

Avoiding AI Fear Responses: Turning FOMO and FOBO into
Democratically Driven Dynamic Use

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Abstract

How can communications policymakers move beyond reactive, fear-driven responses to artificial intelligence (AI), which is characterized by either rapid, perhaps uncritical, adoption (FOMO: Fear of Missing Out) or reflexive prohibition (FOBO: Fear of Being Obsolete), toward stakeholder-informed governance frameworks that enable strategic, contextually appropriate, and democratically accountable AI integration? Instead of top-down mandates for broad use, or prohibitions without context, what framework should be in place to assist users in understanding risks and rewards of informed use? Little is known whether these users are adopting AI because of missing out on the benefits it brings, or whether their use or non-use choices stem from concern about becoming obsolete. Using AI-conducted interviews with 1,250 individuals who use AI in some way, this research examines the discussions for evidence of FOMO and FOBO and how these constructs shape AI use. FOMO and FOBO were significantly and positively correlated, co-occurring as participants adopted AI into their workflows. Adoption was happening often with little official guidance or training. Those with high self-efficacy in AI use made more deliberate, strategic choices in how they applied it. The findings support policy that informs and trains users in the safe and ethical use of AI models. Through democratic, informed, user-centered policy, there is the opportunity for more purposeful and strategic use of AI.

Keywords

AI governance on use
Protection Motivation Theory in AI use
Psychological responses to AI threats
AI literacy

JEL Codes D81, D83, O33, O38, M15

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Introduction

The current AI policy landscape is frequently dominated by two polarizing impulses. On one end, institutions seem to be rushing to adopt AI wholesale to avoid falling behind (e.g., Stanford, 2025), without the normal risk management assessments found in other high risk industries (Campos et al., 2025). On the other end, groups call for sweeping bans or moratoria, driven by fears of job displacement, loss of creative identity, erosion of human agency, and overall risk to society (Rudschies & Schneider, 2025). Both responses share a common root: they are shaped more by fear-based emotional reactions than by evidence of how AI is used, experienced, and integrated by real stakeholders. This paper asks what a third path—grounded in empirical data and participatory governance—might look like.

This research employs a mixed-methods, evidence-based policy analysis approach. The primary empirical foundation is the Anthropic Interviewer dataset (Handa et al., 2025), which comprises 1,250 in-depth interviews with professionals across the general workforce, creative industries, and scientific communities. This rich qualitative dataset—publicly released on HuggingFace for independent scholarly analysis—captures how workers across diverse sectors are actively integrating, adapting to, and feeling about AI in their professional lives.

The analysis proceeds in several stages. First, a systematic thematic analysis of the Anthropic Interviewer dataset is conducted, identifying patterns of AI use, emotional responses, and stakeholder concerns across professional categories. Second, using the findings from the initial round of analysis, develop coding for semantic analysis to explore the sense of FOMO and FOBO and test if these concepts hold up as distinct constructs under analysis. Third, these concepts are tested to explore if FOMO and FOBO are mutually exclusive, if they are both present in the adoption process, or if there are indicators that adoption of AI is a more complex process. Finally,

the paper discusses the importance of supporting AI literacy policy framework, encouraging informed user-centered policies of AI applications.

This research sits at the intersection of communications policy and science and technology studies (STS). The primary disciplinary lens is communications policy analysis, examining how regulatory frameworks shape and are shaped by the communicative practices of stakeholder communities. Protection motivation theory, a threat response framework, is used for understanding how fear responses are amplified or moderated in public discourse—provides the conceptual vocabulary for diagnosing the FOMO/FOBO dynamic.

This paper makes two novel contributions to the AI policy literature. First, it introduces and operationalizes the FOMO/FOBO with a scalar analytical framework for diagnosing the structural pathologies of current AI governance discourse. While scholars have noted polarization in AI policy debates, no prior work has systematically connected this polarization to well-established risk psychology constructs or applied them as a diagnostic tool for communications policymakers.

Second, the paper leverages the Anthropic Interviewer dataset as a novel empirical resource for AI policy analysis. This dataset is unique in the field: it is large-scale (1,250 interviews), professionally diverse, publicly available, and captures the qualitative texture of how workers experience AI integration. Little is known about how workers handle the pressures of keeping up with innovation and possible obsolescence of their work. Thus, not only does this research explore lived experiences of AI users, it harnesses the power of an AI model (Anthropic Fable 5) as a research assistant, using multiple natural language processing (NLP) methods for analyzing the large qualitative dataset.

The paper expects to demonstrate that real-world AI adoption patterns are substantially more nuanced than either enthusiastic or alarmist policy narratives suggest. The evidence indicates that most workers are not choosing between total adoption and rejection but are actively using AI while negotiating contextually sensitive boundaries—often with vague or contradictory guidelines. This empirical reality should anchor governance frameworks to giving the often-overlooked stakeholder group, end users, more voice in how AI is being used. This would require an informative and enabling framework rather than the extremes that tend to dominate legislative and regulatory debate.

Ultimately, the paper argues that moving from fear to informed choice is not merely a communications challenge—it is a governance design challenge. The tools to meet it, including scalable stakeholder interview methodologies and large-scale qualitative datasets, are now available.

Literature Review

The Background of FOMO

Growing capabilities of artificial intelligent AI flood our news streams, the various frontier models competing for passing ever higher benchmarks and demonstrating increased capabilities. There are glowing descriptions of potential use for users of AI models and AI agents. Online influencers have channels dedicated to how individuals can make multiple personalized AI agents that automate most of their daily work activities. The potential power of AI to increase efficacy and quickly do tasks that take humans hours to do is impossible to ignore. Both organizations and individuals are using it, often with users not understanding how to verify output, nor knowing how to control data flows to protect proprietary information (e.g., accidentally leaking source code). As a result, organizations are encouraging use of AI as competent use has increased productivity

(Deloitte, 2026). The buzz around the use of AI and AI agents can lead to fear of missing out (FOMO). The dimension of FOMO has been widely explored in social media engagement and problematic use of technology (Elhai et al., 2021). It is often linked to problematic use of social media and negative work performance as well as impacts on sleep (e.g., Andreassen et al., 2012; Tandon et al., 2020). Social media challenges, fueled by FOMO have even led to individuals performing harmful behaviors in attempts for increased social desirability (Bonifazi et al., 2024; Falgoust et al., 2022). Despite a host of studies on social media use tied with FOMO, little is known about how these same psychological and social drivers are present as individuals use a new technology, one that has the potential to reshape the workplace just as social media reshaped interpersonal communications, AI in the workplace. AI makes tedious chores such as writing communications and research writing comparatively effortless, increasing speed of output and increase in productivity. However, this is accompanied by concerns about accuracy of AI generated output and that novice users might be trusting hallucinated findings. Is FOMO leading to increasing use of AI, especially uninformed or unethical use?

Background of FOBO

At the same time as ever new capabilities of AI are announced, there are periodic announcements of major companies laying off thousands of workers. Just as the industrial revolution of the 18th century caused massive changes in everything from farming to manufacturing, many researchers are seeing the current cyber-physical systems as presenting new challenges as the very nature of work is changing (Kurt, 2019; Peters, 2019; Xu et al., 2018). Researchers are seeing fear in workers as both AI and robotics are performing tasks that used to be done by humans using increasingly sophisticated robotics (Eißer et al., 2020; McClure, 2018).

In this research, this personal concern of being replaced by technological innovations is termed as fear of being made obsolete (FOBO).

Previous waves of mechanization of tasks previously performed by humans were often tasks that required heavy labor (e.g., farming, digging canals, moving rocks) or dangerous settings. Technology improved efficiencies and allowed humans to move from heavy, dangerous, work to more creative and mentally stimulating work. This transition was not always smooth, nor was it always widely accepted as an improvement. For example, the invention of the powered weaving loom and growth of automation in the production of fabric led to a counter FOBO reaction where groups came in to smash the machines they saw as a threat to their future (e.g., O'Rourke et al., 2013). This group, often called Luddites, were not just upset about the machines replacing jobs, but they initially protested the loss of skilled jobs, decline in working conditions, child labor, and the economic upheaval these machines caused (Conniff, 2011). Despite the protests, the use of machines prevailed. The widespread automation of the manufacturing of clothing and fabrics did lead to massive cultural changes. Families were torn apart as workers had to move to dangerous, overcrowded, housing centers. As the industrialists, who were able to invest in the new machines, became rich, thousands remained in poverty. This "gale" of "creative destruction" led to lower costs in clothing and societal changes as production moved from home-based to major industrial centers (Allen, 2018). Unfortunately, the core concerns of the original Luddites were not addressed, and the industrial revolution moved forward pushed by huge economic forces as technology adoption seemed inevitable. The concept of creating and being industrious moved from the small labor unit to the larger, machine-driven, massive scale of production (Vries, 1994).

Over time anyone, who is resistant to a new wave of technology was disdainfully labeled a "Luddite," guilty of resisting an inevitable wave of technological change. A deeper look at the

Luddites finds that they were often protesting the social injustices that were accelerated by the large textile mills replacing home industries. Falling wages, child labor, unsafe working conditions and societal changes as rural residents moved to overcrowded and polluted cities (Conniff, 2011; O'Rourke et al., 2013). In many ways the early Luddites are not far from today's concerns about the loss of skilled jobs and how major LLM models have exploited the product of human work and creativity. We need to examine how to response to this emergent technology, AI, and how it is seen by potential users. Just as the weaving mills made clothing more universally affordable and allowed for greater access to clothing, will AI allow for greater access to advanced information for society, or will only a few individuals profit from the advances? We see some modern Luddites who refuse the technology based on how it was built and the societal and environmental impacts (e.g., McQuillan, 2022). Despite these questions, there are many who are adopting it in the workplace. Research indicates that risk of emerging technologies can be reduced through informed governance (Linkov et al., 2018). Furthermore, educating users so they can make informed, strategic use of AI help build informed stakeholder governance has the potential to maximize the benefits and implement it in ways to minimize harms (Mandel, 2009; Slovic et al., 2004).

Responses to fear and protection motivation

Humans are constantly having to adapt to changes and deal with threats. Some threats are immediate and we can use various strategies for dealing with the visible threat (e.g., seeing an approaching Grizzly bear on a remote mountain trail). However, when threats are slowly evolving, or not easily understood (e.g., health threats because of smoking), the psychological process of dealing with those threats is more complex. Building an awareness of a threat is important for safety and making wise choices. However, finding ways to communicate about threats in a way to inspire proactive, protective actions is a challenge.

There are decades of research into how individuals respond to threats, especially threats that are complex, vague, and evolving (e.g., Aven, 2016; Slovic et al., 2004). Researchers have deeply explored how to motivate individuals to making wise choices in these high-risk and complex situations, especially when dealing with areas that have a strong personal impact such as health. A widely accepted approach, health belief theory, is a type of value-expectancy theory, where an action (e.g., stopping smoking) has an expectancy of benefit (e.g., improved circulatory and respiratory outcomes) (Janz & Becker, 1984; Rosenstock, 1974). This was further refined as researchers more deeply explored the power of tailored communications to inspire individuals take protective steps. Protection motivation theory (PMT) was developed to help explain both the emotional and cognitive processes that resulted in protective behavior (Somme stad et al., 2015). PMT was found to also work in other areas such as online safety and taking cybersecurity precautions (Shillair et al., 2015; Shillair, 2020; Tanner et al., 1989; Tsai et al., 2016). Further developments in PMT research found that as individuals processed threat messages, they often had maladaptive responses (Rippetoe & Rogers, 1987). Maladaptive responses could include ignoring a threat, giving up, or responding in a way that harmed their own interests. On the other hand, many individuals responded to the same threat message with adaptive behaviors. These adaptive behaviors included adjusting behavior to counter a threat. In cybersecurity, these are actions such as having a strong password, using protective software, or avoiding clicking on dangerous links (Shillair, 2018). Witte (1994) developed the extended parallel processing model (EPPM) which envisioned the threat appraisal process as both a cognitive process and an emotional process. Those who were primarily driven by the emotional process had a higher likelihood of a fear response, which often led to a maladaptive response. However, those who had a higher cognitive processing had a higher likelihood of a danger response, which was more

likely to be an adaptive response (see Witte, 1994). Increasing self-efficacy and belief in response efficacy was a major factor in protective behavior that led to optimal outcomes across many domains (e.g., Alam et al., 2025; Downing et al., 2023; Kiran et al., 2025). One of the primary factors in seeing positive outcomes in response to a perceived threat is having response efficacy and self-efficacy.

Since both FOMO and FOBO are fear-based responses to emerging technological capabilities, and fear often leads to maladaptive behavior, which could be avoidance of beneficial use, secretive use against policy, careless use, or unethical use of AI. Increasing self-efficacy (e.g., understanding how to effectively use AI) and increasing belief in response efficacy (e.g., importance of verification of output, ethical use of data) would be imperative for adaptive responses. Just as cybersecurity is a critical issue that supports critical infrastructure, AI is also becoming a critical issue where uninformed use could lead to widespread harm. In cybersecurity, at the national level, when cybersecurity education, awareness, and training (CEAT) was a supported policy and had mandated resources, there were empirical results that demonstrated overall benefits (Shillair et al., 2022). Stakeholders at all levels would benefit from learning how to use AI responsibly. This is especially true as using AI has not only implications in work outputs and productivity, it also has environmental impacts and data center costs. Choosing the correct tool for the appropriate task can only be done through education and training.

Policy response FOMO and FOBO

Since the nature and capabilities of AI are changing so rapidly, the traditional methods of designing policies in these complex and fluid systems seems almost impossible (e.g., Bauer, 2022; Mueller, 2020). Even the foundational goals of AI policy seem to be changing in just a few short years. Early policies towards AI were seen as a promotion of a general “good” much

like access to the Internet. Open data policies and public/ private data sharing helped accelerate development, recommendations called for adaptive and learning processes that encouraged “holistic, open, inclusive, and better coordinated governance models” (OECD, 2021). However, as the ability of the AI models increased, the landscape changed from embracing the rapid changes and accelerating innovation (e.g., Brynjolfsson & McAfee, 2011) to aiming to prevent harm (e.g., Hilliard et al., 2026). As AI models showed increasing capacity, the policy landscape turned into a technological arms race. This shift to national security focus is seen in export controls on advanced AI chips (Frilling, 2026; Turkel, 2025), and restrictions on access to advanced models in the United States (Koren et al., 2026). These limitations include those who are legally in the U.S. and even working on developing the most advanced AI models (Marinotti, 2026).

These policy level responses to AI appear to be strongly driven by both the FOMO and FOBO. There is the fear of falling behind in the technology race (FOMO) as models continue to meet increasingly complex benchmarks. At the same time, there is a concern with preventing others to access cutting-edge chips or models and carefully guarding access to the most powerful models lest others should be able to leap-frog progress (FOBO). Complicating the regulation process is the growing group of stakeholders as AI is being used across domains. The economic, societal, and environmental impacts are being hotly debated around the world. Calls for agile and adaptive governance propose frameworks that address critical impact concerns (e.g., Bauer, 2023; Janssen & van der Voort, 2016; METI, 2022; Xiao, 2025). However, given the human psychological process dealing with heightened fear, it is imperative that helping humans to understand the basics of AI literacy to make informed decisions.

To meet the governance design challenge, many policymakers are already seeing the importance of informing stakeholders (e.g., end users) and building AI literacy. The EU Artificial Intelligence Act, Article 4, mandates AI literacy programs-

Providers and deployers of AI systems shall take measures to ensure, to their best extent, a sufficient level of AI literacy of their staff and other persons dealing with the operation and use of AI systems on their behalf, taking into account their technical knowledge, experience, education and training and the context the AI systems are to be used in, and considering the persons or groups of persons on whom the AI systems are to be used.¹

In the United States, the Department of Labor is providing funding for training “American Youth” for AI literacy (U.S. Department of Labor, 2025). Even though this is aimed at the pre-workforce population, the support for AI literacy training is very important. The support to training and education is gaining traction, for example, the Global South is also supporting policies that enhance AI literacy (Khodabin & Arsalani, 2025). There is growing understanding of the importance of AI literacy as a foundation for AI policy that will be adaptive, rather than maladaptive, and be flexible enough to deal with future changes in AI abilities and applications.

¹ (Regulation (EU) 2024/1689 of the European Parliament and of the Council of 13 June 2024 Laying down Harmonised Rules on Artificial Intelligence and Amending Regulations (EC) No 300/2008, (EU) No 167/2013, (EU) No 168/2013, (EU) 2018/858, (EU) 2018/1139 and (EU) 2019/2144 and Directives 2014/90/EU, (EU) 2016/797 and (EU) 2020/1828 (Artificial Intelligence Act) (Text with EEA Relevance), 2024)

Moving towards democratically driven dynamic use

A growing body of research is focused on how AI will impact the future of work (Gordon & Gunkel, 2025; Howard, 2019). Many large corporations have already embraced AI in their production processes, especially in software development (e.g., Swartz, 2026). Some businesses were reported to mandate high AI use, many even requiring AI tool use (Newsdesk, 2025). Other workplaces are far more cautious about AI use, either banning it or having strong restrictions. Both FOMO and FOBO at the management level in the workplace can cause negative consequences. In considering PMT and how individuals respond to threats, multiple levels of threats (e.g., mandated use, fear of being penalized) would lead to maladaptive behavior. On the other hand, by informing and training employees on the basics of AI literacy, how data is processed, how to verify answers, and understanding limitations can help users to make adaptive choices. Mandating AI use/ non-use without giving explanation would most likely lead to poor use choices and might cause catastrophic outcomes.

In looking at the use of AI as a place of where the function of one's work is profoundly impacted, letting users feel they have a voice (e.g., democratic principles) would be important for how they are engaged. One of the foundations to a functioning democracy is that citizens have the information needed to make choices that are in the best interests of all stakeholders (Goldstein, 2020). In the case of a workplace, it is often important for individuals to feel they have first the training to perform their function and fully participate in the best outcomes. Little is known about the process users of AI go through as they choose to use AI and if they can make choices they feel are truly beneficial or if they are feeling pressured by outside forces (e.g., FOMO/ FOBO) for use or non-use. This research examines 1,250 interviews of individuals who

discuss their use of AI to look for evidence of their choice process and if their choices are fear-driven or if they have self-efficacy in use.

Methods

Participants were solicited from an online crowdwork platform (e.g., MTurk) and had other primary occupations other than crowdwork. Solicitation was focused on testing a new interview tool that was powered by AI and developed by Anthropic. Participants were solicited across a range of professions that were categorized rather than solicited from specific professions. From the larger set of participants, subgroups were selected that held jobs most impacted by AI: creative professionals (e.g., visual artists, writers, authors, musicians) and scientists (e.g., data science, computer programmers, physicists), as well as a sample from the general workforce. The total participants were 1,250 with the general workforce (N=1,000), Creatives (N=125), and Scientists (N=125). Each interview was about 1,000-5,000 words. An earlier analysis of this dataset by Handa et al., (2025) found that 86% of the participants reported time saving, and 65% satisfaction levels, but there were 55% anxiety indicators.

A major limitation of the study is that the participants were comfortable interacting with an AI tool, so this sample would have, if anything, a pro-AI bias. Participants were questioned about how they used AI tools in their typical workday. The tone of the Interview AI was positive and would probe if the participants felt confident about using AI, it also probed if there were frustrations or concerns that they had. Participants were not specifically asked about “fear” or fear triggering phrases.

Thematic analysis of the Anthropic Interviewer dataset

The first step to developing key themes and phrases for coding the data set was a human review of the data. After initial brief review of a dozen interviews, a set of themes were explored pulling deeper insights from the AI interview questions.

- First, look for evidence of FOMO either personally or from the work environment. Were the participants encouraged to use AI beyond what they felt comfortable with? Did the participants adapt AI because of seeing others use it or hearing about its uses?
- Secondly, look for evidence of FOBO, were there concerns about future job loss or major job change because of AI growing capabilities.
- Thirdly, look for evidence of careful and strategic use of AI, especially in complex tasks or high-risk situations.

A random number generation was used to help select twenty-five interviews for review.

Table 1: Types of Interviews Reviewed

Number of interviews reviewed	Category of participant
11	General Workforce
7	Creatives
7	Science

FOMO in the workplace

Most of the interviews indicated a lack of clear guidance on how to use AI in their workplace. There seemed to be little, if any guidance or training on how to use AI. Many starting using it just from watching co-workers.

"I was initially an AI naysayer but many of my colleagues were early adopters, seeing their productivity improve massively and hearing anecdotes about how

much they enjoyed working with AI motivated me to incorporate it more into my work." (work 0092)

Overall, many of the workplaces seemed to have no official guidance on what should or shouldn't be done with AI. Thus, workers were left on their own to figure out how to use it.

"Use of AI has not been officially supported or discouraged at my company, so my coworkers and I tend use it for lower stakes tasks." (work 0008)

In some places the workers are pushing for wider usage, but the managers are hesitant to use, and given the statements by participant transcripts, it is unclear if management even knows if the workers are using AI, even though the output of workers has improved as a result of its use.

"My workplace has been very slow to adopt AI and my direct manager does not see the value in it, but I have seen firsthand the benefits of using it in my work and will continue to do so. I have colleagues who are very interested in AI and have begun incorporating it to generate ideas. I am optimistic in the future AI will play in my workplace..." (work 0739)

In other settings, the workplaces promote AI use, but not a lot of guidance was given on how it should be used, or how to test results.

"My workplaces are pro AI. I was already pro AI, so I have not been influenced one way or another. However, I did learn to turn to AI as a last resort in the process of problem-solving and only when I'm stuck with insufficient time to get the work done properly" (work 0019)

Many workplaces have strong negative stance towards AI, yet surprisingly employees were using it on their own, “for my eyes only”. This was especially seen with those working in higher education. One higher education data analyst said,

“Higher education is largely split on the issue of AI use. Many, especially in senior positions are absolutely against AI” (work 0915)

Yet, this same participant used AI extensively for polishing reports and presentations, but also for initial data analysis. The participant worked in higher education analysis and mentioned using their AI tool to link name of graduate students to their undergraduate institutions with URL links. Even though these reports were later de-identified for final reports, workers without clear training of data privacy might unwittingly risk exposing student data to AI databases.

Educators also struggled with how to use AI ethically. There didn’t seem to be paths for teaching both students and educators how AI could be used ethically.

“AI is still a pretty taboo topic, especially when it comes to student use. There are many instructors who view the use of AI as cheating while others encourage its use. I personally think it comes down to how AI is being used by students.” (work 0022)

FOBO in the workplace

There were definite concerns about the future of many jobs as AI improves in skills. Workers who had more routine tasks were more aware of the risks. For example, a medical transcriptionist said,

“[new software program] substantially shifted the workflow for myself and my team mates on a day-to-day basis. We no longer transcribe and edit dictated

reports but instead have shifted toward more generalized support.... Most of us were shocked.” (work 0736)

Several mentioned that they realized their personal job was in danger. Some had already started training for new roles.

“I think long-term I'm considering leaving the type of role I'm in as I'm definitely aware that AI could cover that scope in the near or distant future.” (work 0011)

Many discussed how they used AI for repetitive work, clarify communications, brainstorm ideas, and get feedback on materials. Several mentioned they saw the roles of support work and entry level work being most impacted.

Surprisingly, FOBO in the workplace wasn't just the loss of jobs, but the concern of personal loss of skills if they delegated more complex or creative work to AI models.

“I don't think I would like to completely delegate tasks to AI because I worry that my competency with certain skills might decline over time due to lack of practice.” (work 0008)

This concern of being made obsolete was often mentioned as a dual process of where the AI becoming more skilled at the same time that the human skills are atrophying from lack of development.

“But ultimately, I try to avoid AI use in my workflow as I don't want to become dependent on it. Creativity is a muscle and if I don't exercise it, it will wither!”
(creativity 0036)

Several of the creatives mentioned the poor quality of AI produced materials and how it can become formulaic. Even though AI was used widely for brainstorming, but often purposefully not used for finishing creative work. There often was a perception that “others” were using it more widely than the interviewee, but most were very proud of the quality of the work they did as a professional, even if others did not hold up to their high standards.

"I do not think that Ai is responsible for the quality dilution, I think that AI is really empowering people who are comfortable with meh quality work to heavily automate their processes. In some ways, I feel like it is helping those of us who have higher standards really stand out." (creativity 0065)

Careful and strategic use of AI

Overall, participants detailed their use of AI as being strategic, purposeful, and cautious. The most basic functions were cleaning up grammar in communications, brainstorming, and making presentations. Many participants mentioned they used AI for repetitive tasks and tracking administrative functions. In most of these situations the AI tools were doing little more than what current word processing and presentation creation tools already do.

Several graduate students mentioned they used AI to help with advanced literature search, but each reference had to be double checked and reviewed by hand as there were high error rates. There were also concerns with errors for programming and advanced mathematics.

“I have seen AI tools make errors with mathematics in the past and sometimes AI tools aren't as good when working with novel questions and information.”
(science 0051)

The most interesting uses described were with advanced scientific methods. They reported working with AI to develop models and experiment with new ways of doing things much faster than they could before.

"I am a mathematician and would eventually come with something after a few days, but to start with a complex paper and end up with it translated into code in one day was extraordinary." (science 0062)

The same scientist was so impressed with AI that they tried to use "vibe" coding to complete a project, but in the end spent so much time de-bugging that it wasn't a time-saver after all.

"It was my first attempt at "vibe coding", where I simply trusted the AI to give me the final product and I had little interest in the inner workings. Alas, after a long time, I had to dig in myself and google lots of things, when I just wanted the app as if waving a magic wand. " (science 0062)

Close review of a sample of the interviews demonstrated that the concept of FOMO and FOBO were present, but were not binary, but scalar and not exclusive of each other. Even as participants were wary of their future as AI grew in capabilities, they also were wanting to embrace the potential of increasing their skills, offloading redundant tasks, and increasing their productivity. Overall, there were several participants who had developed strategic and carefully tested use of AI. Especially among those doing advanced scientific research, the AI was used as a tool to pre-test hypothesis and recommend different approaches to solving a complex problem. However, these strategies were self-developed and not widely shared with peers.

Surprisingly, there seemed to be little training or guidance from the workplace on how workers should use AI. However, there was often broad encouragement or broad prohibitions

expressed as “my office is very pro-AI” or “AI use is discouraged”. The lack of informed guidance for strategic use, even among advanced scientists, was rather shocking. Choices on how to use AI and when to use it appeared to be foundationally emotional (FOMO) as they saw their peers’ production go up, or non-use was also emotional (FOBO) as there were concerns about loss of skills. The lack of formal training in AI use could reduce misunderstanding and protect both employees and the workplace. A principal element in PMT that helps individuals have a positive response to threats is building self-efficacy, then individuals can make informed choices. Without training, the self-efficacy arc is: no training → poor outcomes → self-acquired skill → better outcomes. This was clearly seen in one participant

“I had no training in prompting AI models, so I would often input [redacted], only for the AI to misunderstand what I was going for and give me something useless. It's gotten better since I've had more insight into what makes a usable prompt” (work 0317)

Based on the literature review and the analysis of the sample transcripts, I hypothesize that

1. FOMO and FOBO are not opposing attitudes but move in parallel. Those who are actively using AI (FOMO), especially as they are aware of its potential and capabilities, will at the same time be concerned about it replacing them or taking their job (FOBO). Thus, higher FOMO should also have higher FOBO

2. There will be an interaction with higher deliberate use of AI for those with higher FOMO and FOBO. Those aware of the capabilities of AI will also be more aware of its limitations. Those who use it with heightened awareness will also use it more carefully and check the output.

Based on the few mentions of any training in the sample data reviewed by hand, we could not hypothesize the impact of training. The concept of training was explored post-hoc and is discussed later in the paper.

Development of coding for semantic analysis

Working with Claude, Fable 5, we analyzed the dataset posted on HuggingFace by Anthropic.² All participants gave informed release of their raw interview transcripts, and the data was de-identified. Data was released under CC-BY protocols, the accompanying code is MIT licensed. Initial construct scoring and topic modeling were conducted in Python; the zero-shot NLI validation was run in R via reticulate in RStudio. The unit of analysis was participant turns rather than whole transcripts to allow better understanding of participant feelings and attitudes. Since the Interviewer model was designed to reflect back the participants' comments, only participant language was analyzed. Interviewer comments were only kept as context metadata. FOMO and FOBO were measured as two continuous dimensions rather than binary. The qualitative analysis of the sample data (see previous sections) made it clear that even those who were very enthusiastic about using AI because others were using it (FOMO) had a spectrum of attitudes. The comments frequently showed both attitudes in varying degrees. This allowed for quadrant analysis that gave rich insights into choices of use/ nonuse. The groups were named: anxious adopters, enthusiastic adopters, avoidant, and indifferent.

To measure the construct, we used dual methods: anchor embedding scores and zero-shot NLI classification (BART-MNLI). Anchor embedding scores are used to help reduce LLM hallucinations by doing a three stage analysis that does a parallel run of keyword detection and embeddings . Zero-shot NLI classification is where trained LLM models label data they have

² <https://huggingface.co/datasets/Anthropic/AnthropicInterviewer>

never seen before. Research shows that large-scale reasoning models have a high accuracy rate (e.g., of classifying and making inferences, about the rate of well training human researchers). The analysis is built through a high-confidence measure method and tested by a secondary high-confidence method to improve reliability.

Table 2: Corpus and data quality

Transcripts	1,250
Conversation turns	30,279
	13,221 scored participant turns
Words	941,520 participant words

Machine analysis method summary

1. Unit of analysis: Transcripts are split into speaker turns; only participant turns ≥ 5 words are scored, so the interviewer's standardized script cannot drive topics or sentiment. The preceding interviewer turn is retained as context metadata. Speaker labels are auto-detected and reported.
2. Construct scoring - anchor embeddings: each construct is defined by 8 first-person paraphrase anchors. Turn score = mean/max cosine similarity to anchors (sentence-transformers, 'all-mpnet-base-v2', normalized embeddings). Contrast-adjusted scores subtract a matched control construct (FOMO – critical-adoption; FOBO – confident-stability) so topical relevance alone doesn't inflate scores.
3. Second automated rater: Zero-shot NLI (BART-MNLI, multi-label) with hypothesis templates per construct. This was done using a bag-of-words/LSA fallback and NMF topic model this has a negation-blindness limitation (e.g., 'I don't feel threatened at all' scoring high on FOBO under bag-of-words scoring). However, theoretically, those high on FOBO but with maladaptive attitudes would express this concept Spearman correlation between methods was tested exported as triangulation evidence.

4. Aggregation: per participant: mean (overall tendency) and p90 (strongest expression). Constructs are typically voiced in one or two turns, so p90 is the recommended primary measure; report mean as a sensitivity check.
5. Topic modeling: BERTopic on participant-turn embeddings (UMAP→HDBSCAN→c-TF-IDF, seeded), with topic prevalence per split and mean construct scores per topic ("which themes carry FOMO/FOBO?"). Ran twice with different seeds and reported topic stability.
6. Sentiment: VADER + RoBERTa per turn. Generic sentiment $\neq$ stance toward AI — interpret jointly with construct relevance.
7. Quadrant typology: Median split (sensitivity at $q=.67/.75$) on participant-level FOMO $\times$ FOBO: enthusiastic adopters, anxious adopters, threatened avoiders, low-salience. Crosstab by split with Kruskal–Wallis + Holm correction ('out/group_stats.csv').

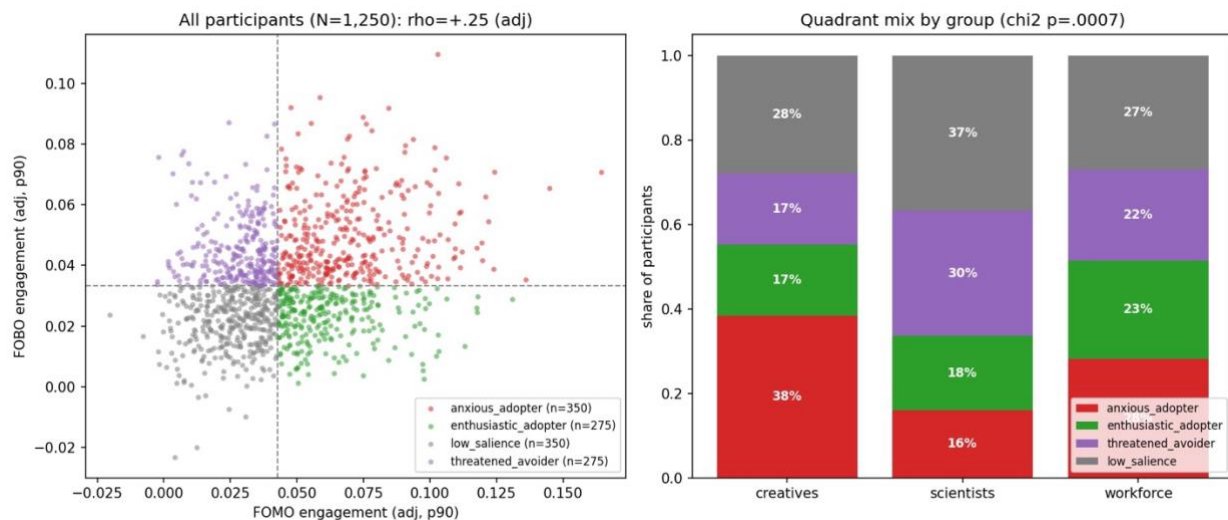
Limitations: Interviewer is Claude asking about AI tools (including Claude): social-desirability and demand effects. Participants consented to public release and agreed to be interviewed by an AI — plausibly truncates the high-FOBO / avoidant tail. Your "reflexive prohibition" pole may be underrepresented by construction. Embedding-anchor scores measure semantic proximity, not certainty of the psychological state; hence the dual testing.

Results

The analysis showed the FOMO and FOBO and AI use fell into four quadrants. The anxious adopters: they were using AI and expressed others were using it but also discussed concerns about AI impacting their future work. The enthusiastic adopters: were enthusiastic about using AI and did not express concerns about future work impacts. Threatened avoider: they avoided using AI and discussed concerns about future work impacts. Low salience: those who didn't express either the FOMO or FOBO constructs. The quadrant mix by group varied. Creatives

were the most likely to be using AI in their work, but at the same time expressing concerns that it would impact their future work options. See Figure 1 for visualization of the groupings. Post hoc analysis by group showed no significant FOMO x FOBO interaction (see appendix 1).

Figure 1: Quadrants



The hypothesis that FOMO and FOBO are not opposing attitudes: that active adopters simultaneously worry about replacement was supported. Three converging results support co-occurrence:

1. Positive participant-level correlation: FOMO and FOBO scores correlate $\rho = +.51$ (raw), $+.25$ (contrast-adjusted), and remain positive and highly significant ($\rho \approx +.14-.17$, $p < 1e-6$) even after partialling out each participant's overall engagement with AI-attitude talk. The association is not purely a measurement artifact.

2. Anxious adopters are over-represented: 350 participants (28%) land in the high-FOMO/high-FOBO quadrant vs ~312 expected under independence ($\chi^2 p = .0004$). A high-FOMO participant has $1.62\times$ the odds of also being high-FOBO (Fisher $p < .0001$); 56% of high-FOMO participants are also high-FOBO.

3. The interaction is significant and robust. Predicting deliberate/critical-use language: FOMO $\times$ FOBO $b = +.0023$ ($p = .0006$), and it survives controlling for overall salience ($b = +.0014$, $p = .008$). FOMO engagement is associated with higher deliberate-use language among participants who also engage with obsolescence —consistent with concept that the fear travels with, and may even sharpen, active use (Fig. 3). These scores measure *engagement with each theme*, not *endorsement of the attitude*. "People who talk about adoption pressure also talk about being replaced" is solidly established here; "people who feel FOMO also feel FOBO" requires the transformer + NLI rerun (which handles the negation problem described below) and the human validation stage. Table 3 shows the FOMO/ FOBO constructs.

Table 3: Group Difference

Measure	Creatives	Workforce	Scientists	Test
FOMO engagement	.052**	.047	.035	KW $p < 1e^{-6}$
FOBO engagement	.036	.035	.033	n.s. ($p = .30$)
Sentiment (VADER mean)	.58**	.42	.40	KW $p < 1e^{-18}$
Anxious-adopter share	38%*	28%	16%	$X^2 p = .0007$
Threatened-avoider share	17%	22%	30%**	$X^2 p = .0007$

** $p < 0.001$

* $p < 0.01$

The model was tested using ordinary least squares regression (OLS). The model measures Df residuals ($r=1244$), Df model 5, R-squared 0.088, adjusted R squared 0.085, F-statistic 17.29, probability (F stat) $1.44 e^{16}$. The log likelihood 2827.6, AIC 5643, BIC 5612. The results are in Table 4.

Table 4: OLS Regression Results*

	Coef	Std Err	Z	P> z	[0.025	0.975]
Intercept	0.0577	0.003	22.384	0.000	0.053	0.063
C(split) [T.scientist]	0.0161	0.004	4.473	0.000	0.009	0.023
C(split) [T.workforce]	0.0077	0.003	2.898	0.000	0.002	0.013
Z_fomo_u	0.0041	0.001	4.510	0.000	0.002	0.006
Z_fobo_u	0.0030	0.001	3.546	0.000	0.001	0.005
Z_fomo_u:z_fobo_u	0.0023	0.001	3.428	0.001	0.001	0.004

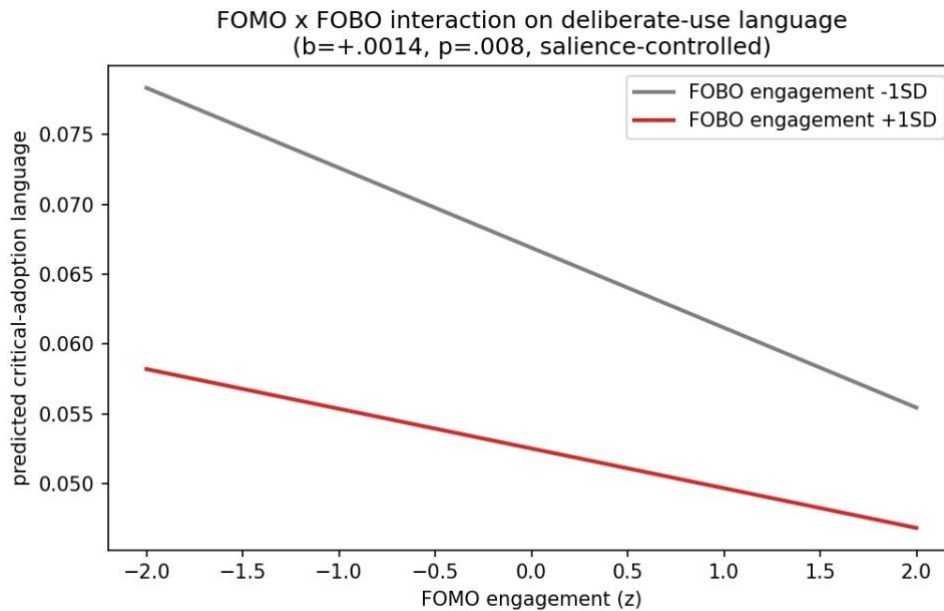
Note: standard errors are heteroscedasticity robust (HC3)

* DV: contrast-adjusted critical/deliberate-use language score

Adoption-pressure talk differs by group; obsolescence talk does not. Creatives engage most with FOMO themes; scientists were mentioned FOMO the least. FOBO engagement is statistically indistinguishable across all three groups. Obsolescence is the common register; adoption pressure is the differentiated one. Creatives are simultaneously the most anxious-adopter-heavy (38%) and the most positive-sounding group this is a striking illustration of fear and enthusiastic adoption coexist rather than trade off. Scientists show the opposite profile: lowest FOMO, highest threatened-avoider share, most data/research-focused talk (54% of their turns). The interaction of FOMO and FOBO indicated that there was an interaction between FOMO and FOBO and that those who were using AI were also concerned out future impact on their workplace. Figure 2 visualizes the interaction effect. The data was tested to see if any of the individual groups were causing the interaction effect (see Appendix 1) and it was found to be insignificant.

Even though the beta of the interaction effect is low, it is significant. Given that this data was gathered using an AI interviewing tool, and these findings are based on a sample that was not asked to discuss their fears or concerns about AI, only how they used AI.

Figure 2: FOMO x FOBO interaction effect



In a post-hoc analysis, the manuscripts were re-analyzed using NLP for mentions of training or awareness of governance. Only 10.8% contained any mention of training. Within that sample, self-teaching was 7.5% leaving less than 3.4% that mentioned formal training. Only 4.3% mentioned policies or approved tools. Some of these few mentions were where participants discussed the absence of policy or lack of clarity, leaving even fewer with a clear understanding of workplace governance.

Discussion

The data showed deeper insights into how the participants had chosen to use AI, and details on how they used it. The findings were both encouraging and sobering. There was clear interaction with both FOMO and FOBO working together in participants' discussions of AI use. For example, those who were using AI because of seeing others' production increase or the result of hearing about it (FOMO); however, rather than uncritical adoption, most participants detailed how they were strategic and careful use. At the same time, many in this pool of participants

discussed how AI could impact their work in the future (FOBO), but rather than avoiding AI they were working to develop deeper, more “AI proof” skills. These expressions of concerns that were easily operationalized as FOMO and FOBO. The interactions and impacts were significant, even. The discussion of the purposeful use of AI led to the ad hoc analysis looking for training initiatives or corporate guidelines for use. The lack of discussion of training or guidelines were sobering.

Theoretically, having meaningful training that would increase self-efficacy would help increase safe and effective use of AI (decreasing motivation). It would allow for end-users to have a “democratic voice” (e.g., informed choices) in how they use AI and how their specific roles could best benefit from safe and verifiable use of AI. Designing AI governance to enable the voice of those using the product will help build more effective and thoughtful use.

Theoretically, following PMT and EPPM concepts, participants were facing huge uncertain opportunities and threats with few ways to build true self-efficacy. This would naturally lead towards fear responses that would be maladaptive. The data demonstrated that this was happening with comments such as:

- Ignoring the threat of change in their future work and not making adjustments or learn about emerging technologies (e.g., “I don’t worry about that at all”)
- Using AI as a “shadow IT” using AI, or unauthorized AI models without authorization at the workplace
- Using AI without acknowledgement (feeling embarrassed or unsure of ethical standards)

All these responses were seen in the participant transcripts. This was especially true among the creatives who were using AI and often mentioned maladaptive use.

Theoretically thinking, if individuals are given clear guidelines and paths to learn more about AI, and had higher self-efficacy, the danger control response would be adaptive. The data also demonstrated this response with comments that discussed:

- Learning to use AI strategically
- Testing AI results to make sure it is accurate and avoids hallucinations
- Using AI to develop deeper analysis and create new models of analysis that would not have been possible without AI assistance.

These responses were seen, especially in the science group who had exceptional self-efficacy. Several advanced researchers gave details of how they both used to advance their work. They detailed how they did not blindly trust results, but carefully tested outputs. Since they had advanced training to do their work, their self-efficacy was high. These users were seeing high benefits of AI use, and at the same time were not as concerned about FOBO as the new technologies were allowing them to test more advanced concepts.

Lack of training in AI use and risks was widely apparent. Many of the participants mentioned use of AI in their work that was probably unknown by their management. As these transcripts were reviewed it was obvious these “shadow IT” uses had potential security and privacy issues. Others were using unapproved programs for part of their work and then approved programs for other, more sensitive aspects. The descriptions the participants made seemed to be self-directed precautions. There was almost no mention of governance, policy, or formal training to help guide workers in using or not using AI models. Most of the participants described their learning process as self-directed, such as watching YouTube videos. Some mentioned their peers were using AI and their productivity had increased, so to catch up they had also adopted AI. We

were unable to find clear mention of workplace training in understanding what certain models were or were not allowed.

Those who had self-efficacy in using AI described fascinating ways that they had utilized it for their workflow. Many described how use of AI had improved both the quality and quantity of what they were able to produce. Those who were working in highly “democratic” settings, where they had high autonomy and independence, were making strategic and innovative choices on AI use. They expressed concerns about their future as AI advanced, but they expressed how they were increasing their skills and knowledge to “future proof” their positions.

This research demonstrates that even as levels of government and industry are rushing to build and deploy AI systems widely across domains, it is important that support for AI literacy and training be core to these efforts. Giving users the self-efficacy to strategically and safely use these emerging systems could become democratically-driven, rather than authoritarian-mandated in ways that encourage human creativity and support human well-being.

Limitations and Future Research

There are many limitations to this sample, as discussed previously, the sample was collected from a group of people who were comfortable using AI and had high enough digital literacy to use an online work platform. To get a sample more representative of the general population, there could be in person samples collected using tablets or other devices that would protect privacy but allow those with lower literacy levels to share their concerns and explore if they also exhibit similar FOMO and FOBO interactions. Also, experiments could be run to explore the impacts of AI literacy training and clear guidelines on why certain AI uses are either encouraged or prohibited.

The collaborative use of the AI model was a clear demonstration of the potential of gaining quantitative insights from data that is qualitative in detail. Firstly, the development of the

Anthropic AI interviewer tool allowed for a valuable sample to be collected. The AI interviewer used feedback and responsiveness that is usually only seen in trained research assistants. Human review of the transcripts showed responses by the AI tool that were reflective and probing for more details at the points where we would usually train research assistants to probe.

Furthermore, these tools allow multi-model research to be done on the same data set. Usually, to statistically test a concept, researchers need to carefully design a survey to try to extract insights. The AI model allowed development and testing of semantic coding to gain insights into a human sample large enough to test for statistical significance. Post-analysis sample testing of the results showed high validity of scripts developed by the AI.

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Appendix 1: Group tests of FOMO x FOBO interaction

Interaction test by group

Sample Group	N	b_interaction	SE	p
Full sample	1250	0.0014	0.0005	0.0076
Excluding creatives	1125	0.0012	0.0006	0.0359
Excluding scientists	1125	0.0018	0.0006	0.0013
Excluding workforce	250	0.0014	0.0012	0.2401
Creatives only	125	0.0033	0.0017	0.0562
Scientists only	125	0.0003	0.0019	0.8807
Workforce only	1000	0.0016	0.0006	0.008
Heterogeneity: interaction diff, scientists vs creatives (ref)	1250	-0.0022	0.0027	0.4193
Heterogeneity: interaction diff, workforce vs creatives (ref)	1250	-0.0016	0.0017	0.3668

Final two rows test if the interaction coefficient differs across occupational groups, the difference was not significant.

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