Turning Up the Temperature: How Twitter Data Reveals Public Perception of Culinary Robots

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

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For decades, the future of robotics has been just five more years away. But for the first time, there are real signs that this never-ending horizon may finally arrive. In the past decade, robotics technology has taken a dramatic leap forward. Boston Dynamics first revealed Atlas in 2013, which would soon become famous for its backflipping agility. Spot, the yellow robotic dog, debuted in 2016. For the first time, these robots saw commercial success in 2020, as a tool for industrial site-monitoring and inspection (Beyer, 2021; Boston Dynamics, 2024). While Boston Dynamics is the best-known frontrunner, the last half-decade has ushered in a wave of new general-purpose humanoid robotics: Tesla's Optimus, Figure AI's Figure02, Apptronik's Apollo, and many more (Koetsier, 2025). The cost of these general-purpose robots is falling quickly, with Diamandis and Tesla promising unit costs below $30,000 and $20,000, respectively (Koetsier, 2025; Lukpat, 2024).

While futuristic humanoid robots are impressive, they are over-capable in many applications. Their simpler counterparts, such as autonomous manufacturing, exoskeletons, and self-correcting surgical instruments, have all existed for decades. (Gasparotto & Scalera, 2019; Hockstein et al., 2007; Kazerooni & Steger, 2005). Given these early advancements, it's surprising that robotics has only recently been applied in customer service industries. This slow crawl of adoption has become a full-on trend in recent years, though, in the food industry. There has been a rush of new applications in all aspects of the food industry, like delivery, food-running, and even cooking robots. But why now? If back-flipping robots are already here, why did we skip over burger-flipping ones? This research asks that question by studying social media discourse to understand how the development of robotics in the food industry has been socially shaped.

Case Context

Robotics now touches nearly all aspects of the food services industry, but food delivery robots were among the earlier successful applications. Starship Robotics was at the forefront of this in 2014. But in the aftermath of the pandemic, their fleet of delivery robots quadrupled (Appleton & Garwood, 2022; Writer, 2021). College campuses were the hot spot for autonomous delivery. Meal delivery apps like Grubhub and Uber Eats capitalized on this by launching partnerships with delivery robotics companies (Sriram & Sriram, 2025; The Grubhub Staff, 2023). The cousins of food delivery robots are in-restaurant delivery robots that are dedicated to point-of-service, food-running, and bussing. These robots, such as Bear Robotics' Servi, have been deployed nationwide with over 10,000 units since 2023 (Yu Bing, 2023). While outright purchasing these robots can be prohibitive, part of their successful adoption lies in service providers like Robot Labs. These providers lower the barrier to entry by offering inexpensive leasing options as low as $333 per month and on-site tech support services (Ngo, 2025).

In the world of preparation and cooking, Sweetgreen opened its first "Infinite Kitchen" in 2023, which automatically assembles most of its salad bowl orders (Haddon, 2023; Jennings, 2023). Likewise, Chipotle has attempted to automate preparation work, with its two robots: the "Autocado" which pits and peels avocados and "Chippy" which prepares tortilla chips (Haddon, 2024a, 2024b). In 2024, Chipotle's founder, Steve Ellis, also launched Kernel, an almost completely autonomous fast-casual restaurant (Creswell & Karlsson, 2024a; Kingson, 2024). Miso Robotic, a relatively old player in the space, created "Flippy," a robotic arm now used in the fryers of chains like White Castle and Jack in the Box (Haddon, 2024a). The past few years have also reigned in a host of startups such as fully autonomous ghost kitchens, pizzerias,

bartenders, and versatile ‘sous chefs’ such as Nala Robotics’ Chef 1.1 and Dexai’s Alfred (SavorEat, 2025).

What was once a relatively slow and limited application of robotics has seen and is projected to continue dramatic growth, with annual market growth up to 12.6% (Bernier, 2023) and a 25% increase in deployment (Softbank Robotics, 2024). The surge in interest is unsurprising as the potential for robotics in food service has had massive cost-saving potential. Restaurants are typically low-margin businesses, and labor costs often account for over a quarter of revenue (Creswell & Karlsson, 2024b). The potential for savings is high, as shown in a case study by the Culinary Services Group, which found that over three years, Bear Robotics’ Servi paid off the initial investment in saved labor cost twice over (Culinary Services Group, 2024).

While growth can be enticing, recent technology bubbles, such as the Metaverse, make it painfully clear that a top-down injection into new technology may not always translate into success. Restauranters are incentivized to adopt automation, however, the restaurant industry is customer-driven and relies heavily on positive customer experience and perception. Therefore, just as important as the cost-saving potential is the willingness of consumers, workers, and regulators to tolerate automation in food services. This is especially relevant as socially conscious consumerism has placed increased pressure on industry to develop sustainable and ethical practices. For instance, Denny’s, Chili’s, and McDonald’s all experimented with service robotics but ultimately rolled those experiments back (Creswell & Karlsson, 2024b; McCarron, 2024). Therefore, the focus of this research poses two questions: why have food applications only recently gained momentum in the food industry, and how has the wider social context shaped this development?

STS Theory

Food and hospitality are uniquely social businesses with razor-thin margins for error. Customer satisfaction drives restaurants to fail or succeed, and this largely depends on positive social interaction (Parvez et al., 2025). Therefore, successful technologies must adapt to this social pressure. To understand how technical artifacts like food robots are socially shaped, I will draw on Pinch and Bijker's framework for the Social Construction of Technology (SCOT) (Pinch et al., 2008). SCOT argues that technology is a fundamentally human construct, and its form and meaning are primarily socially determined. In their rebuttal of technological determinism, its authors argue that while the progress of technological development may seem linear in hindsight, the process by which an artifact succeeds is by competing with potential alternative interpretations. In other words, a singular understanding of a technology prevails—what the authors refer to as reaching closure—through a series of social negotiations.

As an explanatory framework, SCOT introduces several analytical components: relevant social groups, interpretive flexibility, closure and stabilization, and wider context. In the framework, relevant social groups are a collection of individuals that interpret a technical artifact homogenously based on shared norms, identities, and values. In this study, some relevant social groups are the customers, food-service employees, and restauranters. Interpretive flexibility describes the early stages of development in which the use, meaning, and form of an artifact are in flux. Closure and stabilization describe how these interpretations converge; a process in which a consensus for mutual norms and expectations of technology is reached (i.e., relevant social groups consider problems to be resolved). The wider context refers to the wider moment in a technology's development. For instance, the COVID-19 pandemic and the following global inflation.

Research Question and Methods

The primary research aim of this study is to understand how the social context of food robotics technology has changed in the past decade. Text analysis was performed on a decade of publicly available tweets collected with a Boolean search query. The search string was: (**robot** OR **robotic** OR **robots** OR **automate** OR **automation** OR **autonomous**) AND (**food** OR **chef** OR **cook** OR **cooking** OR **restaurant** OR **cafe** OR **delivery**), with filters applied for English-language tweets and a minimum of 10 replies. Trends in the key themes, actors, and sentiment were identified. These results are then contextualized in the SCOT framework as the following research questions:

RQ1. What are the main social groups and issues identified in the discourse? How does the dominant narrative reveal implicit power relationships?

RQ2. How have these issues, themes, and sentiments changed in the past decade? How did the narrative change with contextual events such as COVID-19?

RQ3: How do the sentiment and themes differ between cooking, delivery, and service robotics?

Data Collection Methods

In recent years, platforms have restricted the availability of API-based approaches to text mining. While existing datasets are available, they are often limited in topic or prohibitively expensive. Therefore, in line with other recent academic research, automated text-crawling was used to sample tweets (Balasubramanian et al., 2024). Tweets were programmatically harvested

in Python.[1] Using Twitter's search feature. The search query was designed to filter for English-language tweets with moderate engagement that contained both a food-related and an automation-related keyword. Overall, a total of 2,176 unique posts corresponding to 141,313 total replies were collected, see Figure 1.

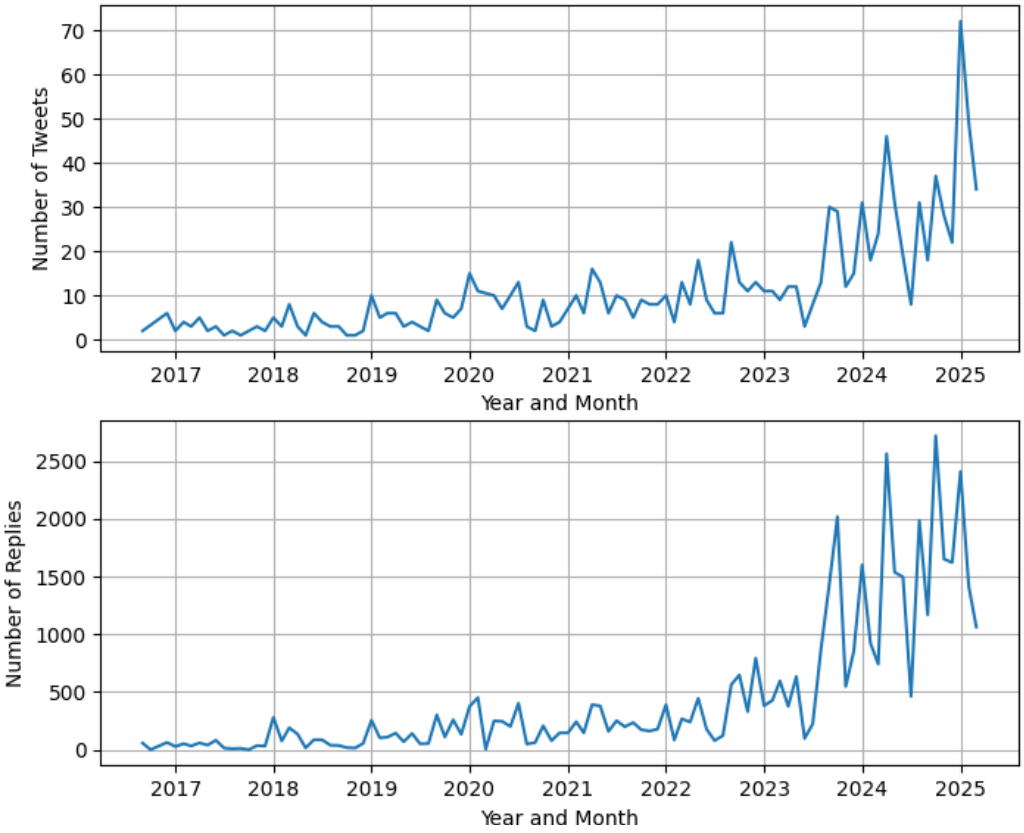

Figure 1. Count of unique tweets and replies sampled by web scraping. Counts are grouped by month. Note the large increase in interest in the topic following 2023.

Basis for Text Analysis Methods

In a digital society, people interact with a profound amount of data. In social sciences, this useful tool allows researchers to test hypotheses and research questions with publicly available information rather than relying on structured surveys and interviews. Computational

[1] Written based on a modified version of the source code in (Gojar, 2023/2025). Functionality to scrape replies was implemented separately.

Social Sciences (CSS) is a relatively recent research area that utilizes various quantitative techniques to analyze this vast amount of human data (Macanovic, 2022). Common research methods range from basic tools like word counting and dictionaries to custom-trained language models. These tools have been used to measure sentiment, reveal hidden language patterns, and identify narrative and political framing of issues (Macanovic, 2022).

However, in the last few years, large-language models (LLMs), such as OpenAI's GPT or Meta's open-source Llama models, have been considered a potential new research method. These pre-trained LLMs have created an open question of research best practices in the social sciences (Bail, 2024; Ziems et al., 2024). Recent research has shown that these tools can have tremendous value while also identifying risks that must be considered, such as hallucinations, prompt stability, sensitivity to model parameters, and the source and biases within training data (Törnberg, 2024a; Yang et al., 2024; Ziems et al., 2024). At their best, LLMs are a tremendously powerful tool. For instance, LLMs perform quite well at categorizing political ideology from context (Ibrahim et al., 2024); with one study showing GPT-4 outperforming trained language models, crowd-sourced coders, and expert coders—the typical gold standard—alike (Törnberg, 2024b). These models are trained with vast amounts of human knowledge, allowing them to identify social context, human dialects, and figurative language. One increasingly common method is as an assistive tool for annotating data, a typically costly and arduous process in text analysis. Recent studies showed pre-trained LLMs accurately and meaningfully annotated data in social sciences research when following best practices (Törnberg, 2023, 2024a; Ziems et al., 2024).

Several authors have created guidelines to address LLM's limitations. The core guidelines focus on appropriate application, prompt structure, and iterative validation. When using a language model for text annotation—the approach used in this paper—the prompts should begin with a

descriptive role and objective, be well-structured, and iteratively validated and tested against segments of the sample data (Törnberg, 2023, 2024b; Ziems et al., 2024). Prompts should provide an ambiguous option when labelling structured data, and during validation, the model should be asked to explain its reasoning as well as its understanding of the prompt. While many authors suggest Open-Source models are preferable for reproducibility of findings and data-privacy considerations; however, this was unfortunately not a cost-effective option for this study. Instead, OpenAI's GPT-40-mini through online API access was used as it was tested in several studies and found to be both effective and affordable. Best practice should also validate against several human coders; however, this study's feasibility limits validation to a single human coder. All prompts were developed and verified in the same approach. An initial prompt was provided as well as a sample of randomly selected sample of data. In the testing phase, the model was asked to provide reasoning for all its classifications as well as explain its understanding of the prompt. The prompt was then refined iteratively until a large enough random sample ($n > 30$) results were considered satisfactory. Prompt stability was also validated by ensuring that changing the wording of the prompt did not change the results of the analysis.

Tweet Classification Methods

To extract meaning from this large corpus of tweets, a several-stage processing pipeline was established, see Figure 2. Because the initial corpus contained tangentially related tweets, it was prefiltered to only relevant tweets using GPT-40-mini (see Appendix A), after which the replies for all relevant tweets were then collected. This left a total of 1,106 tweets and 38,735 replies. Because GPT was shown to have excellent summary and annotation abilities (Ziems et al., 2024), before establishing a rigid taxonomy, GPT was asked to summarize key actors, issues,

and classify the technology, see Appendix B. From these free-form categories, as well as a human review of randomly sampled tweets, a taxonomy of key themes and issues was identified (Table 1). Tweets and replies were then reclassified under these more rigid criteria, see Appendices C and F. Finally, to identify if the exchange was positively, negatively, or neutrally charged, the sentiment in each tweet and reply was classified, see Appendices D and E. Lastly, the analytics such as likes and retweets were used to bias data based on influence.

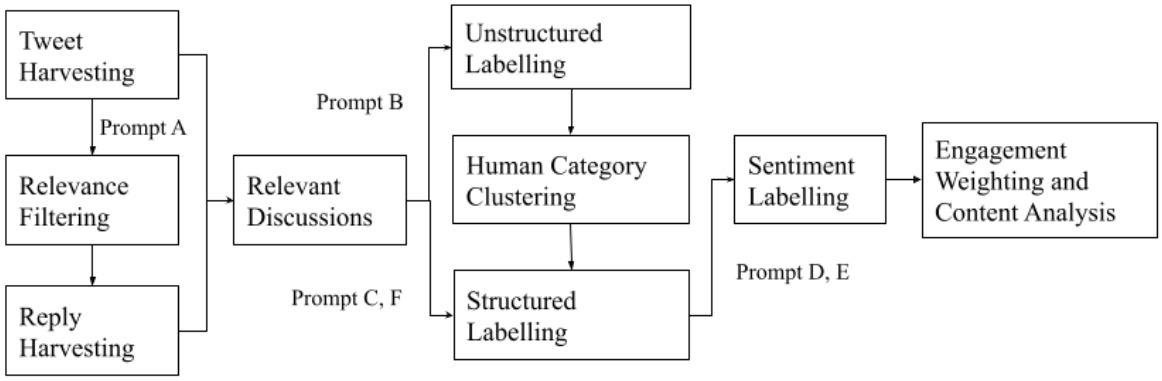

Figure 2. Tweet processing pipeline showing how tweets and their replies were harvested, filtered by relevance, sorted by GPT, and evaluated based on sentiment. This data was then biased by meta-analytics such as likes and replies for human content analysis. See prompts in Appendices A-F.

Table 1. Coding scheme for themes and values that represent key issues, values, and descriptors of food robotics technology in the Twitter discourse.

Social and Contextual Issues	**Values and Cultural**	**Aesthetic and Functional**
Sustainability, Social Justice & Inclusivity, Tipping Culture, Labor Shortages, Public Health & Safety, Job Loss, Affordability, Economic Inequality, Crime-Theft-Vandalism, Policy & Regulation, Minimum Wage, Workers' Rights	Traditionalism, Cultural & Regional Differences, Artistic & Creative Expression, Human & Social Interaction, Political Ideology, Autonomy & Laziness, Innovation & Progress, Distrust of Technology & Authority,	Creepiness, Cuteness, Dystopian Themes, Efficiency, Customer Experience, Technological Reliability, Food Quality

Results

Overall, to study the social context of food robotics, a decade of publicly available Twitter data was harvested and analyzed using LLM-assisted text analysis, and qualitatively by human analysis. In total, 1,106 relevant tweets and 38,735 replies were categorized based on sentiment into one of twenty-seven narrative themes. Research questions were designed from a basis in SCOT Theory, which sought to identify the actors, sentiment, and themes in the public discourse over a decade of data and several technological artifacts. Through both quantitative and qualitative analysis, the findings show that food automation is still in a period of broad interpretive flexibility.

To quantitatively examine the corpus of Twitter data, weighted sentiment for each key issue (RQ1) is recorded over time (RQ2) and subdivided into each core technology category (RQ3). This methodology can be conceptualized as a narrative model of SCOT's problem-solution model. That is, observing how sentiment and themes change over time models the stabilization of an artifact. These quantitative results are summarized in the three figures below.

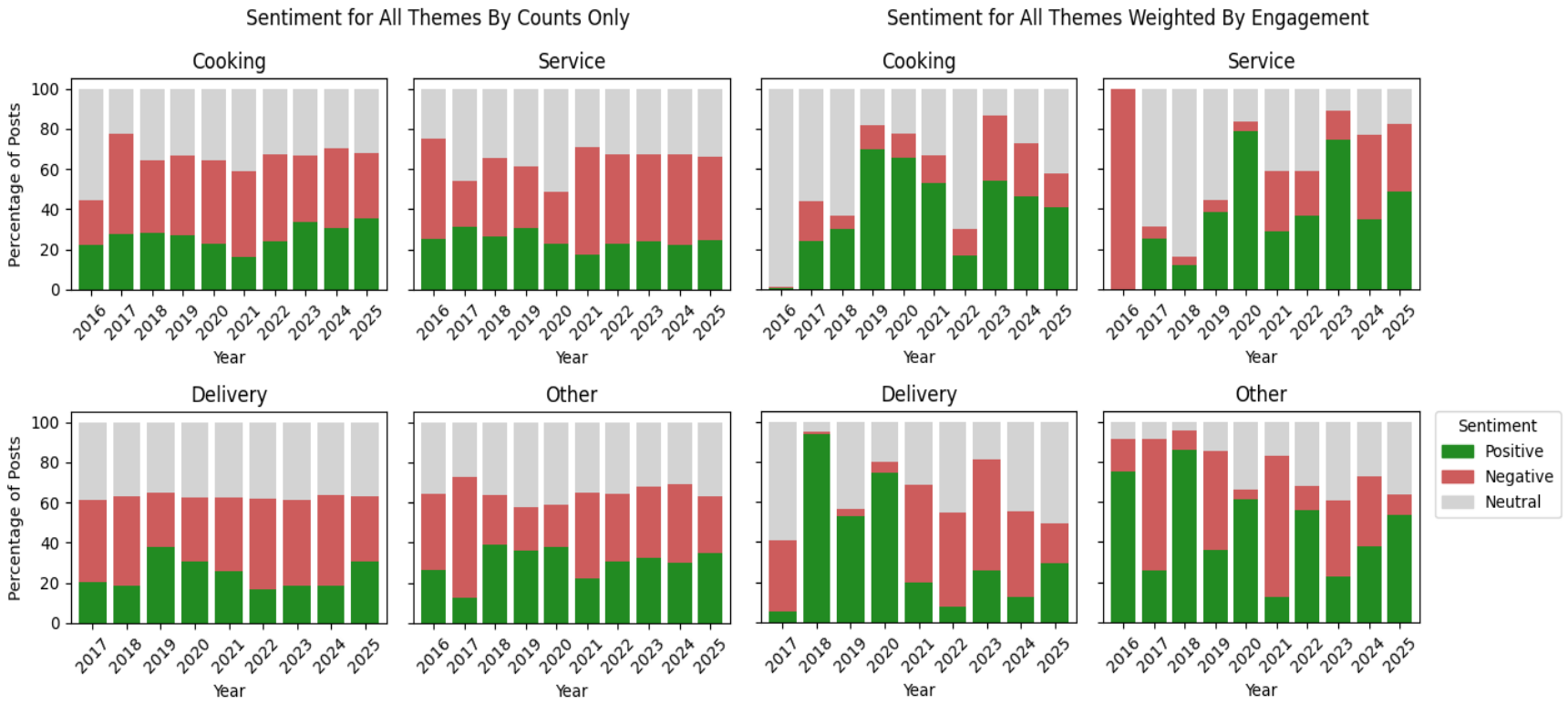

Figure 3. Ratio of positive, negative, and neutral sentiment for major categories of food automation technology by count of posts (left) and by count of posts and biased by engagement (right). Note the overall trend seems to fluctuate mildly but is overall towards increased negativity in later years for cooking, delivery, and service.

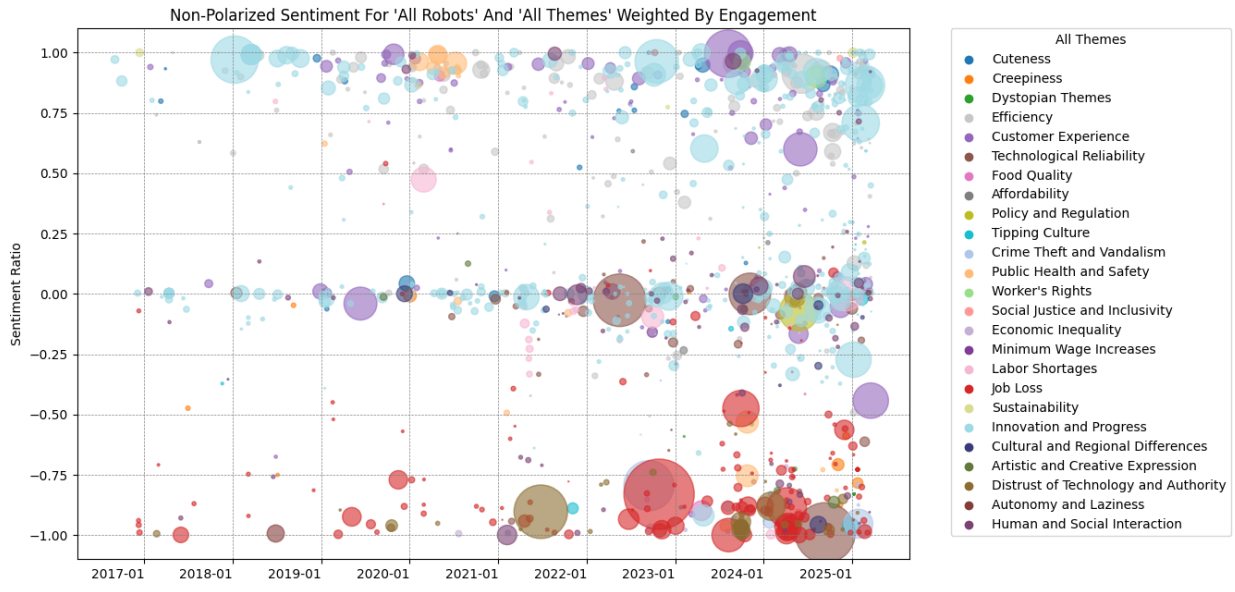

Figure 4. Time series representation of Twitter discussions for all narrative themes and robotics categories. The sentiment ratio is the sum of the sentiment times engagement of all posts in a discussion (tweet and its replies) divided by the total engagement received. In essence, it represents a consensus of how positive or negative the narrative issue was. The size of the points is their total engagement received.

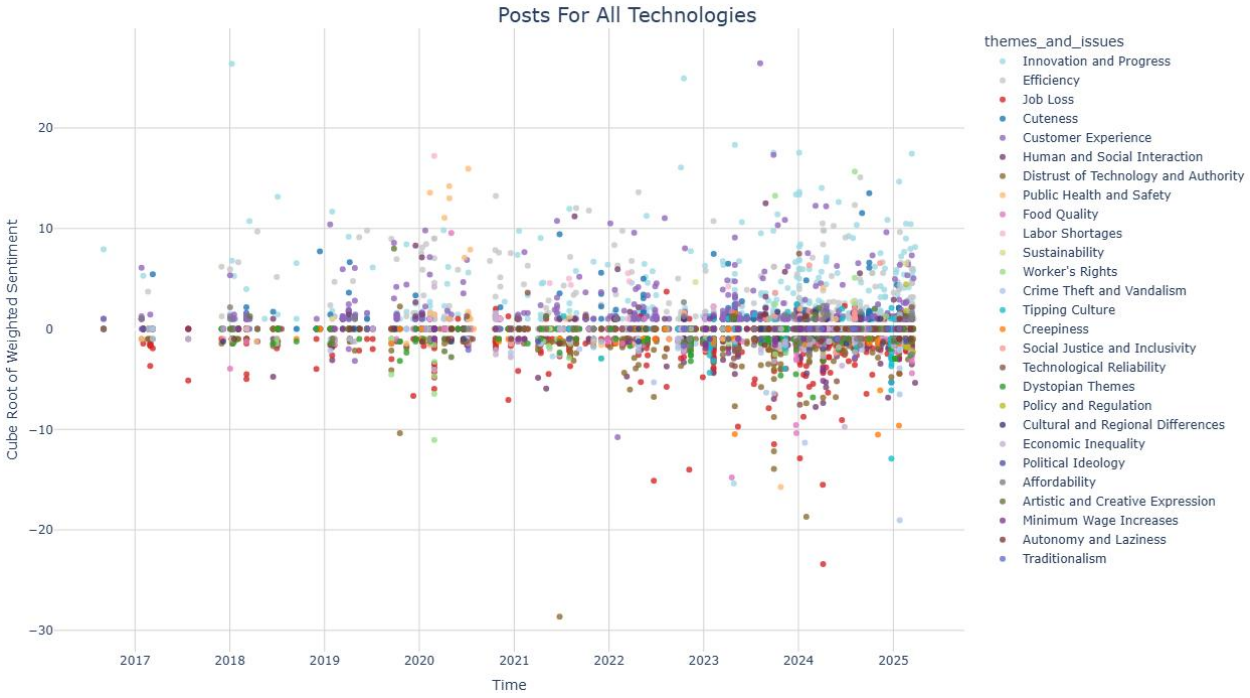

Figure 5. Time series data for all posts with their weighted sentiment (on a cubic y-scale) broken down by major narrative themes. Engagement is along the absolute vertical axis.

Overall, these results elucidate a few key insights into the social context of food automation technology. Sentiment across all technologies has not improved, and if anything, it has become considerably more negative in recent years in cooking, service, and delivery technologies (Figure 3). From Figure 4 and Figure 5 it becomes quite clear that much of the discussion is centered around just a few narrative themes. Grouping by broad strokes, the most positive themes are related to innovation, efficiency, and customer experience. Meanwhile, the most negatively charged sentiment relates to economic issues, distrust and crime, and human interaction. An interesting finding is that the themes of public health and safety shifted markedly from positive during the pandemic to among the most negative themes. From a pure quantitative analysis, these results hint at the main issues in food automation. The composition of themes did not markedly change over time relative to the increase in overall discussion, but the sentiment seemingly worsened. This suggests that food robotics is still in a period of broad interpretive flexibility and is far from stabilizing. As for differences among technologies, in general, the negative emphasis on delivery robotics was oriented towards distrust and crime more than its counterparts, but less on human interaction and job displacement. The charged conversation around service and cooking robotics was dominantly about economic unease of job displacement and wealth inequality, and a loss of human interaction and expression.

While quantitative results hint at the broad social context of food automation, they only offer a surface-level understanding of these issues. For instance, while crime was identified as a substantive technical issue for delivery robots, that knowledge alone does little to aid designers and regulators. These stakeholders would obviously want to know the who, what, and why of these crimes. For this second-level analysis, the most engaged tweets for each year were manually sampled and analyzed for the most impactful themes.

The sole theme that markedly shifted from positive to negative sentiment was ‘Public Health and Safety’, see Figure 4. The most positive period is from the COVID-19 pandemic era, which is indeed born out in the most engaged tweets from that period (Figure 6)**.** There was also some evidence of a post-pandemic follow-through in sanitary concerns, specifically regarding food tampering by delivery drivers and poor practice by food service employees (Figure 7). Surprisingly, there were also notable concerns that, without human oversight, these technologies could be equally unsafe, especially in food preparation roles, (Figure 8**).**

Delivery robots have their unique challenges as they are deployed into public spaces. These challenges overlap with public safety, vandalism, and a distrust of technology. People brought up concerns that these robots would be vandalized, stolen, or tampered with in low-trust communities, by the homeless, and by hooligans (Figure 9)**.** There were quite a few examples of this collected, showing vandalism and theft mostly. Indeed, there is an online subculture of its own dedicated to harassing or tipping over delivery robots to prevent them from getting to their destination, see examples in Figure 10. These concerns have real implications, beyond simple vandalism that only harms restaurants and delivery companies. Nefarious tampering with delivery robots could spread illness, and in the very worst cases, these robots could be appropriated by criminals or terrorists, as with the bomb threat that occurred at Oregon State. See the prediction and real-life coverage in Figure 11.

The final challenge with delivery robots is their perceived invasion of public spaces. Disability advocates point to their obstruction of accessible egress (Figure 12). All combined, these issues could precipitate regulatory changes for delivery robots, as community safety and disability advocacy have long been salient issues that translate into meaningful regulation.

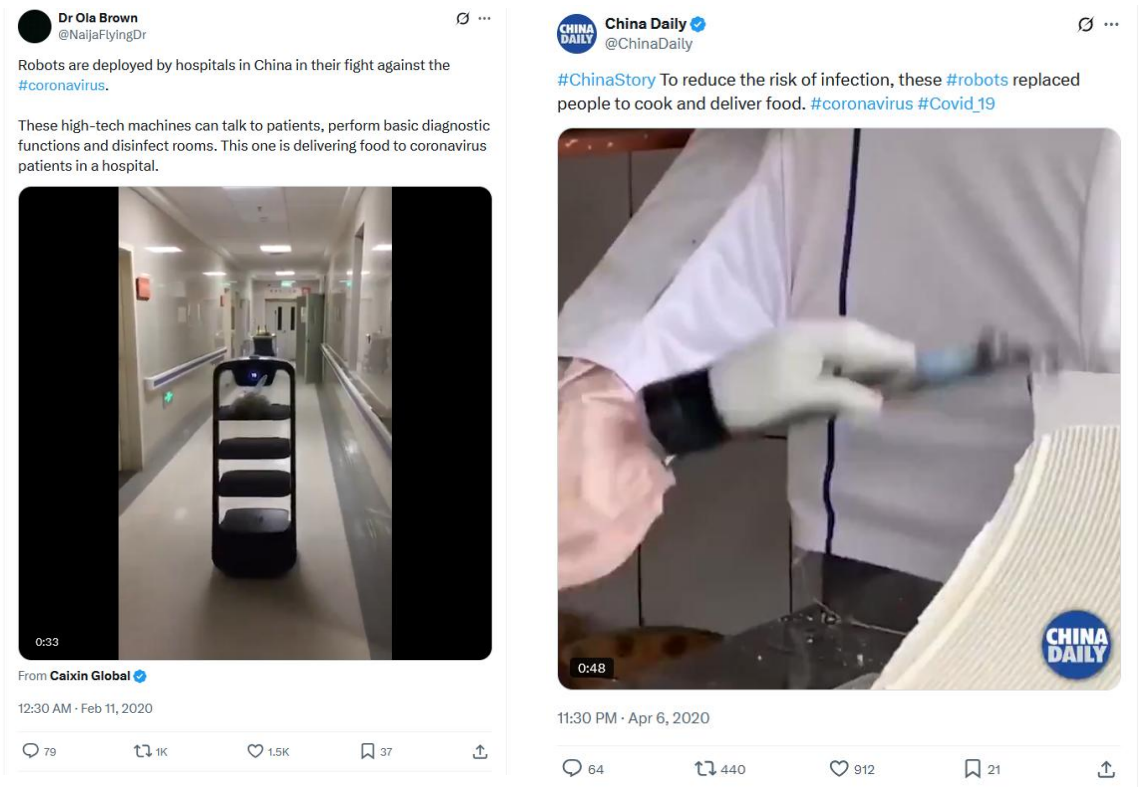

Figure 6. Sample of top tweets during the COVID-19 pandemic related to public health and safety. These were tagged as having overall positive sentiment in their discussions.

Figure 7. Tweets that bring up sanitary concerns addressed by automation.

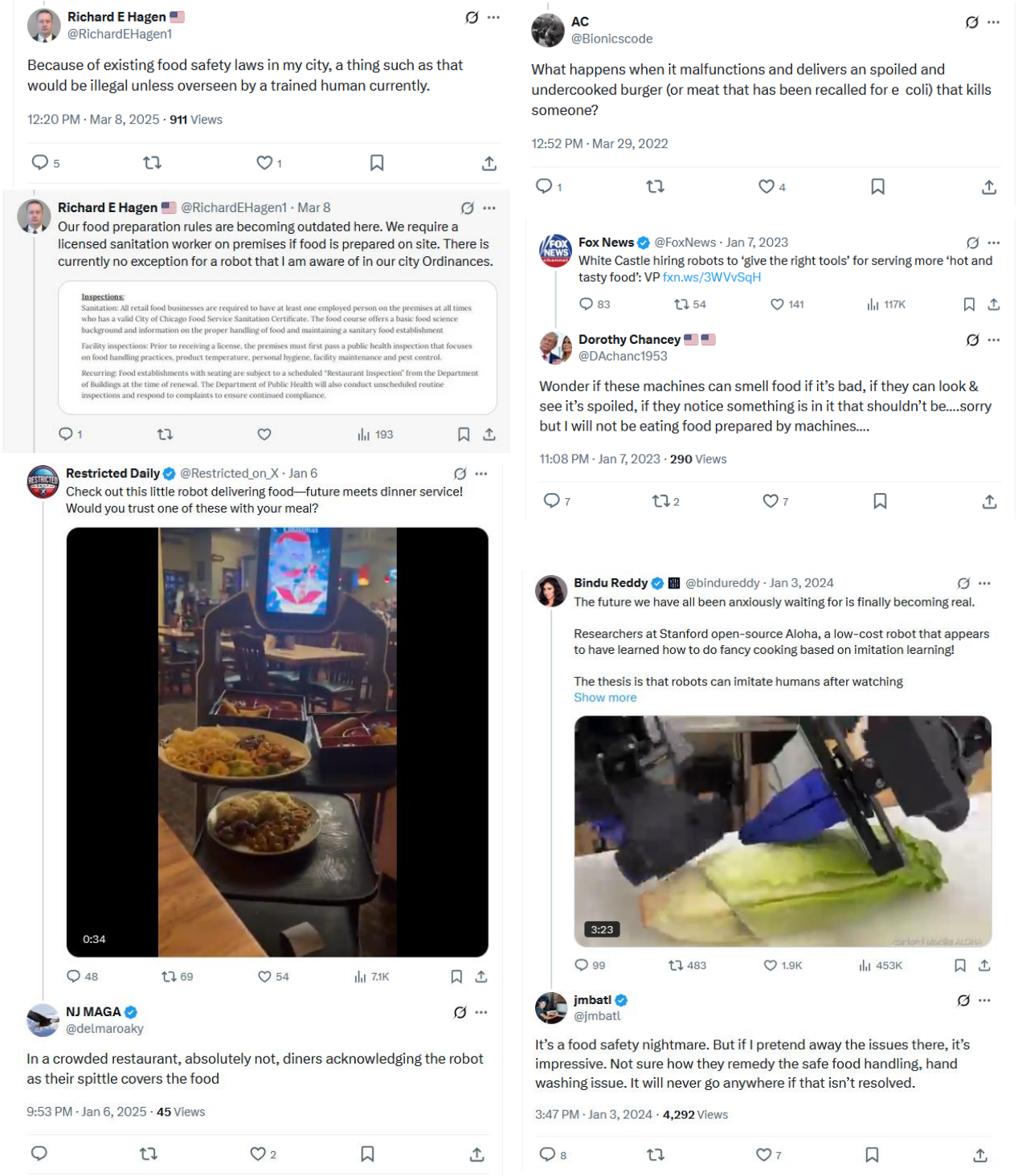

Figure 8. Tweets raising food safety concerns that were introduced by automation. For instance, a lack of oversight, technical challenges, and regulatory concerns.

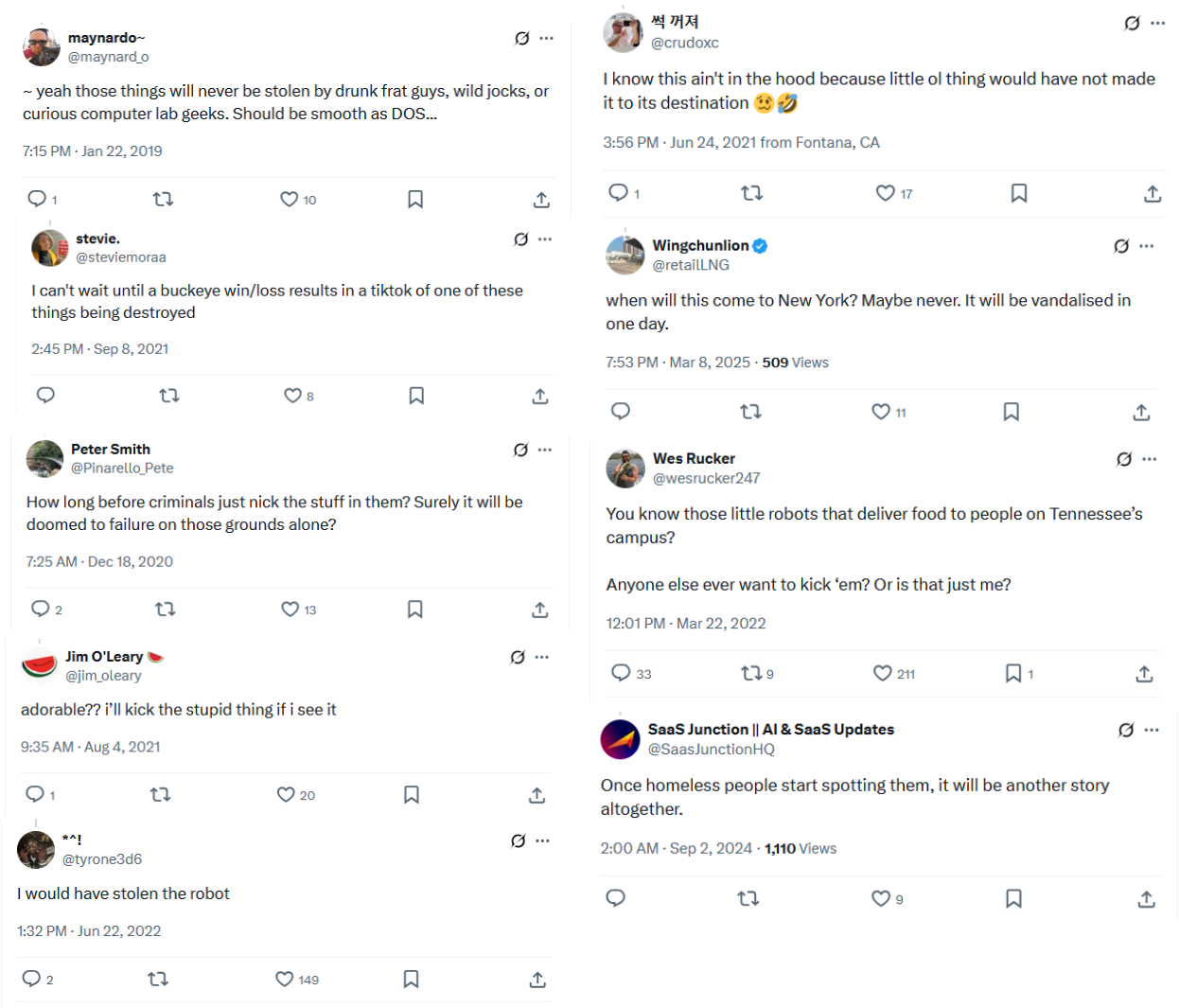

Figure 9. Sample of discussion from users specific to delivery robots. For instance, fears that delivery robots could be tampered with by criminals, the homeless, or otherwise vandalized or stolen.

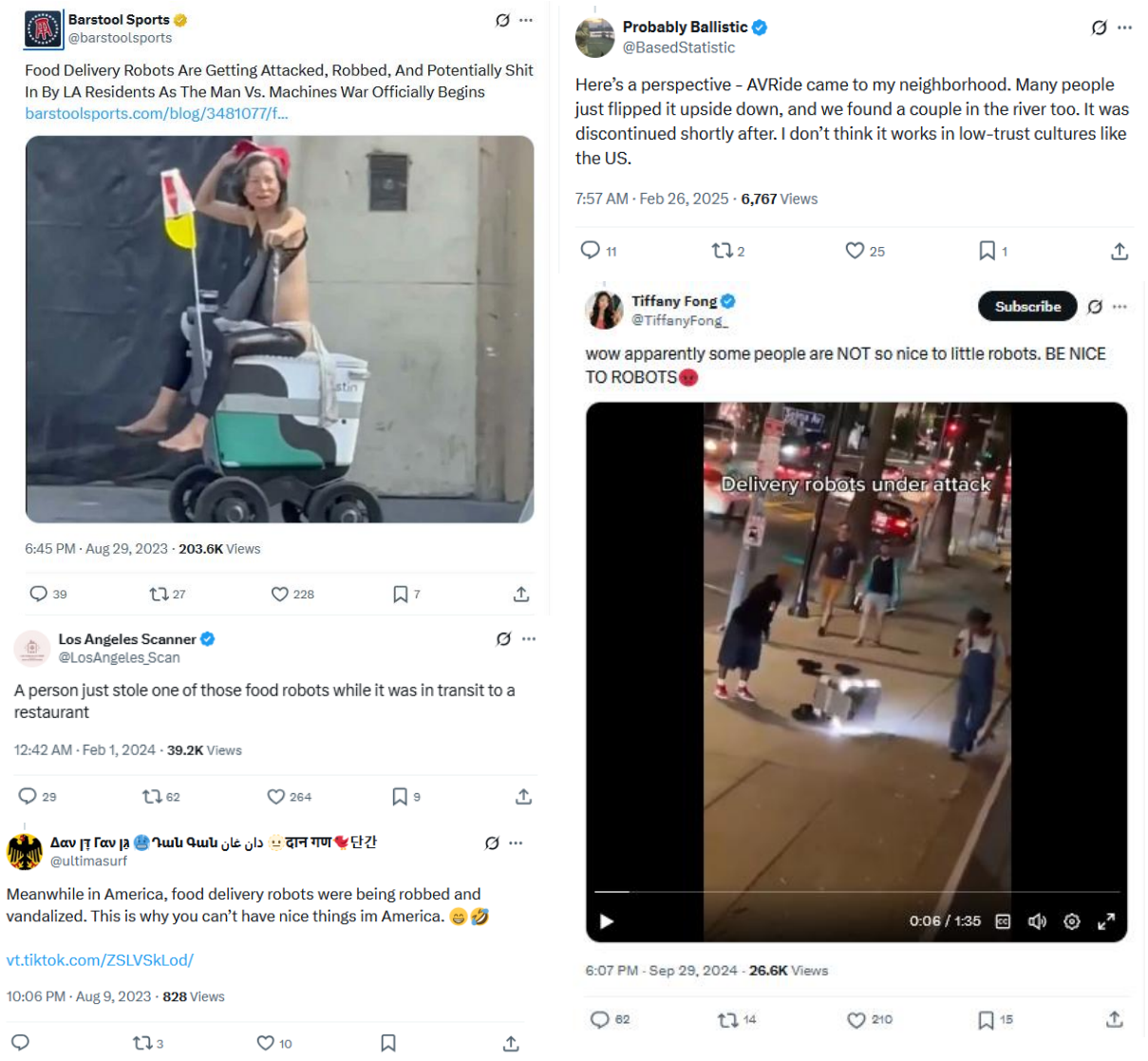

Figure 10. Testimonials and stories of crime and vandalism are specific to delivery robots.

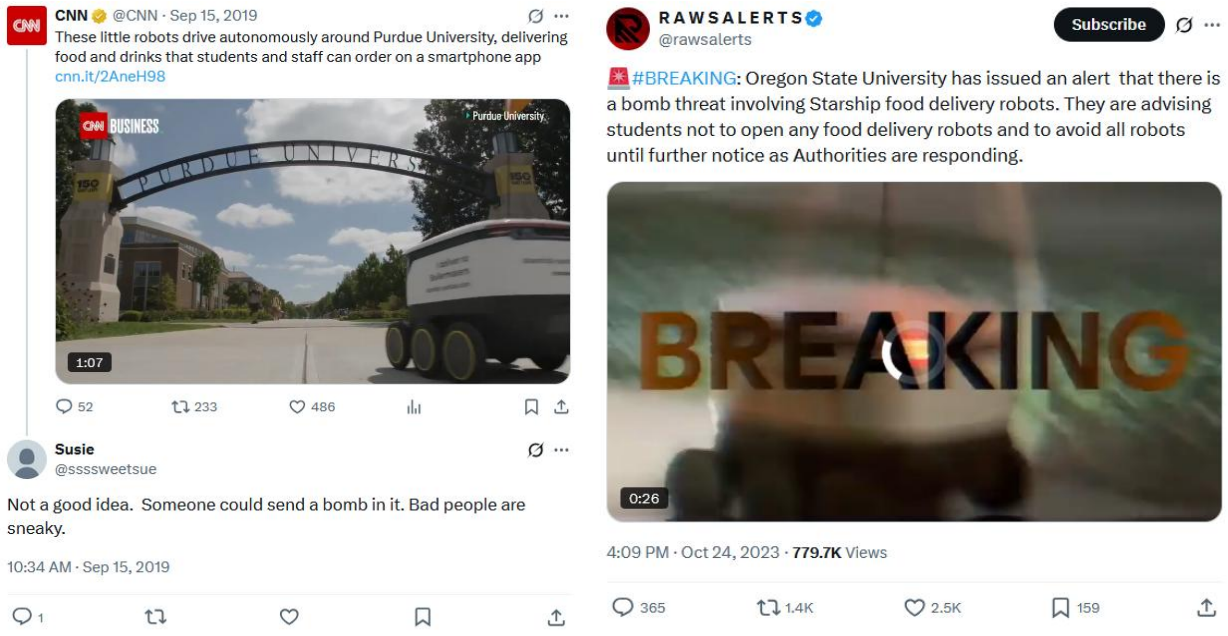

Figure 11. Tweets that mention the potential for bombs in delivery robots. A user foreshadowing the potential issue (left) and the unfortunate real-life occurrence of their warning (right).

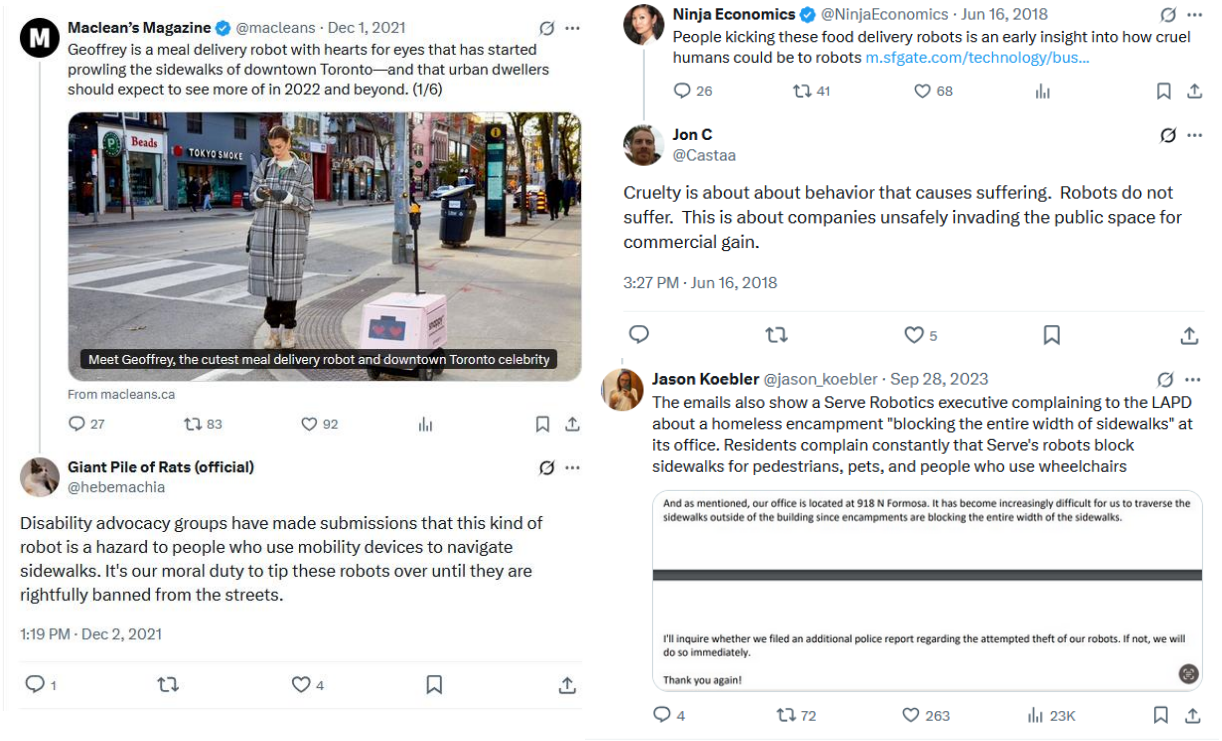

Figure 12. Tweets related to the disability of access implications of delivery robots.

Another highly salient issue, especially concerning service and cooking robots, is the human element in food. Both quantitatively and qualitatively, there was a clear distinction here between delivery and service and cooking applications. Qualitatively and perhaps unsurprisingly, only a couple of posts mentioned the human aspects of delivery and gained relatively little engagement. Meanwhile, there was a rich and sustained discourse around the human aspects of an in-restaurant experience and food as a form of cultural and artistic expression. Beginning with food service

For these issues, there was an apparent difference among delivery, service, and cooking applications. There were only a couple of low-traction posts resisting the dehumanization of delivery. However, in comparison, there was a relatively popular conversation about the human element of in-restaurant service. Generally, the discourse reflected that wait staff were an important part of the experience, or that highly automated restaurants had an impersonal or empty feel, see Figure 13 and Figure 14.

Figure 13. Tweets addressing the deployment of food service robots and their human impact (part one).

Figure 14. Tweets addressing the deployment of food service robots and their human impact (part two).

Despite being the youngest and least adopted, a vast majority of the discussion was centered around automation in cooking. These discussions elicited a strong sense of how food is an important cultural and human form of expression. Posters repeatedly brought up the idea that food is a form of interconnectedness, of self-expression, of creativity, and of love and passion, see Figure 15. That part of the culinary experience lies outside of the food itself. A widely shared sentiment was that automation should replace the banal rather than the creative. Not only was there skepticism and hesitancy about culinary automation, but also that people would refuse to patronize themselves at automated restaurants, see Figure 16.

Figure 15. User-raised concerns that touch on the human elements of service, such as passion, culture, and creativity.

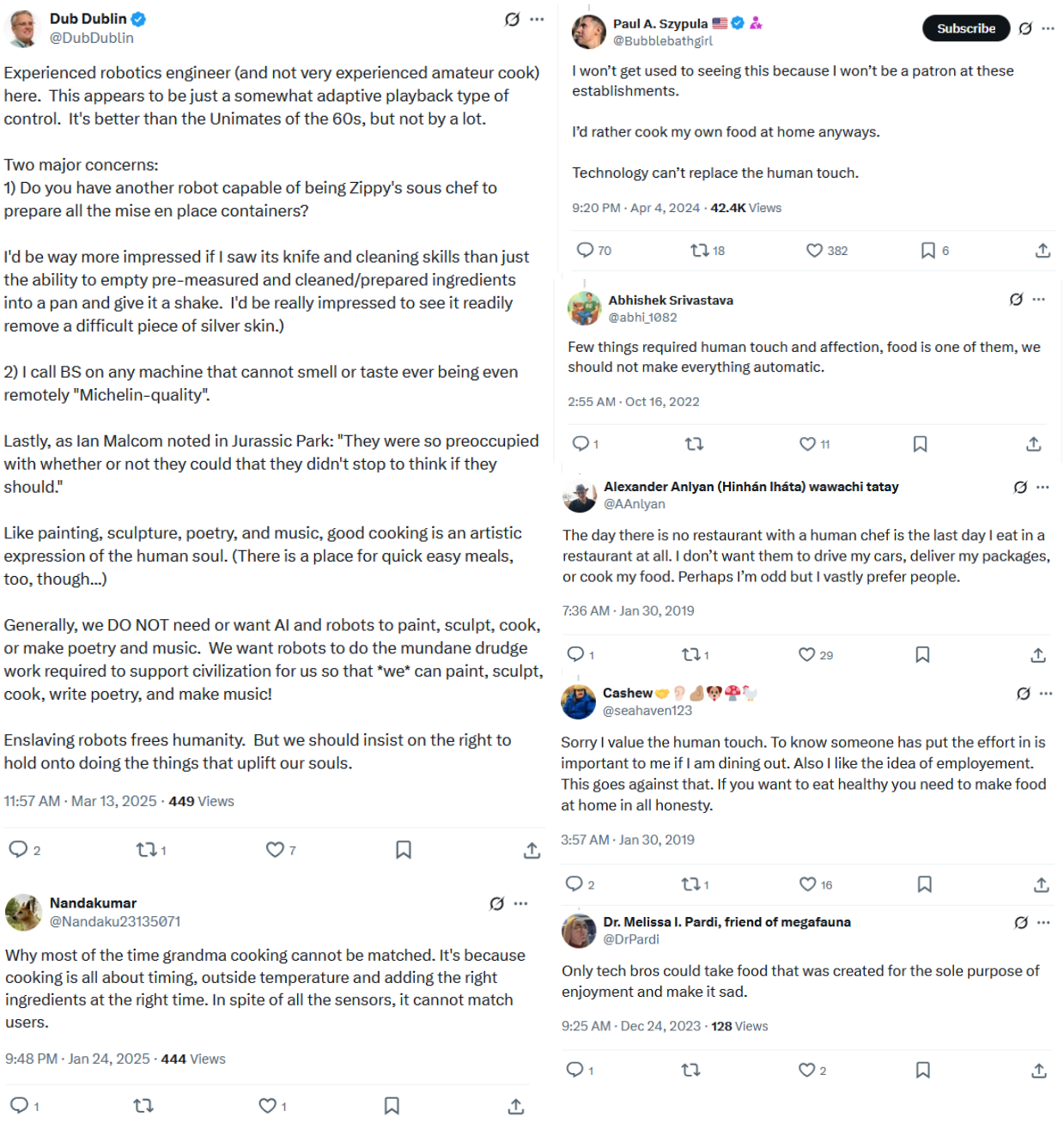

Figure 16. Additional user-raised concerns expressing opinions about the purpose of automation, and a hesitancy to visit restaurants that implement automation in cooking.

Finally, the most salient and polarizing themes were socioeconomic. The key issues of the discussion were automation's role in job displacement, minimum wage policy, and economic inequality. This discussion, as will be shown, had a clear political narrative framing. While

overly simplistic, for the sake of this analysis, these camps will be broken down into a liberal-leaning and conservative-leaning narrative frame based purely on the key actors in each group. These two groups understand the impact and underlying cause of automation differently.

The messaging within the liberal-leaning camp has a clear differentiation before and after the COVID-19 pandemic and the 2020 Election. Before the 2020 Presidential Election, much of the discourse was related to the fight for a $15 minimum wage and the movement for a universal basic income (UBI) as a solution to the inevitable proliferation of automation. Andrew Yang further popularized this movement, becoming something of a figurehead for it in his 2020 presidential bid.

However, this messaging largely subsided in the wake of Joe Biden's accession to the presidency. Post-pandemic effects only exacerbated an already strained restaurant labor supply. However, much of the left-leaning discussion of food automation argued that labor shortages were caused by poor pay, corporate greed, and treatment of workers, see Figure 18. This permeated some discussion about regulatory protection of workers in the case of delivery.

The food automation discourse strongly permeated conservative media circles. Some of the most prolific conservative influencers and media outlets posted about it, with a large amount of engagement signaling its salience as an issue (Figure 19). The conservative-leaning discourse has a few threads. There is a reactionary thread that blames increasing automation in food services on an increased minimum wage in states such as California. However, within this discourse, there is a divide between those who welcome and those who oppose food automation. Yet, most of the discourse does seem to generally consider increased automation negatively.

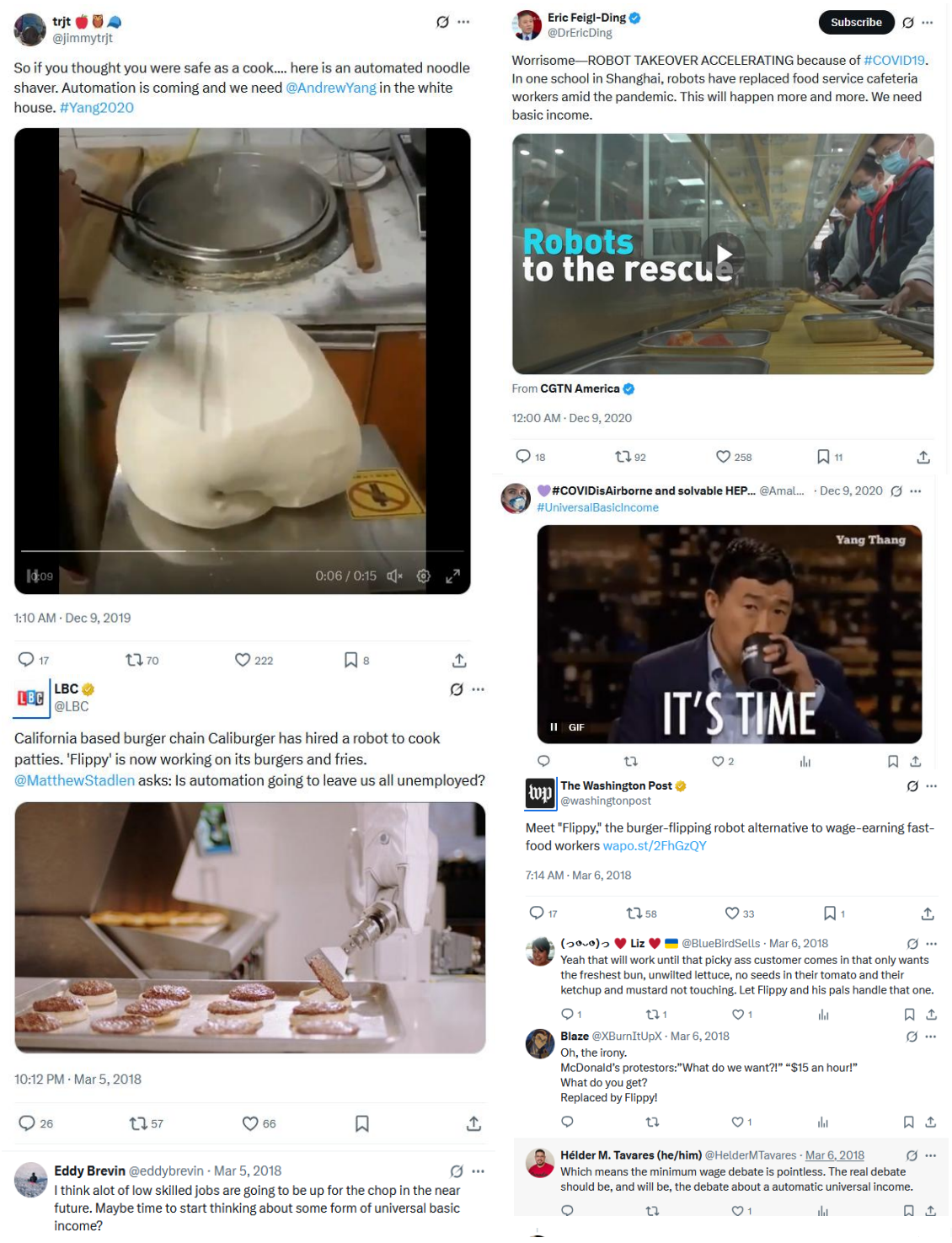

Figure 17. The political salience of Universal Basic Income as an optimistic message to address food automation, much of which is centered around Andrew Yang's presidential bid.

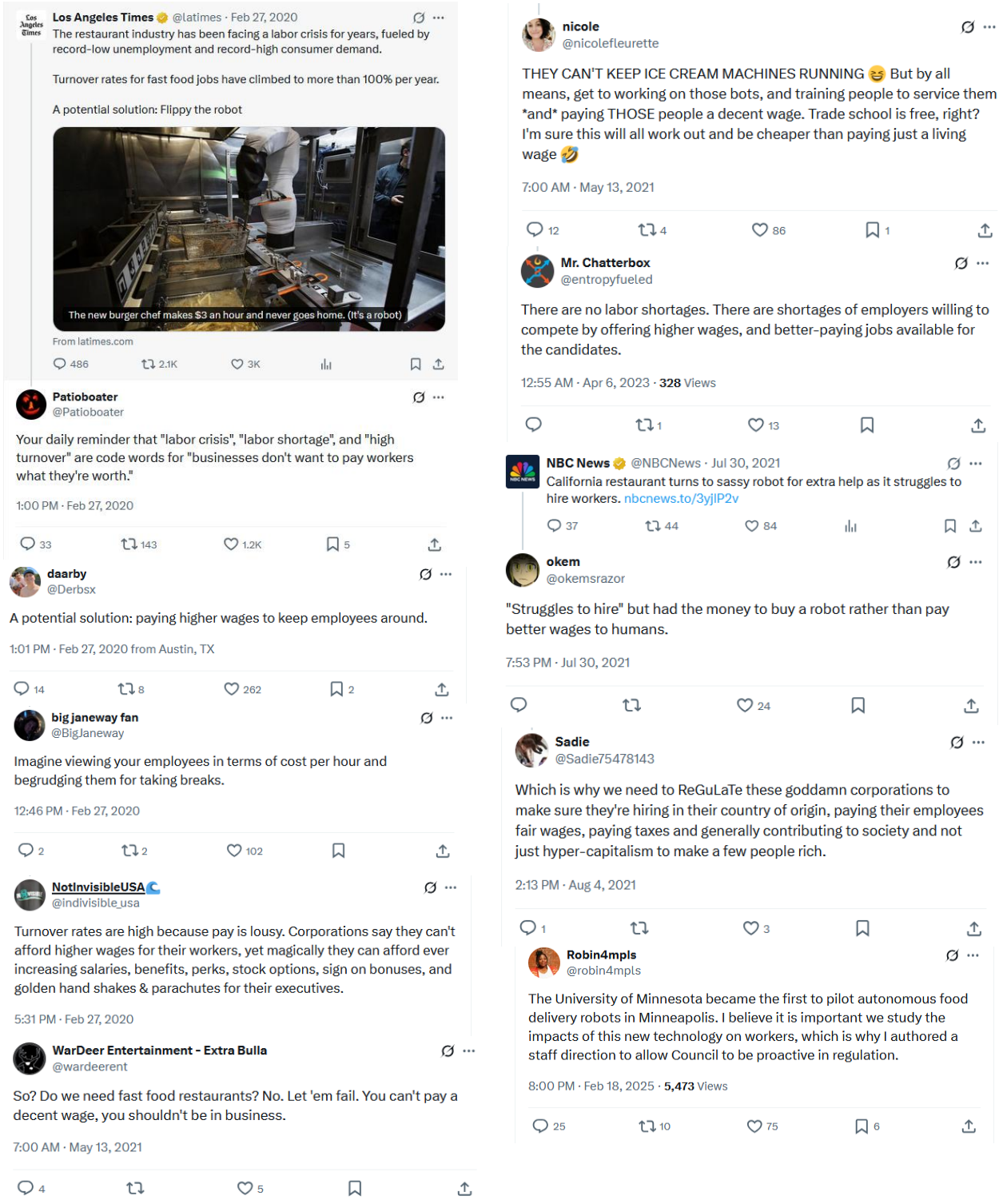

Figure 18. Sample of left-leaning Twitter discourse in the wake of the 2020 Presidential Election.

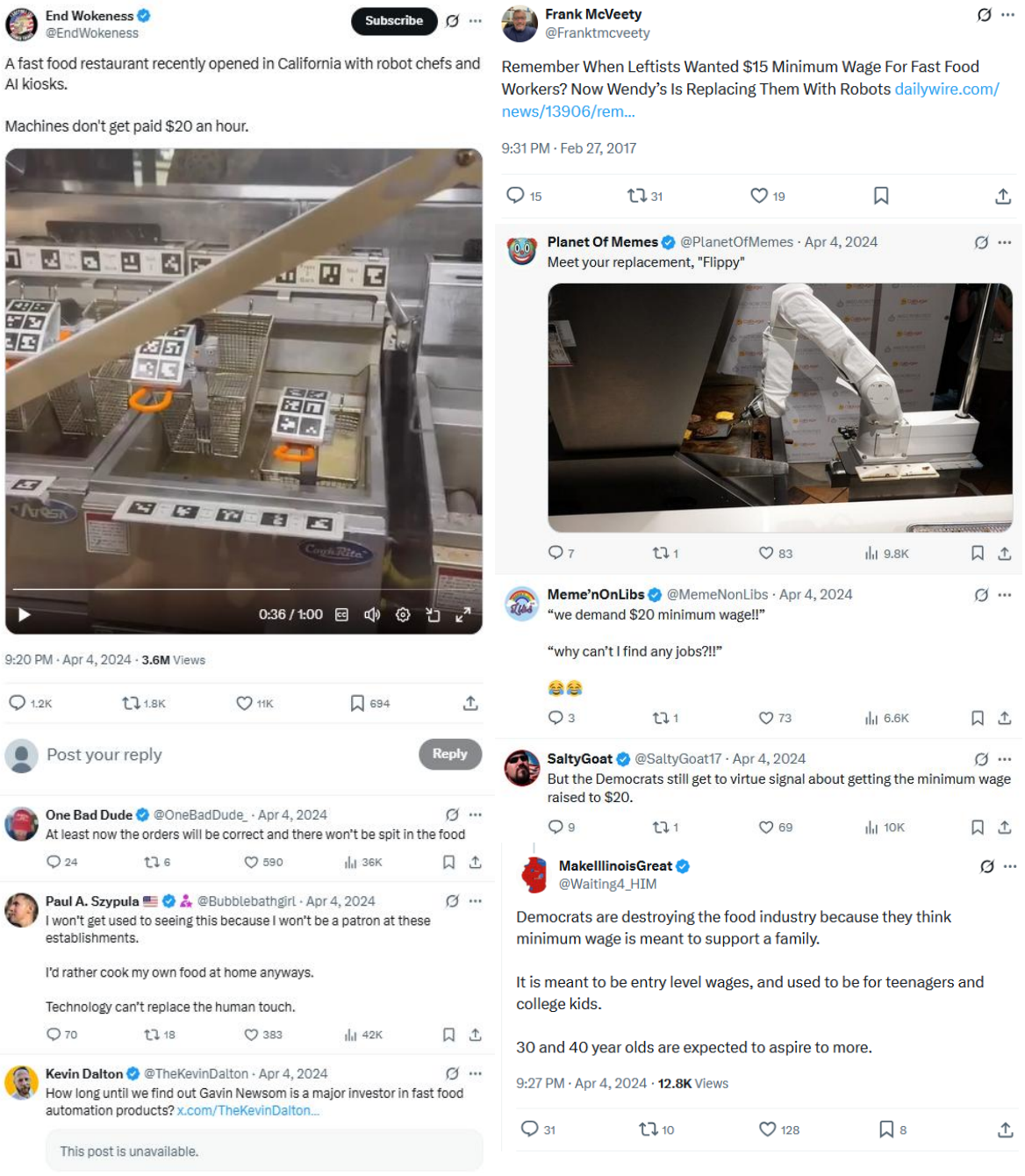

Figure 19. Salience of minimum wage policy grievance in the discussion of food automation among conservative media circles.

Within the anti-automation conservative camp, among the most impactful issues was the already discussed loss of humanity in food service. Much of the previous discussion was pulled directly from replies to and posts within these conservative media circles. Another faction within

the discourse negatively regards food automation, as they regard entry-level food service jobs as a pivotal steppingstone for youth. Yet another health-focused faction takes issue with automation as it is perceived as processed and unnatural. Darker, are groups that see automation itself as threatening to create a "useless class" or to usher in mass poverty (Figure 20 and Figure 21)**.** These groups are important to consider as their oppositional views on automation very well could be translated into practice. For instance, a group that considers food automation to be an existential threat to social order could not only boycott, precipitate regulatory action, but also escalate to destructive measures.

While the issues with food robotics are notable, it's worth considering the aspects of successful robotics technologies. In some of the discourse comprised solutions were considered which may shed insight into where and how these technologies could be accepted. For instance, robots that were perceived as cute, especially delivery robots and service robots, were better received. Some common design choices in these were fake eyes on delivery robots, and animated cat faces on service robots. Also common in cute design were smaller robots and colors such as pink.

Novelty and cultivated experiences were also common in positive discussions. Many of these well-received posts were of people's first experiences with delivery robots and service robots. Kids were brought up repeatedly enjoying food service robots in restaurants. Restaurants that made their robots a part of the theme also tended to receive positive engagement, as the automation became part of a wider aesthetic and experience. This contrasts with some of the most negative content, which was focused on well-known chains such as Denny's, McDonald's, and Wendy's, replacing humans with automation.

Figure 20. Sample conservative-leaning tweets about food automation. Note replies raise issues such as a changing labor market and fears of replacement by migrant workers.

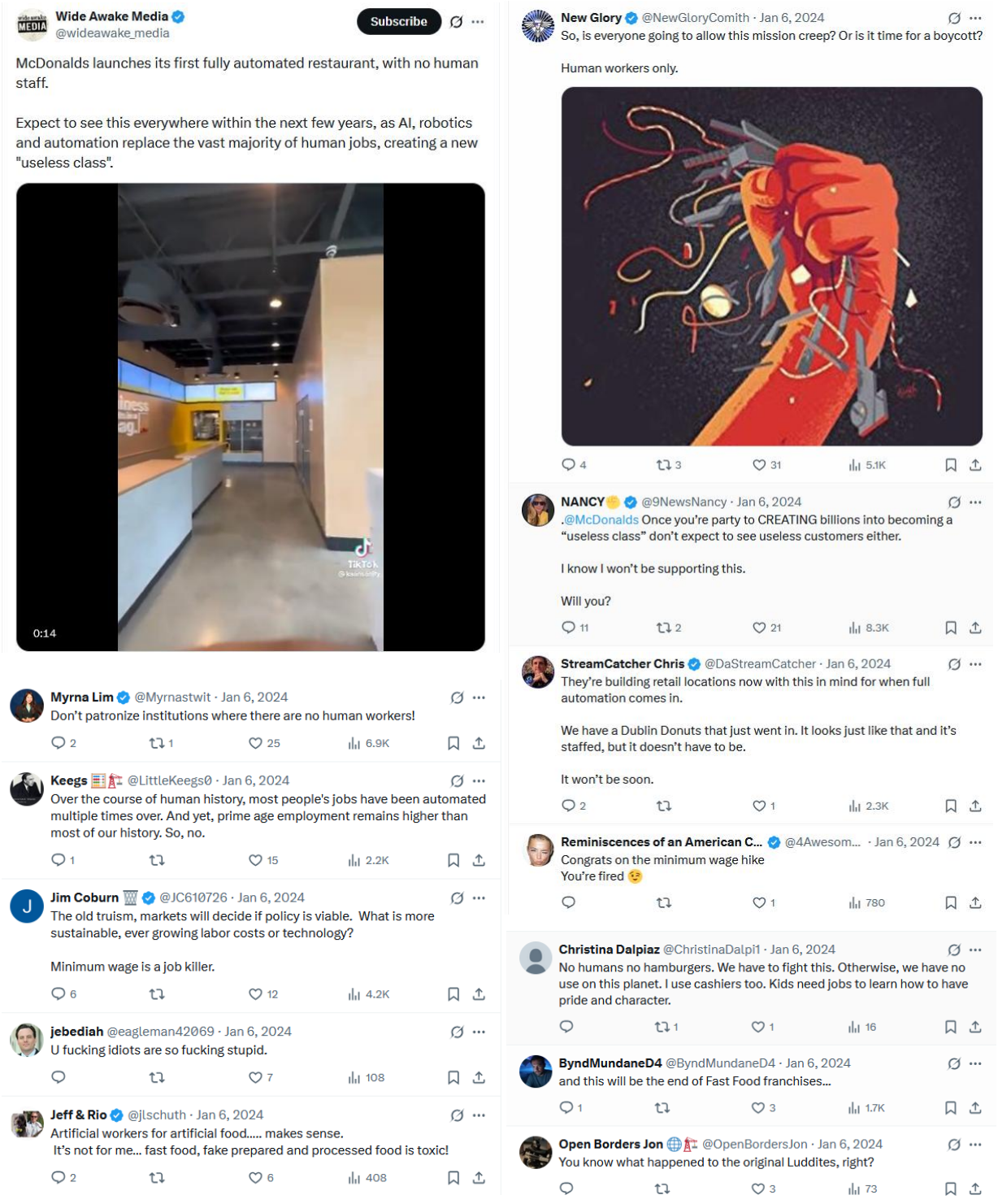

Figure 21. Conservative-leaning tweets, some of which actively signal resistance to human-replacement in the food service industry, while others denigrate these posters as Luddites. Note that the resistance messaging tends to garner more positive engagement.

Perhaps familiarity and comfort are an important part of robot acceptance, as people are less willing to allow change in areas that they are familiar with and more willing to give the benefit of the doubt in restaurants that make automation part of a novel and cultivated experience. Generally, the setting matters. There was a consensus among most of the discussion that quick-service applications were generally more amenable to automation. In Japan, some cafes introduced servers teleoperated by people with disabilities, which was among the most well-received discussions, see Figure 22.

Figure 22. Sample of tweets with positive reception of food robotics. For instance, service robot teleoperated by disabled workers. Others mention the joy of novelty in the dining experience and added convenience.

Discussion

Once a novelty, automation in the food industry now seems like an inevitability. The market for these robots has grown dramatically in the past decade, a trend that's only expected to continue. This was certainly accelerated by the COVID-19 pandemic, which not only directly wiped out restaurants during shutdown, but was followed by a great resignation, labor shortage, and inflation. While the practical incentives have certainly realigned, causing over a third of restaurant operators interviewed to reconsider automation. Customer and employee acceptance will play a key role in mediating this trend of automation (McCarron, 2024; Ngo, 2025).

This research sought to identify how the social context of robotics has changed during the last decade, and to understand the technological and social changes made in the last decade. A dataset of approximately 1,106 tweets and 38,735 replies posted in the last decade containing keywords related to food robotics was harvested. LLM-aided text classification was performed to identify key social groups, themes, issues, and sentiment to perform a Social Constructivist analysis of food robotics technology. While this approach was able to identify a broad trend of negativity and identify key issues, it lacked depth and specificity. However, by augmenting this analysis with a qualitative analysis of the most influential posts, several key actors and issues became clear.

Overall, several conclusions may be drawn from the Twitter discourse. In general, delivery robots face different problems from their service and cooking counterparts (RQ3). The main concerns with service and cooking robots tend to focus on the human elements of these technologies, from the loss of interpersonal interaction and human expression to a feeling of job loss and human replacement more broadly. Meanwhile, many of the issues facing delivery robots are more practical, such as mediating shared community spaces, vandalism, and safety (RQ1).

There does appear to have been a shift over time (RQ2) in issues of public safety as the issue changed from positive COVID-19 applications to sanitation and shared community spaces. Economic issues have also evolved with time. The most engaged content generally shifted from politically left-leaning to right-leaning. So too did the contextual understanding within these political frames. Popular discussion of an optimistic technological argument in the form of a universal basic income that embraces automation as a liberating force, shifted into a grievance-based argument that labor shortages—and the automation that is used to address them—are a symptom of corporate greed, poor compensation, and wider economic inequality. The values here tend to focus on empathy with workers and the human elements of food.

The discourse in conservative-leaning circles is similarly rooted in grievance. While much of the discussion faulted democratic policy, such as increased minimum wage, there is a deeper perception of automation as a disruptive force. The values emphasized tend to be rooted in preserving an existing social order. Again, there was a value placed on the human and natural aspects of food. However, many also lamented the loss of entry-level service jobs as these jobs were considered an important steppingstone for young people. The last, and most concerning, conservative subculture considers automation itself as threatening the current social order, with fears of creating a "useless class", ushering in mass poverty, or dehumanization altogether.

These results are important because they may be early warning signs about the limits of automation. To quote Michael Giebelhausen, a professor at Clemson University studying technology in hospitality: "We should be thinking about not what jobs robots will take, but what jobs consumers will allow robots to do." (McCarron, 2024). Food automation so far has moved rapidly, yet as it entangles itself in society, this fast adoption will encounter both practical and social challenges. Delivery robots were able to deploy quickly into municipalities without

existing legislation to regulate their use. This echoes the rapid mass deployment of electric scooters. While tech companies can "move fast and break things," eventually, regulatory and practical challenges catch up. In the case of rental scooters, many municipalities later adopted wholesale bans. For delivery robots, food safety carries with it higher regulatory scrutiny and greater public sensitivity. Just the perception that food robots may be unsafe is sufficient to dissuade hesitant consumers entirely. And in the Twitter results, there was a real concern that food robots will face tampering or be misappropriated by criminals.

The success of restaurants is heavily entwined with the environment they foster. The results show that human elements in service can add value to that experience. Restaurants that had fully replaced human service were described as 'cold' or 'empty'. However, some that augmented human waiters with robotic food runners were more accepted. The most negatively received application was clearly in cooking. Cooking automation was seen as decoupling food from creativity, culture, and human expression. Many users expressed that removing the 'love' and 'passion' from cooking defeats the entire point of eating out. This is parallel to the feeling that automation has gone too far; a belief that automation should only replace the banal, not the artistic and cultural.

The food industry has an economic incentive to pursue food automation as the supply of inexpensive labor dwindles. However, the results clearly show a growing feeling of economic grievance across political ideology concerning automation and feelings of technological overreach. While the precise values differ between left-leaning and right-leaning narratives, growing disdain with automation could very well have a concrete effect on food robotics technology. Movements that see food automation as an inherent threat to social order, or

humanity itself, very well could escalate into political movements that affect regulatory changes, boycotts, or even widespread vandalism.

To see how economic grievance can fester into action, consider the recent tariffs of the Trump administration. Such industrial policy was once unthinkable in the United States, which has long been aggressively pro-business in its regulatory policy. But this shift was rooted in years of sustained deindustrialization and offshoring of heavy industry in the United States. This created a politics of economic grievance in America, especially in the 'rust belt' with its loss of automotive and steel manufacturing. A direct line can be drawn between this brewing economic grievance politics and the rise of Trump's protectionist policy and desire to rekindle heavy industry in the United States. Businesses once considered the offshoring of industry from the United States to be inevitable and without consequence. Now it seems that offshoring has been replaced by automation. This makes this research's findings of anti-automation grievances across the political spectrum potentially troubling in the long term. Therefore, it will be important for stakeholders in food robotics to consider the social and political effects of automation.

Limitations and Future Work

The results considered have two obvious limitations. The first is an inherent bias in the type of user active on Twitter. While Twitter data can provide a useful reflection on public sentiment, its users tend to be both highly engaged and politically polarized. These results may then only reflect the extreme perceptions of food automation technology. Perhaps these technologies could thrive in an ideological middle ground that was lost in this discussion.

Regarding the use of language models, this work was limited to using GPT-40-mini, against best academic practice that suggests open-source models are preferable for collaboration

and replicability. While GPT was overall quite effective at broad classifications, one of its weakest limitations was the inability to analyze non-text media. Twitter as a platform makes heavy use of visuals such as reaction GIFs and video content. In a few instances, this led to misclassification of tweets, for instance, see the tweet in Figure 23, which GPT mislabeled as a positive customer experience. However, with the added context of the video, this is clearly sarcasm as the man is seen stealing a service robot from the restaurant. So, the quantitative results of this study should be considered as having some error due to missing media context.

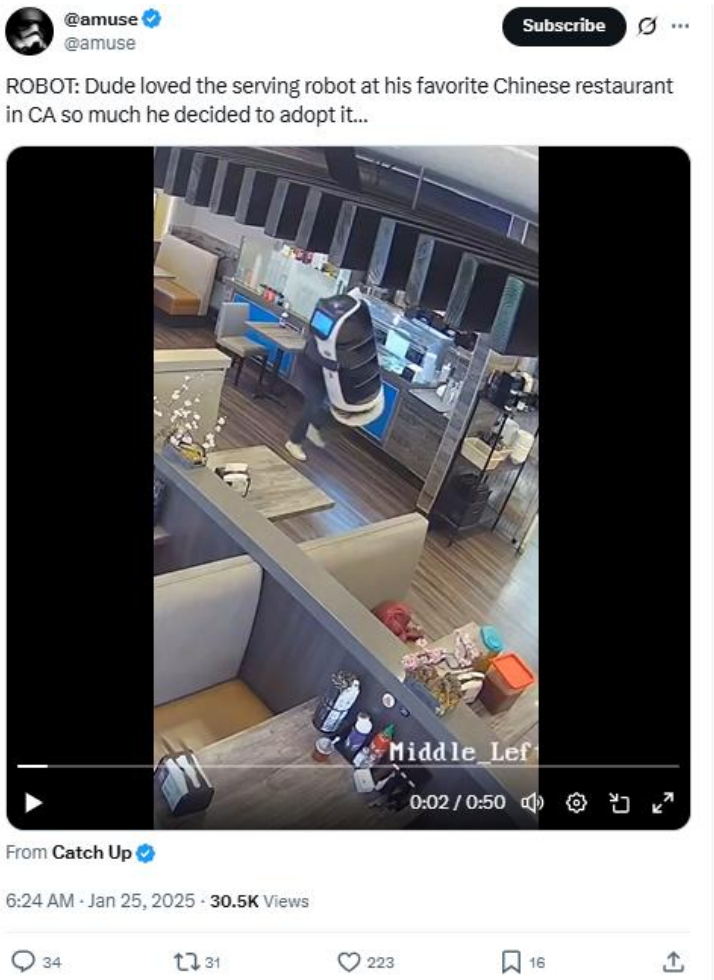

Figure 23. Example of mislabeled Tweet. The text content appears to have a positive tone, which GPT labeled as a positive sentiment in “Customer Experience”. With added context the caption is sarcastic as the video shows a man stealing a service robot.

Additionally, anonymous platforms such as Twitter are ill-suited to identify stakeholders. While an initial attempt was made to do such an analysis, classifications were highly inaccurate as GPT tended to hallucinate meaningless social groups and delineations. Further research could consider adopting similar methods to study other sources of public data. For instance, by studying recorded local government meetings to understand the regulatory role in mediating technology (see Barari & Simko, 2023). Another potential avenue is an analysis of news coverage, which was excluded from this study due to copyright concerns with using a proprietary language model.

Professional Takeaway

This research emphasizes the importance of balance in engineering design. While it may be tempting to think of progress as a linear march, it is rarely so simple. More technology may not always be, or may not be perceived as, necessarily a force for good. In design as an engineer, we must be aware of the social context in which we are embedding technology. This social context can warp even the noblest intentions into lasting harm. For instance, the misappropriation of delivery robots for terror or crime. We should also consider what type of society we want to construct. Automation that replaces human and cultural expression in food and art may leave behind a duller future. Therefore, in my future professional development, I will approach automation and other disruptive technologies with healthy caution.

Conclusions

Food automation is certainly here to stay in one sense or another. However, by analyzing a decade of Twitter discourse, this research shows that the form this ultimately settles into is still a very open question. While there is every incentive for businesses to consider automating, they will need to be cautiously aware of what customers, localities, and society more broadly are willing to accept. There are also practical challenges, such as vandalism and food safety, that will need to be carefully considered and mediated. In some ways, these problems can be addressed with careful design, deployment, and regulatory cooperation. By making robots anthropomorphic and cute, they have already won over some favor. Yet it is just as important to strategically deploy automation so that it is seen as a tool, rather than a replacement. Designers will need to mediate with consumers to establish what is seen as too far for automation: are diners willing to accept food cooked without the 'love' of a human hand? An intrusion into artistic and cultural expression? Can a robot server fill the void of human service? Businesses and engineers must be aware of the potential for social backlash and politics of economic grievance that are coupled with job displacement, lest they brew into a wider resistance to food automation. All things considered, we have every reason to be optimistic about the future of food automation, but we should also all question the type of society that we are using it to build.

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Appendix

Appendix A

Relevance Prompting

You are a social science researcher studying how various social groups perceive robotics specifically in the food industry (i.e., robots that cook, serve customers, or deliver food). As an expert annotator, your role is to analyze tweets to determine if they are relevant to the study of food-related robotics and automation.

A tweet is relevant if it explicitly mentions or strongly implies the use of robots in food preparation, food service, or food delivery. Tweets about general delivery robots (e.g., FedEx package bots) or robots in non-food industries are not relevant unless there is a clear food-related context.

Please classify the following tweet in the following JSON format,

```
{
  "relevance": "1/2/3/4/5"
}
```

Classification Options:

1 - Completely irrelevant (no connection to food or robots).
2 - Very minor relevance (mentions food or robots, but not in a relevant context).
3 - Low relevance (vaguely related, but not specific to food robotics).
4 - High relevance (mentions robots in a food-related context, but not directly focused on food service).
5 - Fully relevant (direct, detailed discussion of food-related robotics with significant context).

Remember to prioritize accuracy and clarity in your analysis, using the provided context and your expertise to guide your evaluation.

Twitter Message: [POSTER]:[TWITTER_MESSAGE]

Answer:

Appendix B
Unstructured Classifications

You are a social science researcher studying how various social groups perceive robotics specifically in the food industry (i.e., robots that cook, serve customers, or deliver food). As an expert annotator, your role is to identify the relevant social actors, their sentiment towards the technology, and key themes in the discourse around the technology.
In the following, you will be given a dated tweet as well as all of its replies. Your task is to identify the key social groups and issues related to the technology of robotics in food service.
Provide your classification in the following JSON format:

```
{
   "technology_type": {
      "result": ["cooking, "preparation", "service", "home-use", "delivery", "other"],
      "explanation": "A brief explanation for your classification"
   },
   "themes_and_issues": {
      "result": ["list", "of", "key", "phrases"],
      "explain": "A brief explanation for your classification"
   },
   "social_groups": {
      "result": ["list", "of", "social", "groups"],
      "explain": "A brief explanation for your classification"
   },
   "is_relevant": {
      "result": "yes/no",
      "explain": "A brief explanation of why the tweet is relevant or not relevant to the real-world application of robotics in food service."
   }
}
```

Example Classifications:
- Technology Type: Choose from the predefined categories, or use "other" if no category fits well. Try to choose as few options as strictly relevant wherever possible.
- Themes and Issues: Examples include worker's rights, job loss, public health, economic inequality, accessibility, etc.
- Social Groups: Should refer to those affected by or directly involved with the technology (e.g., restaurant workers, fast food workers, business owners, customers, regulators).
- Relevance: Only include issues that are clearly connected to real-world applications of robotics in food service.

For each category, capture broad social groups while maintaining specificity. Themes and issues should only include **relevant** social concerns surrounding the technology.

[INSERT_TWEETS_AND_REPLIES_HERE]

Appendix C
Structured Categorization

You are a social science researcher studying how various social groups perceive robotics specifically in the food industry (i.e., robots that cook, serve customers, or deliver food). As an expert annotator, your role is to identify the themes and issues in the discourse around the technology.
In the following, you will be given a dated tweet as well as all of its replies. Your task is to identify the key social groups and issues related to the technology of robotics in food service.
Provide your classification in the following JSON format:

```
{
   "technology_type": ["cooking, "preparation", "service", "home-use", "delivery", "other"],
   "themes_and_issues": ["list", "of", "key", "themes"],
   "is_relevant": {
      "result": "yes/no",
      "explain": "A brief explanation of why"
   }
}
```

Classification Categories:
- **Technology Type**: Choose from one of the given options or select "other" if none well describe the technology.
- **Themes and Issues**: Choose from the following list of themes and issues:
Tipping Culture, Minimum Wage Increases, Artistic and Creative Expression, Human and Social Interaction, Affordability, Efficiency, Food Quality, Labor Shortages, Public Health and Safety, Job Loss, Distrust of Technology and Authority, Worker's Rights, Customer Experience, Economic Inequality, Crime Theft and Vandalism, Technological Reliability, Cuteness, Creepiness, Dystopian Themes, Social Justice and Inclusivity, Traditionalism, Cultural and Regional Differences, Innovation and Progress, Policy and Regulation, Sustainability, Autonomy and Laziness, Political Ideology
- **Is Relevant**: Is the tweet relevant or not relevant to the real-world application of robotics in food service? Yes or no.

Try to be as specific as possible and select themes only when relevant.

[INSERT_TWEETS_AND_REPLIES_HERE]

Appendix D.
Reply Theme & Sentiment Analysis

You are a social science researcher studying how various social groups perceive robotics specifically in the food industry (i.e., robots that cook, serve customers, or deliver food). As an expert annotator, your role is to identify the relevant social actors, their sentiment towards the technology, and key themes in the discourse around the technology.
In the following, you will be given a tweet as well as a single reply to that tweet, which you will classify in the following JSON format:

```
{
   "overall_sentiment": "Positive/Negative/Neutral",
   "themes_and_issues": "theme from list below"
}
```

Overall Sentiment:
-Refers to the sentiment of the reply in reference to the food technology
Themes and Issues:
-Identify the theme that best relates to the sentiment of the reply from the following list: Tipping Culture, Minimum Wage Increases, Artistic and Creative Expression, Human and Social Interaction, Affordability, Efficiency, Food Quality, Labor Shortages, Public Health and Safety, Job Loss, Distrust of Technology and Authority, Worker's Rights, Customer Experience, Economic Inequality, Crime Theft and Vandalism, Technological Reliability, Cuteness, Creepiness, Dystopian Themes, Social Justice and Inclusivity, Traditionalism, Cultural and Regional Differences, Innovation and Progress, Policy and Regulation, Sustainability, Autonomy and Laziness, Political Ideology
-For instance, a negative sentiment discussing robots replacing workers could be identified as "job loss", whereas a positive sentiment discussing cheaper labor could be categorized as "efficiency".
Note: Themes can draw from the original tweet for context, especially if the reply references or responds to it.

Original Tweet (TWEET_DATE): [INSERT_TWEET_HERE]

Reply: [INSERT_REPLY_HERE]

Appendix E
Tweet Theme & Sentiment Analysis

You are a social science researcher studying how various social groups perceive robotics specifically in the food industry (i.e., robots that cook, serve customers, or deliver food). As an expert annotator, your role is to identify the relevant social actors, their sentiment towards the technology, and key themes in the discourse around the technology.
In the following, you will be given a tweet which you will classify in the following JSON format:

```
{
   "overall_sentiment": "Positive/Negative/Neutral",
   "themes_and_issues": "theme from list below"
}
```

Overall Sentiment:
-Refers to the sentiment of the tweet in reference to the food technology

Themes and Issues:
-Identify the theme that best relates to the sentiment of the reply from the following list:
Tipping Culture, Minimum Wage Increases, Artistic and Creative Expression, Human and Social Interaction, Affordability, Efficiency, Food Quality, Labor Shortages, Public Health and Safety, Job Loss, Distrust of Technology and Authority, Worker's Rights, Customer Experience, Economic Inequality, Crime Theft and Vandalism, Technological Reliability, Cuteness, Creepiness, Dystopian Themes, Social Justice and Inclusivitiy, Traditionalism, Cultural and Regional Differences, Innovation and Progress, Policy and Regulation, Sustainability, Autonomy and Laziness, Political Ideology

-For instance a negative sentiment discussing robots replacing workers could be identified as "job loss", whereas a positive sentiment
discussing cheaper labor could be categorized as "efficiency".

Original Tweet (TWEET_DATE): [INSERT_TWEET_HERE]

Appendix F
Tweet Technology Reclassification

As an expert annotator, your role is to classify food robot technologies mentioned in tweets. Classify each tweet in the following JSON format:

```
{
   "technology_type": ["cooking", "service", "home-use", "delivery", "bar", "generic", "other"],
   "explanation": "A *very* brief explanation for your Classification"
}
```

Cooking: Refers to a robot that cooks, prepares, or assembles a meal. These are often referred to as 'chef' robots.
Examples: Miso Robotics' Flippy (automated frying), Sweetgreen's Infinite Kitchen (automated salad assembly).
Service: Refers to a robot in a customer-facing role designed to replace a formerly human service role.
Examples: Robot waiters, bussers, food runners, and hosts. Example: Bear Robotics' Servi (robot waiter).
Delivery: Refers to a robot designed to transport food to customers, via last-mile delivery and *NOT* in a restaurant (that is service).
Example: Starship Technologies' autonomous delivery bots.
Bar: Refers to a robotic bartender.
Example: Cecilia.ai (automated cocktail mixing robot)
Home-use: Any form of robot primarily intended for personal home use rather than commercial applications.
Generic: Use this category if the tweet discusses food robotics in general without specifying a particular type.
Other: Anything that does not fit into the categories above, such as agricultural robots.
Classification Guidelines:
Select only one category whenever possible.
If the tweet explicitly mentions multiple distinct technologies (e.g., a delivery robot bringing food to an automated kitchen), assign multiple labels.
Avoid selecting extra categories if they are only implied or vaguely referenced.
Note: Select only one category whenever possible. If the tweet explicitly mentions multiple distinct technologies (e.g., a delivery robot bringing food to an automated kitchen), assign multiple labels. Avoid selecting extra categories if they are only implied or vaguely referenced.
Original Tweet (TWEET_DATE): [INSERT_TWEET_HERE]

Appendix G
Extended Methodology

Within a single discussion unit sentiment was calculated in the following manner. This engagement, which will be referred to as 'mass', is calculated as the sum of likes and retweets. The 'charge' of a post is either -1, 0, or 1 based on whether the post is negative, neutral, or positive. The overall sentiment, S_i, for each discussion was calculated:

$$S_i = \frac{\sum_{replies} 1 + m_i * q_i}{\sum_{replies} 1 + m_i}$$

Which effectively represents the ratio of positivity to total engagement as q_i is one in magnitude but signed.