belief that companies benefited from marketing themselves as “AI” companies regardless of the nature of their underlying technology. They expressed frustration with their peers who “got to use the hype term [P18]” without employing any technical practices that entrepreneurs judged as legitimate. Entrepreneurs described feeling annoyance with these AI imposters, but nevertheless admitted to employing the same AI marketing tactics themselves. Faced with a competitive landscape in which startups’ technical and business value cannot be objectively verified, entrepreneurs leverage the institutional expectations around the legitimacy of AI because it “gives credibility that we’re on the cutting edge of stuff [P2].”

Despite the prevalence of this narrative in our interviews, only rarely were entrepreneurs able to provide specific explanations or concrete examples of how the abstract idea of AI yielded a tangible benefit. One entrepreneur, however, pinpointed investors’ fear of missing out on deals as a key driver of the “AI hype cycle [P6]:”

I think [the AI space] feels very confusing to [investors], but they also feel like there’s every signal that it’s super lucrative. [...] The key thing that keeps all of the subordinates [up at night], the ones whose job it is to go find those deals and make sure their bosses don’t miss any great deals [...] is a version of the world, where you passed on Lyft. And then your boss comes back to you five years later and is like, ‘I would’ve made a billion dollars off of Lyft. [...] What’s wrong with you? [P10]’

Entrepreneurs emphasized that although some investors and clients have AI expertise, most do not have the technical background required to adequately evaluate an AI solution or were simply “totally disinterested in the technical details [P6].” As a result, entrepreneurs face institutional pressures to describe their technology using homogenized, hype-filled language about AI even though their underlying algorithmic approaches were heterogeneous and often carefully devised. Through their instrumental use of hype AI messaging, AI startups engage in what Oliver [43] refers to as “concealment.” Externally startups affect the appearance of compliance with institutional expectations surrounding technology entrepreneurship even as their internal practices diverged, often significantly, from this affectation; “AI” became a discursive tool for avoiding institutional pressures via a process of “window dressing” [43].

In contrast to their external messaging, internally, entrepreneurs sought to achieve high standards of scientific rigor and validity. For example, entrepreneurs emphasized their rigorous data selection and curation processes [P4, P5, P18], described checks on the validity of their systems [P4], designed algorithm evaluations to appropriately assess the performance of their systems [P2, P4, P5,
P9], and even employed independent validations by academic collaborators to ensure that their models had good generalizability [P5]. Entrepreneurs also described translating methods and findings from the academic literature in their products [P7, P17, P15] and employing scientific subject matter experts either directly on their development teams or indirectly through advisors or boards of directors [P7, P17, P18].

Yet these scientific priorities could engender serious conflicts with the priorities of users, clients, and investors. For example, when entrepreneurs attempted to use scientific legitimacy as a differentiator in pitches, this attempt was sometimes regarded by investors or potential clients as confusing or unconvincing. Two entrepreneurs described remarkably similar experiences, in which presentations about the scientific merits of their technologies were dismissed by investors as being merely "science projects [P5]" or "high school projects [P3]," having little business relevance, which from one entrepreneur’s perspective, felt "like an anti-science trivialization of what scientists do [P5]."

External stakeholders’ beliefs about the potential of AI also created a barrier for entrepreneurs to be readily transparent in their external messaging about their models’ methodological strengths and weaknesses. Instead, dovetailing a finding briefly touched upon by [24], we observed institutional pressure around how 'quality' in AI ought to be reported [P4, P5, P14, P21], specifically in external stakeholders’ arbitrary notions of what constitutes "good" model accuracy. Though an algorithm’s accuracy may seem objective, in practice, accuracy metrics involve many subjective choices. For example, the practical applicability of a measure of an algorithm’s accuracy is contingent upon its mathematical formulation (e.g., area under the curve (AUC), F1, sensitivity, etc.) as well as contextual relevance (e.g., the severity of a false positive versus a false negative for a medical test) and which data are selected. In our interviews, entrepreneurs felt that in order to obtain the resources necessary for their companies to survive, they needed to engage in rhetorical messaging that complied with stakeholders’ expectations about model performance, even if these metrics were not the best reflection of the task at hand, nor a valid reflection of their algorithms’ capabilities.

How it’s measured is what we have to make sure it’s 90% or above [...]. So, if we need to switch from top 3 accuracy to top 5, just people seeing a 9, they don’t even think about what it’s measuring. People just have artificial concepts of what’s good and what’s bad [P4].

Pressure to present model metrics that have the right "psychological effect [P14]" on outside stakeholders was in conflict with entrepreneurs’ desire to adopt methodologically rigorous AI approaches internally. Strikingly, one explained that his attempts to include diverse training data in the service of higher out-of-sample generalization damaged his company’s credibility when his models’ performance was compared to competitors who use less realistic data.

Ultimately, our results aren’t going to be as stellar as a lot of others because now we have to account for [...] all the variability within the data set whereas, if we’re just focused on one homogeneous data set, our accuracy stats will be higher. So, that has been one sticky, difficult point in terms of head-to-head comparisons [P5].

In the service of survival, entrepreneurs sometimes conformed at least superficially to the pressures of stakeholder expectations, adapting their external messaging over time to provide a level of scientific detail that was persuasive to the target audience. In this way, they again engage in what Oliver refers to as concealment tactics. However, these pressures did not entirely undermine their desire to externally project the methodological rigor they prioritized internally. Instead, entrepreneurs chose to target their products to specific stakeholders who would be more receptive to messages about the product’s scientific credibility or its technical utility within a domain. For example, one entrepreneur highlighted that having extensive scientific references available on their product’s website attracted desirable early users:

"[... most marketers are like, "I don't think that sells the product," but we disagree. [...] I'm not sure it makes it so it's a blockbuster of a product, but it brings in the right type of people for your product [...]. It brings in good early adopters, anyway" [P7]."

In this public commitment to scientific integrity, entrepreneurs engage in a form of "defiance" [43]. Oliver hypothesizes that defiance is more likely when the perceived cost of resistance to institutional norms is low and "when they can demonstrate the rationality or righteousness of their own alternative convictions or conduct." AI entrepreneurs who externally project their strongly-held personal values of the scientific process may do so because they can promote science as a virtue while still attracting science-inclined external stakeholders.

Entrepreneurs recognized that in order for their companies to grow, their products must eventually translate into market success and that their companies’ investors were ultimately motivated by whether or not the company would "provide liquidity [P17]" on their investment. Nevertheless, entrepreneurs demonstrated a wide range of compliance and resistance tactics when it came to their decisions regarding financial backing. They described pursuing a variety of strategies to fund their businesses including revenue [P8, P13, P21], friends and family raises [P1, P10], grants from government or private entities [P2, P12, P17], angel investors [P4, P5, P6, P7, P13, P14, P15, P17, P21], debt financing [P12], VC financing [P4, P10, P14, P16, P17, P18, P20], and crowdfunding [P7, P9, P13, P21, P23]. Even still, several entrepreneurs pointed out that VC is regarded as a default financing path:

"We looked at the VC funding route in the beginning because that’s what you’re told to do, right? That’s how you get funded. This is the path. You go pre-seed, it’s angel investors, after that it’s VCs, and then you go through the Series process [P12]." For some, capital from VC firms formed a cornerstone of their strategy for building their business [P4, P10, P16, P17, P18, P20]. These entrepreneurs saw investors not only as a source of financial capital, but also of valuable industry domain and business expertise as well as a mechanism for accessing important professional networks. Entrepreneurs viewed the fit between the needs of the company and the expertise of investors as a critical component of establishing a productive relationship.
So, we have a number of investors, and the asks really change based on business needs. So it’s really, what do we really need today, this week, this month, that can help us take the business to the next level, and who do we have as investors that we can ask for help in those areas? [P17].

However, entrepreneurs did not blindly acquiesce to the demands of investors. Where their own goals conflicted with the goals of investors, VC or otherwise, they would sometimes decline further involvement. For example, one entrepreneur described ending early conversations with an investor because their desired exit strategy was not consistent with her own goal to eventually take the company public [P1]. In another case, an entrepreneur described evaluating potential investors based on their alignment with the company’s ethical values:

We are trying to raise capital from investors that have the same kind of values and mindset with us and people who are not afraid to lose certain revenue or sales just to follow the same values. We had clients asking us to do things that we said, you know what? No. No, this is not something we feel comfortable with doing [P23].

One entrepreneur noted that because of intense investor interest in the field of AI, instead of entrepreneurs doggedly pursuing financiers, “they find you [P10].” In a resource-rich environment, entrepreneurs have more latitude to resist institutional pressures arising from dependencies on investors. To some extent, we saw this resistance in how entrepreneurs described choosing specific investors; however, we saw even greater resistance amongst entrepreneurs who expressed hesitancy about pursuing VC financing [P7, P9, P12, P13, P16, P21]. In these cases, VCs were seen as having financial goals that conflicted with entrepreneurs’ long-term business or product objectives. One entrepreneur noted that unlike traditional software, AI software development typically requires specialized algorithm expertise, infrastructure, expensive data labeling, and continuous model performance monitoring; however, if VC firms’ valuation of AI companies is based on their knowledge of traditional software startups, they may impose timelines or key performance indicators that undermine what entrepreneurs believe to be methodologically-sound practices in AI development. Recognizing that VCs’ profit motives and responsibility to their limited partners (LPs) could conflict with their own goals, entrepreneurs often described actively avoiding VC financing.

That was my whole experience [at a previous startup]. The VCs wanted to hype things up, get a lot of press, make a splash, so they could raise the next round at a higher valuation and look good to their LPs, which was actually contrary to what we needed to do for the slow growth to build the business [P13].

Instead of VC funding, several entrepreneurs described using crowdfunding to finance their businesses [P7, P9, P13, P21, P23]. Crowdfunding and other financing vehicles that provide investors with little direct control over the companies’ behavior were viewed by entrepreneurs as a way to maintain autonomy over their businesses, control progress towards the product vision, and to maintain the equity of current employees. Moreover, although prior literature has indicated that the disclosure requirements of crowdfunding platforms can create a risk for companies’ subsequent financing prospects [5], entrepreneurs valued the transparency associated with public disclosures on crowdfunding platforms and the opportunity to directly engage with potential crowd investors. The choice of crowdfunding over the “default” VC financing path constitutes another form of organizational defiance; these entrepreneurs challenge the culturally dominant mode of startup funding by choosing financing paths that they felt would better serve their long-term objectives. As predicted by Oliver [43], startups are able to engage in resistance because doing so does not compromise their chances of survival since they can rely on alternatives to VC to fund their businesses.

4.2 Organizational Responses to Regulatory Pressures

In addition to financial pressures, entrepreneurs also described their compliance with and resistance to pressures in the form of regulation, especially regulations surrounding privacy and the Food and Drug Administration (FDA) approval processes for applications of AI in medicine. On the whole, entrepreneurs viewed privacy protections as normatively good, a competitive necessity, or even a competitive advantage compared to industry peers who are slower to adopt privacy-protecting practices. One entrepreneur described how his company had chosen to temporarily avoid adapting to the “landscape of privacy and privacy laws [that are getting] a lot more strict [P19]” by operating selectively in markets that were subject to less stringent privacy regulation (e.g., in the US versus European Union where GDPR is applicable), but even this entrepreneur noted that circumvention was only tenable in the short term. Yet in contrast to [24], most entrepreneurs in our study did not express resistance to or subversion of privacy regulations but openly endorsed them as well as the ethical values underlying them, such as personal autonomy. In their discussions about privacy, entrepreneurs sometimes contrasted their own beliefs and policies with those of large technologies such as Facebook, whose privacy-related behaviors they generally regarded as reprehensible [P9, P6, P23].

Unlike privacy regulation, the FDA approval processes for AI in healthcare was viewed less favorably. Entrepreneurs who discussed the FDA viewed these regulatory requirements as unnecessarily onerous and in some cases, unscientific [P2, P4, P5, P7, P16]. A theme that arose in our interviews with multiple entrepreneurs was that the lack of standardization in the FDA approval process for AI-enabled healthcare products created a serious burden for startups with an unclear upside. One entrepreneur from a more mature startup described how challenges posed by the FDA approval process contributed to her company’s decision to eventually pivot away from the AI products she felt had life-saving potential to a core product and business model that she thought was more profitable but ultimately less useful to society. She highlighted the opportunity and financial costs of pursuing FDA approval as well as the difficulty of providing evidence to meet FDA performance standards.
Whenever you’re thinking about a rule-out device—in our case, [the finding that a medical test is normal]—that means you rule out every possible thing, it’s statistically insanely hard to do. And in order to get approved, you would literally have to do better than humanly possible [P16].

All but one entrepreneur [P18] who discussed relevant FDA regulation found the ad-hoc approval process to be legally or financially arduous; however, there was less consensus on whether the FDA’s model performance standards were unreasonable. One entrepreneur noted:

The data that needs to be provided in order to get clearance in our opinion is relatively low, but it does take a lot of money and other things to get [P5]

Similar to this perspective, another noted that if the financial demands for securing FDA approval were lower, they would begin reallocating their research and development efforts to undergo FDA approval as soon as possible since their model performance was already strong.

Entrepreneurs either implied or stated explicitly that the onerous FDA approval process stifled innovation, but they also noted that such regulations were necessary to protect users from harmful products. Another entrepreneur noted that regulatory approval could even be beneficial to his businesses because ‘customers are much more receptive to the FDA stamp than they are to stats [P5]’. Still, the perception that the FDA approval process was “a whole monster [P4]” that was often not worth pursuing motivated AI entrepreneurs to attempt to operate in regulatory gray areas or exploit loopholes so that they could continue to pursue technological or product objectives. Such entrepreneurs described using other, non-regulatory avenues to demonstrate their legitimacy such as publishing their model details and performance in academic journals or technical whitepapers. It is important to note that entrepreneurs’ opposition to the idiosyncratic FDA approval process was not merely a matter of logistical difficulty; they also viewed the discretionary nature of the FDA review process as an opportunity for established companies to be unfairly advantaged:

It’s also, I think, unfair how the FDA, [...] they have existing relationships with Pfizer and Johnson & Johnson. I get it. But they’re obnoxiously hard on startups because they’re not known [P16]

Thus, entrepreneurs’ personal values only partially aligned with the institutional pressures from the FDA—they value the consumer protection intent, but decrie its consequences for innovation and believe it to be at odds with a fair, competitive marketplace. In contrast, entrepreneurs were more likely to adopt privacy preserving practices, which were consistent with their own normative beliefs, even in cases when companies were not yet subject to strict privacy regulation. In other words, consistent with Oliver’s [43] prediction about legal coercion engendering less compliance than institutionally diffuse norms, there appears to be an association between internal adoption of institutional rules derived from regulation when such rules aligned with field-level values.

4.3 Organizational Responses to Technological Pressures

Institutional theorists posit that emerging organizations can bolster their own legitimacy by adopting the values, structures, and practices of established organizations [13, 36]. That is, organizations can improve their chances of survival by mimicking what incumbent organizations already do. Yet this idea is in tension with the Silicon Valley notion that the most legitimate innovations are those that “disrupt” existing ways of operating [18, 21]. So-called radical innovations are those that break from or are discontinuous with prior scientific and engineering practices whereas incremental innovations are those that build upon and extend the existing technological paradigm [9]. In our interviews with entrepreneurs, their rhetoric typically suggested they viewed deep learning models as constitutive of radical innovation in that they distinguished deep learning models from other machine learning techniques; however, their implementations of deep learning models—typically via transfer learning—were, in contrast, fundamentally incremental.

Despite the murkiness around definitions of AI more broadly, entrepreneurs often held deep learning out as distinct, which sometimes manifested in how entrepreneurs defined AI. Many entrepreneurs provided definitions that contrasted algorithms’ capabilities with human capabilities [P6, P7, P14, P16], that differentiated between general and narrow intelligence [P5, P6, P7, P15, P23], or that described high-level processes that are applicable to any AI model [P1, P2, P4, P7, P8, P15, P18, P19, P20, P21, P22, P17]. However, several entrepreneurs implicated deep learning specifically in their definitions [P2, P9, P13, P11], using deep learning as a threshold of “real” AI:

The most concise answer I can give you is just deep learning. That is almost the new cutoff for AI, in my mind at least [P9].

Even for those that did not equate deep learning with AI, the ways entrepreneurs discussed deep learning relative to other AI approaches suggest that they consider such techniques separate or superior. For example, some described using “machine learning and deep learning [P14]” or explained that their companies constrained their models to “classifiers and regression [P3]” instead of “doing any deep learning or anything nutty like that [P11]” as though deep learning models were not a subset of machine learning techniques. In one case, we interviewed the chief technology officer of a company that intended to develop an AI-enabled solution but that had not yet begun data collection. Even in the absence of any empirical evidence to support his conclusion or expertise in deep learning, he preemptively concluded that simple, linear techniques would be insufficient to achieve the high accuracy he hoped to obtain with deep learning methods [P14]. Thus, entrepreneurs distinguish the “magic [P13]” of deep learning from other “rudimentary data science [P11]” techniques.

Yet in conflict with widespread framing of deep learning as “magic” and perhaps radical innovation, most entrepreneurs’ implementations of deep learning constituted a more incremental form of development that draws on the scientific products of researchers in the AI community. Many entrepreneurs described relying heavily on transfer learning for their deep learning applications. Transfer learning is technique where models that are initially trained with
massive datasets for one task can be adapted for related tasks with much lower data requirements. The use of transfer learning can reduce the computational and data costs associated with training models from scratch while still affording entrepreneurs "the accuracy that we feel we need from that model [P9]." Through the use of pretrained models initially developed by AI researchers in academia or at large technology companies, AI startups "build upon the state of the art, all the advancements that are being driven by the Googles of the world [P13]." In a paradoxical way, entrepreneurs’ discursive distinction of deep learning techniques complies with the institutional pressures to seek rapid and disruptive innovation, even though the pretrained models used for transfer learning coordinate practices of AI entrepreneurs, possibly down to the specific pretrained models they employ. Entrepreneurs’ rhetoric surrounding the distinction of deep learning, which conforms with institutional expectations about the utility of disruptive technology, acts to conceal their use of publicly available, incremental technologies that while not fundamentally disruptive in a scientific or technical sense, are nevertheless sufficient to meet AI startups’ needs. Interestingly, the disconnect between entrepreneurs’ rhetoric and practices in deep learning did not appear to be driven by attempts to appeal to external stakeholders who would be unlikely to appreciate the difference between deep learning and other machine learning techniques, but potentially to signal status to other AI startups or industry peers or to bolster their sense of the company’s legitimacy internally.

4.4 Organizational Responses to Normative Pressures

As an organizational field becomes more institutionalized, professionalization is enacted through education, membership in professional bodies, and other aspects of professional culture. These professional mechanisms can drive organizations within that field to adopt similar norms and values, which become embedded in their organizational practices [13]. Recent scholarship on professional norms within the AI research community has found that pervasive professional norms include efficiency, universality, and impartiality [51]. In our interviews, we observed instances where entrepreneurs articulated personal ethical values that were either distinct from, or resistant to, professional norms.

The demands of operating within the fast moving technology industry constrain the extent to which industry practitioners can fully realize ethical values into substantive practices [35, 64]. Consistent with these findings, some entrepreneurs hoped to incorporate their personal ethical values into their product or business model in the future, but had yet to make much tangible progress towards those ideals [P1, P2, P10, P13]. Yet, in other cases, entrepreneurs took a strong stance on ethical issues and described how they built these values into their technology and organizational cultures. For example, several entrepreneurs described how their algorithms [P21, P23, P19, P6] or data practices arose from normative beliefs about the ethics of privacy protection [P2, P9, P11, P14].

Racial bias also came up repeatedly in our interviews, but did not always inform product or business decisions. In a handful of cases, startups’ AI approaches had been explicitly designed to ensure that their algorithms would perform equally well across demographic groups [P4, P21, P23]. Similarly, some entrepreneurs had designed non-algorithmic elements of their products to prevent racial bias [P17, P12]. In several cases, entrepreneurs’ motivations for developing algorithms that perform well across racial groups were not only based on personal value systems, but also based on the belief that fair algorithms realized market value. For example, several entrepreneurs pointed out that in order to serve international clients and diverse users, it was important for AI-enabled products to be equitable. On the other hand, some entrepreneurs were aware of the types of racial biases that can be reproduced by AI algorithms [P6, P7, P9, P11, P22], but either thought that race was irrelevant to their models [P6, P11] or that racial biases were only a priority in high-stakes contexts such as healthcare and finance [P9, P11].

Although less common than algorithmic strategies, several entrepreneurs touched on how they promoted racial and gender equity within their companies [P12, P22]. Drawing from his own experience of racial marginalization, one entrepreneur noted:

A fundamental shift in power from straight white men to the rest of the world is really something that needs to happen. [...] I want to be able to show people that look like me, that they can also use things, and they can also build something that’s great and can also help build those communities [P22].

Even outside of explicit interview questions about ethics or social impact, entrepreneurs often espoused values related to democratization and expanded access to technology [P1, P8, P17, P16, P19, P4, P2] (e.g., “democratizing access to data [P17]”). Entrepreneurs described wanting to provide financially valuable expertise or insights to other businesses, especially small businesses and startups [P1, P19], to provide needed services to emerging economies [P16], or to empower users to take on tasks that are more typically performed by specialized professionals [P4, P8, P16]. In line with these values, entrepreneurs were critical of insider cultures, implicating “old boys’” networks [P6, P7, P22] or “traditional male VC [P12]” in gatekeeping behaviors related to client acquisition, external financing, or in other ways that affected their businesses’ success. Entrepreneurs’ skepticism of centralization and insider culture was also manifested through their choices about funding. Whereas VC served as a stand-in for centralized power, crowdfunding was viewed as consistent with the ideal of democratization since crowd investors do not need to meet the same financial accreditation standards required to invest in a VC fund.

Entrepreneurs’ normative values reflect a mix of the technoliberal and libertarian leanings of Silicon Valley that have been documented elsewhere [11, 25, 30, 35] as well as beliefs in social equity and fairness. Sometimes these values conflicted, as is highlighted by the tension entrepreneurs expressed around racial bias in AI; they believe that all users should be treated equally, but under the same resource-constrained system that encourages developers to “move fast and break things” [66], they do not always prioritize development around that belief.

5 DISCUSSION

Our current study adds to the growing literature on organizational challenges to ethical AI by describing how broader interorganizational and institutional forces shape the practices of AI
startups. In this section, we discuss both the theory-based as well as pragmatic contributions of our research. This discussion is structured along the same categorical lines of our findings, discussing in turn financial, regulatory, technological, and normative pressures.

5.1 Financial Pressures
A central tension recurred between entrepreneurs’ desire to preserve the scientific integrity of their AI approaches and the demands of technology entrepreneurship that often ran counter to this desire. As one entrepreneur noted, “the value in the technology that you use doesn’t necessarily even have to come from the technology [P9]”. In contrast to purely scientific enterprises, the import and meaning of novel technologies is not entirely determined by scientific inventiveness or rigor, but is also constructed within an economic, social, and cultural context.

The demands of external stakeholders with power to affect the financial outcomes of AI startups exerted influence over the narratives entrepreneurs constructed about the benefits of their technology. In response to stakeholders’ expectations of “silver bullet [P21]” AI solutions, entrepreneurs tended to adopt their external messaging accordingly, but they did not necessarily alter their internal practices. In this way, entrepreneurs engaged in a resistance strategy of concealment [43], decoupling the symbolic and homogeneous marketing tactics they adopted to accrue legitimacy from business partners, from the substantive and often heterogeneous approaches they employed internally.

That entrepreneurs placed a strong value on scientific integrity points towards an ethical opportunity within the startup ecosystem. As several entrepreneurs themselves pointed out, models with inequitable outcomes are necessarily less valid since they do not generalize well. Moreover, they are less able to realize business value since they cannot meet the expectations of diverse clientele. Thus, entrepreneurs’ values of scientific legitimacy might act as a “value lever” [54] through which principles of AI ethics can be imported into AI startups. On the other hand, external stakeholders’ tendency to treat decontextualized accuracy metrics as a superficial indicator for AI quality is suggestive of a risk for institutionalization of AI ethical ideals. For example, the “80% rule” for establishing AI fairness research without regard for its original legal nuance, may have already created an artificial standard within the research community [69]. This metric as a target could create further ethical risk if stakeholders in the AI startup ecosystem also adopt it without considering its relevance and caveats within context. Our observations around the use of “AI” as a marketing “buzz word,” reflect recent concerns around “AI as snake oil” [27], and the exploitation of AI’s vague definition as a loose umbrella term. Thus, strategies that ensure that AI ethics constitute more than an ethical Potemkin facade are needed [8].

Consistent with prior literature [71], entrepreneurs also demonstrated more heterogeneity in financing strategies than the culturally dominant VC-startup narrative would suggest. While some entrepreneurs conformed with institutional pressures to pursue VC funding and found benefits beyond financial capital in their partnerships with VCs, others actively avoided VC funding. This opposition was sometimes based on philosophical opposition to VC as antithetical to democratic ideals and other times informed by entrepreneurs’ personal experiences of VCs driving startups away from sound technological and business practices. Some evidence suggests that entrepreneurs’ avoidance of VCs could harm their companies’ growth potential [2, 3], but other evidence shows that the benefits of VC do not always extend to profitability [47]. Moreover, even if VC does improve the financial outcomes of companies on the whole, this financial benefit does not necessarily redound to founders themselves since their stake in the company is significantly diluted by VC investment [17]. Thus, resistance to the institutional norm of VC financing could be conceptualized as economically rational as well as in line with entrepreneurs’ desire to retain control over their businesses since VCs sometimes use their power to replace the founding team with professional executives [20].

Entrepreneurs’ desire to match their financing strategies with their business goals and normative values presents an opportunity for ethical practices. Even if AI ethics interventions are seen as antithetical to profit goals as demonstrated in [67], entrepreneurs may be able to preserve AI ethical ideas by matching with investors who share these priorities, especially if public scrutiny around the ethical implications of investor strategies increases [26]. It is important to note, however, that the entrepreneurs who are able to exercise more discretion in terms of when they seek funding and from whom they seek it are likely already advantaged in the entrepreneurial ecosystem, as one of our entrepreneurs himself noted: “I know we have the luxury that we could decline money. I know that that is a luxury [P6]”. Black and Latinx founders [10] and female founders [61] secure less financing than other founders, and as a result are likely to have fewer options when attempting to find financing partners who prioritize ethical objectives. Thus, selective matching between entrepreneurs and investors could also further magnify inequality.

5.2 Regulatory Pressures
With respect to regulatory pressures, entrepreneurs typically endorsed privacy regulations but expressed more frustration with FDA regulations. While privacy regulations were perceived as aligning with the values of personal freedom and autonomy, which have been documented in other research on technology sector actors [30, 35], FDA regulations were seen as a barrier to innovation and entrepreneurial autonomy and a mechanism through which industry insiders receive favor from other institutional actors. These contrasting results support both theory and evidence that a mismatch between an organizational field’s normative values and coercive regulatory pressures will result in less meaningful internalization of policies [43, 52]. However, an alternative resource-based explanation is also possible. Privacy regulations are likely to apply uniformly, but FDA regulations are idiosyncratic, and therefore require more expertise and financial resources to navigate. Regardless of the cause, as legislators debate proposals to further regulate AI, they should take care to consider what negative, second-order effects regulations might have on AI startups. Greater engagement with AI entrepreneurs could improve both policy and its adoption within startups since active participation from business owners has been shown to increase regulatory compliance [33].

796
5.3 Technical Pressures
The resource constraints of startups also fed into our findings regarding the use of deep learning amongst AI startups. Both entrepreneurs who did use deep learning and those who did not tended to discuss the use of deep learning techniques with a reverence not afforded to other algorithmic approaches. Yet deep learning startups most often developed their technology on top of preexisting pretrained models, especially those developed to perform natural language processing and computer vision tasks. As with most scientific advancements, applications developed through transfer learning are incremental innovations, inextricably tied to established approaches developed by a broader community of researchers and practitioners. That is, the use of deep learning in most AI startups is not a radical departure from the dominant machine learning paradigm, but an endorsement of it. This is not to say that deep learning applications developed through transfer learning are not valuable, creative, or innovative. Experts have implicated transfer learning being employed in ways other than how they were designed, which itself could be dismissed as irrelevant by practitioners or be employed in contexts in which they are intended to apply. Otherwise, they could be dismissed as irrelevant by practitioners or be employed in ways other than how they were designed, which itself constitutes an ethical risk.

5.4 Normative Pressures
As we have already discussed, entrepreneurs’ beliefs played a significant role in how they developed their technologies and their business practices. In some cases, AI entrepreneurs espoused libertarian ideals, such as individual autonomy and personal responsibility. Much of AI ethics research focuses on establishing the fairness of model outputs or mitigating unfairness in model predictions. In this way, AI ethics interventions often center on equity in outcomes. In contrast, entrepreneurs expressed valuing democratization, which emphasizes the importance of equality of access, rather than equity in outcomes. This distinction points to further risks for translating the technology and ideas developed in AI ethics research contexts into AI startups or the technology industry on the whole. Institutional pressures deriving from the technology industry will likely interact or conflict with the values embedded in ethical AI interventions. Designers of ethical interventions should consider the normative context in which they are intended to apply. Otherwise, they could be dismissed as irrelevant by practitioners or be employed in ways other than how they were designed, which itself constitutes an ethical risk.

6 FUTURE RESEARCH
Our findings on the significant influence exerted by institutional pressures on AI startups, and the variance in entrepreneurs’ decision-making around compliance, avoidance, and resistance, open a number of potential research pathways. First, as mentioned above, more research is needed to better understand how the social impacts of AI models may be exacerbated through transfer learning in industry settings. Second, identifying and interviewing other stakeholders in this sector would allow us to analyze the interactive dimension of these field-level dynamics, yielding data about how investors, regulators, competitors, and customers participate in and contribute to complex system dynamics of institutionalism in AI. Findings around the alignment between regulatory pressure and normative pressure, further, suggest that such alignments lead to better take-up within organizations, and so collaboration with policy researchers could lead to the design of AI policy better positioned to act as an effective guardrail against the harms of such systems.

7 LIMITATIONS
Our study design presents several limitations which may influence our findings. First, a limitation of the interview instrument was its exploratory nature. Due to the broad scope of our research questions, themes could not be identified prior to the study, but rather were identified in our data as a set of findings. As a result, we were unable to reach depth within particular themes, nor did we find that we reached theoretical saturation for any thematic category. Instead, the exploratory nature of this study identifies pathways for future research opportunities. Second, our recruitment and sampling strategies also present limitations. Our sample size was relatively small, and cannot – and is not intended to be – generalizable to the larger population of AI startup entrepreneurs. Within qualitative research, sample size requirements are a subject of debate, and are always a reconciliation between research interests and goals, access to participants, and maintaining rigor. We used theoretical sampling, which is intended to ensure that there are enough participants to surface “a range of concepts and characteristics that are deemed critical for emergent findings,” [14, 19], which we determined was achieved with our sample.

8 CONCLUSION
On the whole, our research shows that although institutional forces do shape AI startups’ beliefs and practices surrounding AI, they do not dictate them entirely. As a result, while future interventions to support ethical AI should be mindful of the organizational contexts for which they are intended, they also should not assume that startup practitioners have no agency to act in the service of ethical values. Even if the ethical practices adopted by startups at their outset evolve over time in response to shifting market demands, founders typically have a lasting influence on startups’ trajectories, even after they leave the company [48]. As a result, though startups face more resource constraints than the more mature companies that have been the focus on most applied AI ethics research, they also may be an ideal stage for ethical interventions.
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