How Platform Workers Contest Algorithmic Management: Theorizing the Dynamics of Algoactivistic Practices

—Online Appendices—

Online Appendix A: Overview of Key Studies

Study	**Focus**	**Key findings (in relation to algoactivism)**
Cameron (2024)	…elucidates how algorithmic management (AM) manufactures worker consent through constant, confined choices.	Ride-hailing drivers respond to AM with two types of tactics: engagement tactics (e.g., following algorithmic nudges) and deviance tactics (e.g., manipulating input data). Although deviance resembles resistance, both tactics foster a sense of agency and skill that aligns drivers with platform objectives. It is implicitly assumed that the identified deviance tactics are uniformly accessible across drivers and broadly oriented toward the platform's AM system.
Cameron & Rahman (2022)	…analyze how algorithmically mediated customer control on online labor platforms (OLPs) restructures the labor process and redistributes opportunities for resistance.	Temporally structured tactics of worker resistance emerge across the labor process, including shaping customer interactions, soliciting favorable ratings, and preemptively managing algorithmic signals. As workers' degree of control gradually decreases, their resistance shifts toward subtler tactics such as constrained compliance and input manipulation. Resistance practices are treated as largely reactive responses, framing them as a means of pushing back against structural constraints and regaining autonomy under conditions of precarity.
Curchod et al. (2020)	…investigate how customer evaluation systems generate power asymmetries and shape worker agency in online work settings.	Worker resistance takes the form of gaming metrics, managing visibility, selectively engaging customers, exploiting practical knowledge of ranking algorithms, or using online forums to coordinate collective responses. These tactics are framed as reactive efforts to counter algorithmic evaluation and customer dominance by restoring a measure of control and autonomy.
Kellogg et al. (2020)	…synthesize interdisciplinary research to theorize algorithmic control/management as a new contested terrain of work and derive a framework of six control mechanisms ("6R").	Algoactivism is broadly defined as various forms of worker resistance, ranging from "individual practical action to platform organizing, discursive framing, and legal mobilization" (p. 368). These forms arise in response to algorithmic direction, evaluation, and discipline and are portrayed as targeting organizational AM systems in general. Still, the authors indicate that algoactivistic practices unfold across multiple, interlinked 'arenas' (e.g., organizational and legal/regulatory ones).

McDaid et al. (2023)	…interrogate how Uber drivers engage with AM through the politics of demand and processes of self-formation.	Resistance to AM manifests through enduring, subverting, and exiting platform control. Subversion includes selectively rejecting rides, gaming surge pricing, and bending platform rules, while exit functions as refusal through disengagement. The identified strategies are implicitly framed as oriented toward the AM system in general and are treated as uniformly accessible to drivers, with resistance operating through processes of self-formation rather than collective challenge.
Meijerink & Bondarouk (2023)	…develop a conceptual framework to explain the duality and recursivity of AM in shaping autonomy and value.	Algoactivism involves novel resistance practices such as data obfuscation and non-cooperation. These practices are framed as reactive responses to workers' perceptions of constrained autonomy and value extraction and as generally directed toward contesting the AM system. Algoactivistic practices may, in turn, prompt the redesign of AM systems as part of a recursive cycle.
Möhlmann et al. (2021)	…explore the nature of work on OLPs and the role of AM in organizing such work.	Consisting of algorithmic matching and control, AM creates several tensions (in terms of work execution, work compensation, and work belonging). These tensions trigger market-like (i.e., bypassing and switching) or organization-like (i.e., striking and embracing) responses from platform workers, which are fed back into the OLP's AM system.
Rahman (2021)	…theorizes how platform workers react to opaque algorithmic evaluations under conditions of uncertainty.	Workers experience the evaluation algorithm as a form of control, but are unable to align their behavior with its ambiguous criteria. They react differently to this situation (experimenting vs. constraining). Their reactivity varies with their level of success on the platform, their dependence on the work, and their experience of setbacks. Worker responses are framed as defensive reactions to opacity, which undermines coordinated resistance.
Weber et al. (2025)	…identify how food delivery workers cope with perceived threats posed by AM.	Distinct coping tactics include collective meaning-making and emotional support, technically savvy algorithm manipulation, denial and disengagement, and over-adaptive compliance. Proactive tactics foster resilience and agency, whereas reactive tactics contribute to emotional exhaustion and withdrawal. Algoactivism is reconceptualized to include both reactive pushback and proactive coping.

Online Appendix B: Data Collection

This appendix provides additional details on the data collection procedures and sampling strategy underlying the multiple empirical sources used in this study, including forum posts, interviews, a discussion panel, vlog entries, press releases, news articles, and app release notes. Figure B1 summarizes the data collection waves and corresponding analytical steps.

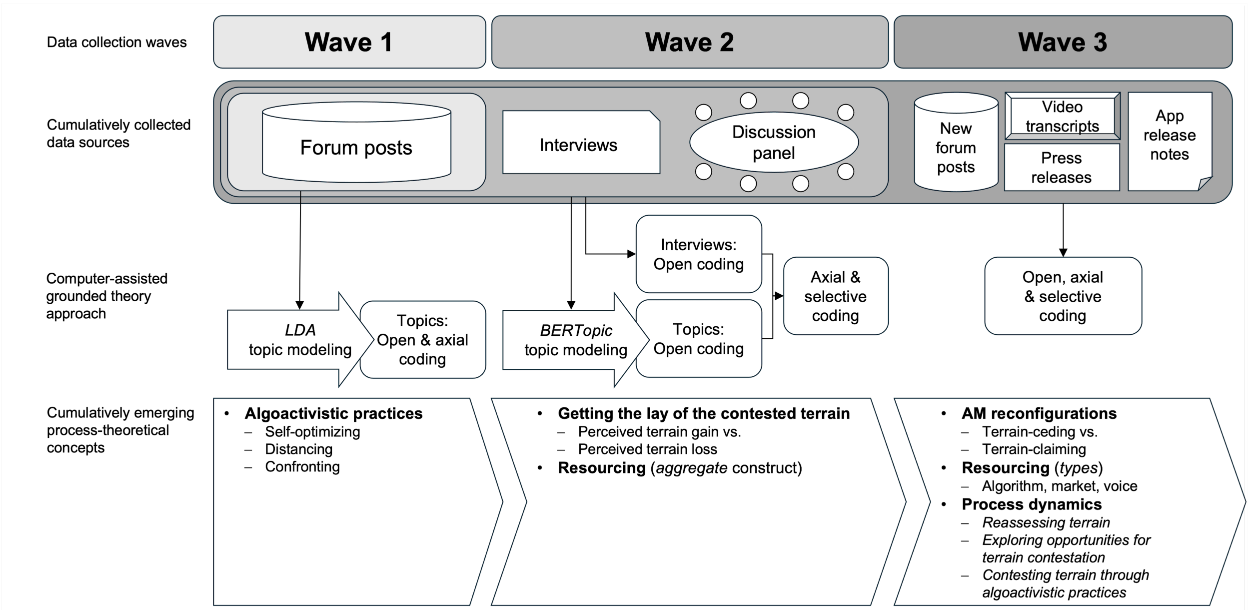

Figure B1. Data collection waves and analytical steps

Forum posts: We collected two complementary sets of forum data from *Uberpeople.net*, a large peer-to-peer discussion forum described as "a forum community dedicated to Uber drivers and enthusiasts" (Uber-People 2023). These datasets were gathered across two waves consistent with the iterative logic of computer-assisted grounded theory (Miranda et al. 2022).

First, during wave 1, we assembled a large corpus of posts from subforums whose thematic focus suggested relevance for understanding drivers' experiences with AM. Subforums unrelated to AM (e.g., *Insurance* and *Tax*) were excluded. In August 2021, we scraped all posts from the *Advice*, *Advocacy*, *Complaints*, *Notifications*, *Quit*, *Ratings*, *Stories*, and *Technology* subforums using the Python library *BeautifulSoup* (Debortoli et al. 2016). This resulted in approximately 980,000 forum posts covering the period from January 2015 to August 2021. These posts subsequently served as input for topic modeling, which functioned as a form of pre-analytic computational scaffolding in wave 1 and generated heuristically valuable entry points for subsequent qualitative coding.

Second, consistent with our iterative sampling logic, we later collected posts from local subforums (e.g., San Francisco and Los Angeles & Orange County) after observing geographic variation in discussions of AM-related app changes. Because most evidence of AM reconfigurations in our other empirical materials (see below) pertained to the U.S., we focused on U.S.-based subforums. Between April and September 2023, we manually collected approximately 200 forum posts in which local drivers discussed specific changes to the Uber driver app, including update notifications, new features, and algorithmic adjustments. These posts were incorporated into wave 3 to support our analysis of how drivers perceived and interpreted AM reconfigurations over time.

Interviews and discussion panel: To deepen our understanding of why and under what conditions drivers engage in different forms of algoactivism, we conducted semi-structured interviews with U.S.-based Uber drivers in wave 2. Participants were recruited through outreach on *Uberpeople.net*, direct contact with driver advocacy organizations such as *Rideshare Drivers United* (2024), and participant-driven snowball sampling. This recruitment strategy enabled us to access drivers with diverse tenures, geographic locations, and experiences with AM.

At the beginning of each interview, we collected contextual background information, including participants' driving histories and motivations for engaging in platform work. We then explored how drivers experienced and responded to Uber's algorithmic instructions and constraints. Consistent with grounded theory principles, we engaged in theoretical sampling (Corbin & Strauss 1990), iterating between data collection and preliminary analysis. As new themes emerged, we refined the interview guide—for example, adding questions about drivers' perceptions of how Uber reconfigured its AM system over time (see Table B2). We continued interviewing participants until theoretical saturation was reached; that is, until additional interviews no longer generated novel insights (Corbin & Strauss 2015). In total, we conducted 22 semi-structured interviews with 18 drivers (see Table B3 for participant details).

Table B2. Outline of the (refined) interview guide

1. **Background information**
    a. When did you start driving for Uber?
    b. Do you currently drive for Uber? Part-time or full-time?
    c. In what areas and at what times do you typically drive? Why?
    d. Why did you choose to work in ride-hailing?
2. **AM perceptions**
    a. How does Uber use algorithms to affect your work as a driver?
    b. Is there anything you do not like about Uber's use of algorithms?
3. **Algoactivistic practices**
    a. How did you respond to Uber's use of algorithms? What were your goals?
    b. Did your responses change over time? How did they change, and why?
4. **AM reconfigurations**
    a. Since you started driving for Uber, are you aware of any updates to its algorithms? If so, how have they changed?
    b. How did you become aware of these updates?
    c. How have these updates affected you?
    d. How did you respond to them?

Table B3. Overview of interviews

#	Interviewee ID	Tenure as an Uber driver	Full- vs. part-time driver	Interview date	Interview duration
1	1	Since 2016	Part-time	Oct 21, 2021	00:55:17
2	2	Since 2016	Both	Nov 1, 2021	01:22:50
3	3	2017-2019	Part-time	Nov 19, 2021	00:40:14
4	4	Since 2016	Part-time	Nov 22, 2021	00:52:17
5	5	Since 2017	Both	Jan 05, 2022	00:46:19
6	6	2017-2020	Full-time	Jan 06, 2022	00:32:37
7	7	Since 2017	Full-time	Jan 17, 2022	00:52:39
8	8	Since 2017	Part-time	Jan 25, 2022	00:53:35
9	9	Since 2016	Full-time	Jan 27, 2022	00:24:21
10	10	Since 2016	Part-time	Jan 31, 2022	01:23:32
11	11	Since 2016	Both	Feb 1, 2022	00:48:24
12	12	Since 2016	Full-time	Feb 1, 2022	00:38:38
13	13	2014-2021	Full-time	Feb 8, 2022	00:34:01
14	14	2015-2021	Part-time	Feb 9, 2022	00:41:52
15	15	2015-2021	Full-time	Feb 10, 2022	00:51:50

16	16	Since 2018	Both	Feb 14, 2022	00:35:39
17	6	2017-2020	Full-time	Mar 14, 2022	00:50:31
18	11	Since 2016	Both	May 18, 2022	00:40:12
19	10	Since 2016	Part-time	May 19, 2022	00:38:34
20	15	2015-2021	Full-time	May 19, 2022	00:27:47
21	17	Since 2017	Both	Nov 1, 2022	00:54:23
22	18	2018-2019	Full-time	Dec 14, 2022	00:39:47
				Average:	**00:46:33**

To validate emerging insights and ensure that our interpretations resonated with drivers' lived experiences, we organized a one-hour online discussion panel with 15 Uber drivers on September 22, 2022. During the panel, we presented our refined data structure and an early version of the process-theoretical model. Panelists were invited to comment on the accuracy, completeness, and interpretive relevance of our theorization. Their feedback helped us further refine our analysis, particularly regarding how drivers assess the contested terrain, mobilize resources for contestation, and interpret changes in Uber's AM system.

Vlog entries: As part of our effort to unpack how Uber reconfigures its AM system over time, we collected a substantial body of vlog material from U.S.-based ride-hailing drivers in wave 3. These vlog entries typically included screenshots of in-app notifications and update announcements alongside drivers' situated interpretations of AM-related changes. The material provided rich insights into how drivers made sense of and responded to Uber's ongoing AM reconfigurations, often in real time.

We began with *The Rideshare Guy*, one of the most widely followed ride-hailing channels on *YouTube*, featuring approximately 204k subscribers and 4,300 videos (The Rideshare Guy 2025). The channel offers advice to U.S.-based ride-hailing drivers on how to increase their earnings and regularly features interviews with Uber executives, including the Head of Mobility and the CEO. Starting with videos published in 2014, we systematically screened content and employed a snowball sampling strategy to identify related channels (e.g., *Rideshare Professor*, *The Rideshare Hub*). This process yielded 167 scripted *YouTube* videos totaling approximately 23 hours of empirical material.

Press releases/news articles and app release notes: To complement the driver-centered perspective with Uber's official framing of AM reconfigurations, we collected approximately 50 U.S.-published press releases and news articles, including content from the *Uber Newsroom* and the *Uber Blog*, as well as major outlets such as *The Washington Post*. These documents provided insight into how Uber publicly communicated changes to its driver app, including modifications to ride-assignment logics, reward systems, or performance metrics.

In addition, to obtain a systematic record of the evolution of Uber's AM system, we compiled 275 app release notes published between October 2016 and September 2023 using repositories such as iPa4Fun (2024). The release notes enabled us to reconstruct the chronology, frequency, and substantive focus of the OLP's AM reconfiguration efforts. Combined with our other empirical materials, these sources deepened our understanding of how drivers interpret changes to the AM system and mobilize resources to navigate the contested terrain of algorithmically mediated platform work.

Online Appendix C: Topic Modeling

In this appendix, we provide a detailed account of how topic modeling was used within our computer-assisted grounded theory approach (see also Figure B1). Consistent with established principles (Carlsen & Ralund 2022; Nelson 2020), topic modeling served not as a stand-alone analytic method but as a form of pre-analytic scaffolding that supported the iterative development of theoretical insight. Specifically, topic models were employed to surface latent semantic structures within large volumes of unstructured textual data (Kulkarni et al. 2024), thereby helping us identify theoretically meaningful entry points for subsequent inductive coding and interpretive analysis.

To ensure methodological transparency and replicability, we outline the topic modeling procedures employed in waves 1 and 2 of our analysis. These procedures can be organized into four sequential phases:

1. **Data cleansing:** Preparing the raw textual material by removing duplicates, noise, formatting inconsistencies, and irrelevant tokens in line with standard preprocessing procedures for computational text analysis.
2. **Data filtering:** Narrowing the corpus to AM-relevant discourse by applying theoretically informed keyword filters and excluding content unrelated to Uber drivers' contestation practices or experiences with AM.
3. **Model training:** Generating topic structures using Latent Dirichlet Allocation (LDA) in wave 1 and BERTopic in wave 2. These models produced semantically coherent clusters that helped us navigate the large corpus and identify theoretically promising segments for manual coding.
4. **Descriptive insights:** Examining model outputs (e.g., keyword lists, representative posts, and topic coherence patterns) to guide human-driven coding. These outputs were not treated as coded data but rather as heuristic cues that informed where and how to focus subsequent qualitative analysis.

Across waves 1 and 2, topic modeling functioned as an integral component of our computer-assisted analytical process, enabling iterative movement between computational surfacing and interpretive theorizing while preserving sensitivity to emergent grounded-theory dynamics. The following paragraphs provide a detailed account of each phase, including parameter settings, model choices, and illustrative outputs.

Data cleansing: As a first step, we cleansed the 977,833 forum posts collected from theme-based subforums on *Uberpeople.net* (e.g., Debortoli et al. 2016; Hannigan et al. 2019). We began by removing duplicates and missing entries, which reduced the dataset by 28,458 posts. We then removed emoticons, symbols, and pictograms, as well as forum posts containing a "Click to expand..." link, which typically indicated short responses (e.g., "Thanks a lot.") to previous posts. This link appeared in 541,859 posts (see example in Figure C1).

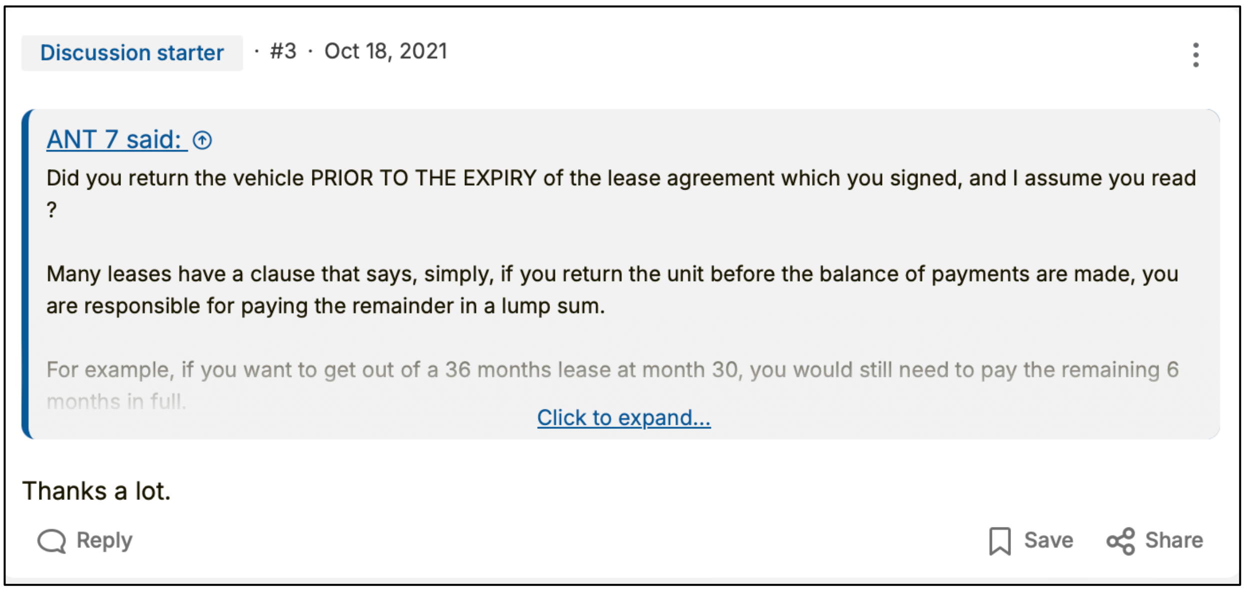

Figure C1: Screenshot of a forum post on *Uberpeople.net* (example)

The cleansed forum posts averaged 265 words in length, with a standard deviation of 380 words and a median of 149 words. Most posts originated from three theme-based subforums: *Advice*, *Complaints*, and *Stories* (see the diagram at the top of Figure C2). Posting activity remained consistently high across these subforums over time (see the graph at the bottom of Figure C2), peaking between 2019 and mid-2020. This surge likely reflects the legal disputes surrounding the employment status of U.S.-based Uber drivers during that period, particularly debates over independent contractor versus employee classification.

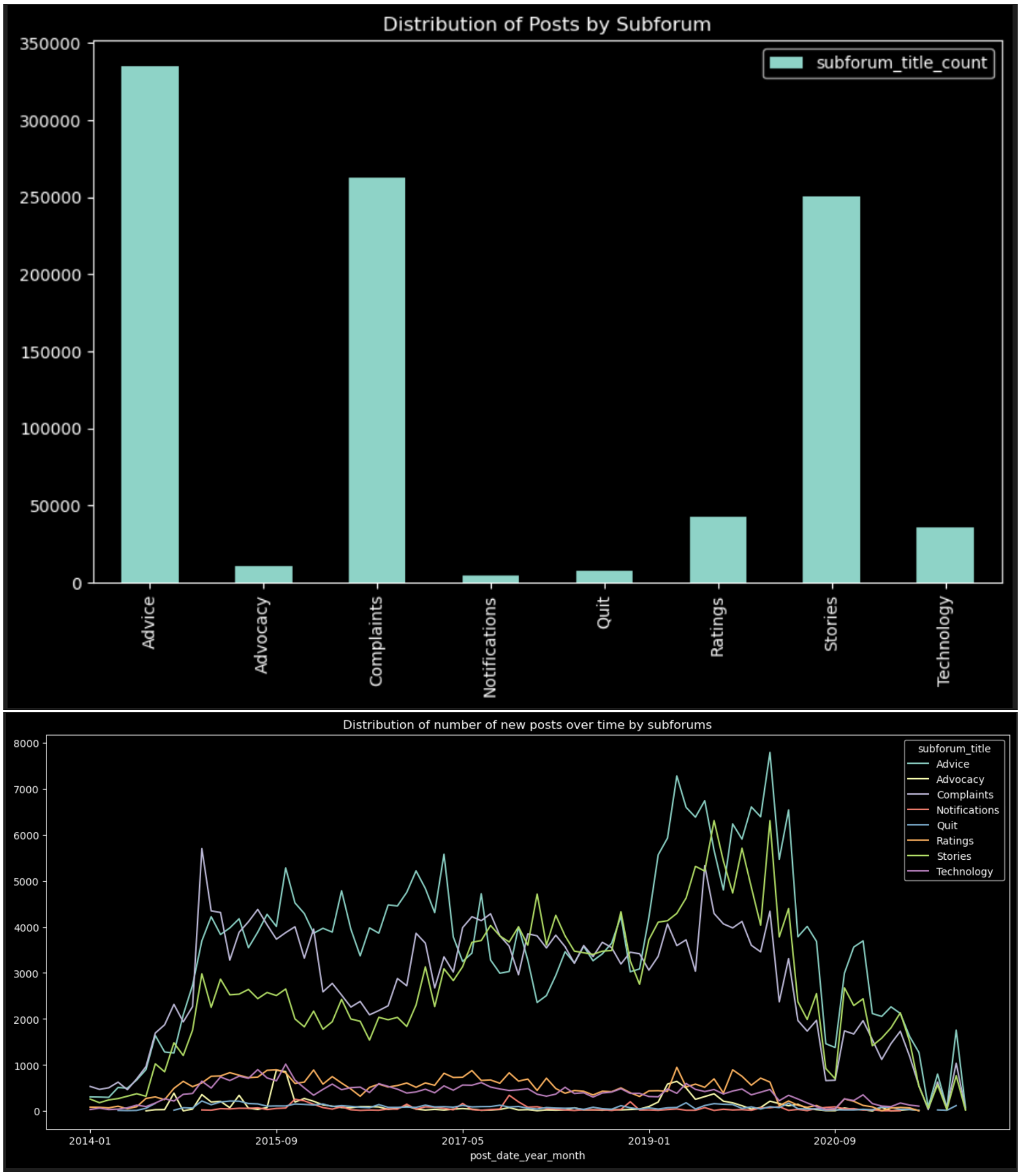

Figure C2: Distribution of posts by theme-based subforums of *Uberpeople.net*

Data filtering: Initial topic modeling of the cleansed data yielded many topics unrelated to AM (e.g., discussions about handling rides involving minors or dogs). We therefore decided to further filter the forum posts before using them as input for topic modeling in order to reduce the proportion of AM-unrelated content. To do so, we returned to the literature and derived an initial set of keywords related to both AM and algoactivistic practices. For example, we identified "surge" and "deactivate" as potential AM-related keywords (e.g., Möhlmann et al. 2021), and "strike" and "dashcam" as potential keywords associated with algoactivistic practices (e.g., Kellogg et al. 2020). We also drew on insights from our interviews with Uber drivers to identify keyword candidates (e.g., “diamond” or “queue” for AM, and “shuffle” and “cherry pick” for algoactivistic practices). For each candidate, we randomly selected 20 forum posts containing the respective term. A term was retained as a keyword if more than half of the sampled posts (i.e., at least 11) described concrete manifestations of AM and/or platform workers’ algoactivistic practices; otherwise, the term was excluded. To identify further keyword candidates, we randomly selected 50 posts containing at least one previously retained keyword and manually examined them for relevant terms. This iterative process yielded additional keywords associated with algoactivistic practices (e.g., “gps spoof” and “ping”) and was repeated until no further relevant terms emerged. Newly identified keyword candidates were evaluated using the same procedure described above. On this basis, we arrived at the following keyword sets for…

AM = [“algo”, “request”, “accept”, “cancel”, “decline”, “rating”, “incentiv”, “dynamic pric”, “surge”, “fraud”, “deactivat”, “upfront pric”, “diamond”, “bonus”, “queue”, “app”, “pool”, “uberpro”, “email”, “e-mail”, “ping”, “promotion”, “star”, “automat”]

Algoactivistic practices = [“resist”, “negotiat”, “ignor”, “gaming”, “contest”, “turn off”, “log off”, “avoid”, “reverse engineer”, “filter”, “bypass”, “circumvent”, “fight”, “cherry pick”, “longhaul”, “shuffle”, “gps spoof”, “lawsuit”, “dashcam”, “switch”, “strike”]

We used these two sets to filter the corpus for forum posts containing at least one AM-related keyword and one keyword associated with algoactivistic practices. This procedure reduced the dataset to 21,047 posts, which formed the basis for subsequent topic modeling.

Model training: In wave 1, inspired by earlier studies (e.g., Hannigan et al. 2019; Schmiedel et al. 2019), we employed the widely used topic modeling algorithm Latent Dirichlet Allocation (LDA) (Blei et al. 2003). To prepare the data for LDA, we followed established guidelines (e.g., Debortoli et al. 2016) and performed the recommended preprocessing steps, including tokenization, lemmatization, and stop-word removal. We then tuned the model’s hyperparameters (e.g., the number of topics) and optimized them using the coherence score, which measures the semantic similarity among a topic’s keywords (Mimno et al. 2011; cf. Kulkarni et al. 2024). The optimized LDA model yielded 100 topics.

Although some of these topics were clearly related to algoactivistic practices, many remained difficult to interpret analytically. To address this issue, we returned to the methodological literature and identified newly developed topic modeling approaches. In particular, Egger and Yu (2022) systematically compare state-of-the-art algorithms and conclude that BERTopic (Grootendorst 2022) outperforms alternative approaches, including LDA. We therefore adopted BERTopic for our subsequent analyses in wave 2.

The main difference between LDA and BERTopic is that the former relies on a bag-of-words representation and therefore cannot capture semantic relationships between words. In contrast, BERTopic uses transformer-based language models (Bidirectional Encoder Representations from Transformers) in combination with class-based TF-IDF (Term Frequency-Inverse Document Frequency) to capture semantic relationships within texts (Grootendorst 2022). Furthermore, whereas LDA requires extensive preprocessing and hyperparameter tuning (as described above), BERTopic generally does not (Distante 2022; Egger & Yu 2022). In fact, such preprocessing may even be detrimental because it can remove contextual information needed to generate accurate embeddings. As noted in the BERTopic documentation, "removing stop words as a preprocessing step is not advised as the transformer-based embedding models that we use need the full context to create accurate embeddings" (Grootendorst 2024). Moreover, BERTopic automatically determines the optimal number of topics. We therefore fit our cleansed and filtered forum data directly into BERTopic without additional preprocessing steps (see Figure C3).

```
# import the Python libary of BERTopic
from bertopic import BERTopic
# import Python libary "pandas" for data handling
import pandas as pd
# load data from Excel into a data frame
data = pd.read_excel('data_algoactivism_keywords_match.xlsx')
# extract only the post texts
data_post_texts = data.post_text.tolist()
# create an instance of BERTopic
topic_model = BERTopic()
# fit the BERTopic with the post texts
topics, probs = topic_model.fit_transform(data_post_texts)
```

Figure C3: Python code to train BERTopic (excerpt)

Descriptive insights: The BERTopic model generated 151 topics, one of which represented the standard outlier topic containing posts with highly heterogeneous content lacking meaningful semantic coherence. This outlier topic comprised 9,566 posts, a proportion consistent with benchmark demonstrations reported by the algorithm developer (Grootendorst 2024). The remaining 150 topics formed the basis for further analysis using selected manual coding procedures from grounded theory (see Online Appendix D). Each topic included up to 10 keywords and representative posts strongly associated with that topic. Topic size ranged from 10 to 1,005 posts (see Figure C4 for an overview).

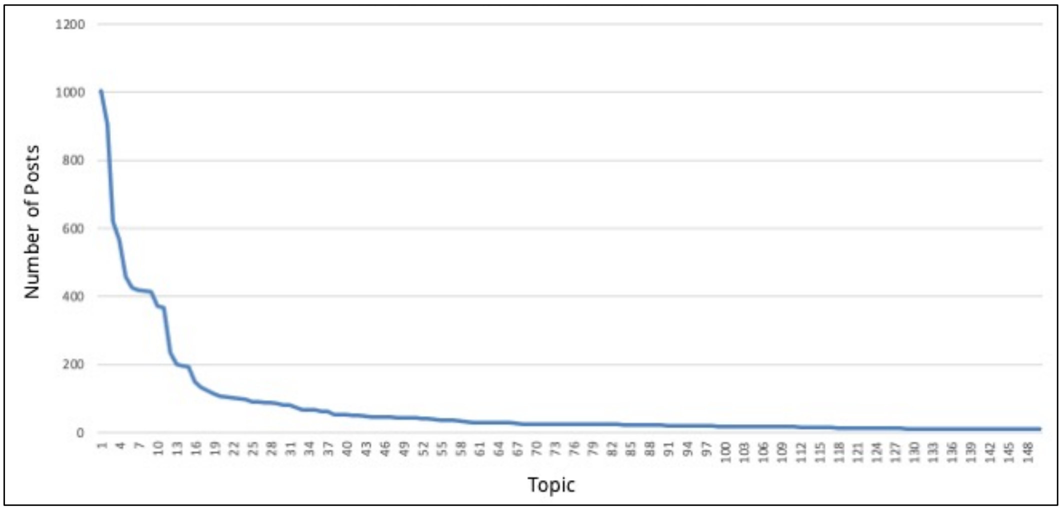

Figure C4. Distribution of the number of posts per topic

To generate descriptive insights into the semantic structure identified by BERTopic, we created an inter-topic distance map visualizing the spatial relationships among the 150 topics in a two-dimensional embedding space (Figure C5). Each bubble represents a topic, with bubble size indicating topic prevalence and spatial proximity indicating semantic similarity. For example, topics related to collective mobilization and legal disputes—such as Topic 4 ("strike, drivers, will, uber, we") and Topic 131 ("prop, 22, ab5, independent, independents")—appear in close proximity, consistent with their shared focus on labor organizing and regulatory conflicts surrounding driver employment classification (e.g., Assembly Bill 5 and Proposition 22 in California).

Although these descriptive visualizations provided an initial scaffolding for navigating the large volume of forum content, we did not treat BERTopic outputs as analytic categories. Instead, these computational artifacts served as heuristic entry points (Kulkarni et al. 2024) that helped us systematically identify promising segments for manual open, axial, and selective coding. Our interpretive analysis remained grounded in qualitative inquiry, with topic modeling outputs supporting—but not determining—the identification of constructs related to how and why drivers contest their OLP's AM. Nonetheless, topic modeling played a critical enabling role within our broader analytical approach by reducing nearly 1,000,000 forum posts into a manageable set of semantically coherent clusters (Grootendorst 2024; Hannigan et al. 2019), thereby enhancing the transparency, scalability, and reproducibility of our computer-assisted analytical process.

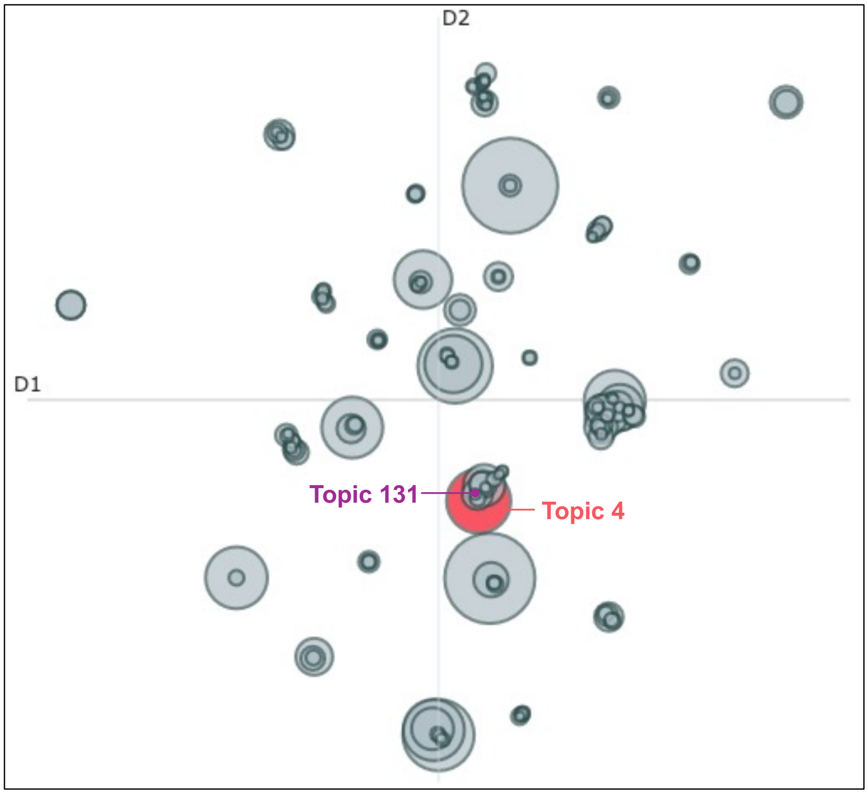

Figure C5. Inter-topic distance map of the BERTopic model

Online Appendix D: Coding Procedures

As noted above, our study adopted a computer-assisted grounded theory approach that integrates topic modeling (see Online Appendix C) with manual inductive coding techniques (Carlsen & Ralund 2022; Nelson 2020). Consistent with common practice in information systems research (Wiesche et al. 2017), this approach allowed us to engage with existing literature during analysis to enhance theoretical sensitivity. In line with the grounded and exploratory orientation of our inquiry, we treated the contested terrain lens from labor process theory as a sensitizing device (Klein & Myers 1999). This lens informed and oriented our analysis while allowing codes and relationships to emerge inductively from the data rather than being imposed a priori (Strauss & Corbin 1998). Specifically, we employed three coding techniques commonly associated with grounded theorizing: open, axial, and selective coding (ibid). Across multiple iterations, we applied these techniques to both the topics generated through topic modeling and our additional empirical materials (e.g., interviews). Throughout the analysis, we also relied on analytical tools such as memos and visualizations to support data interpretation and document the evolving analytical process (Strauss & Corbin 1998). The author team discussed emerging themes and constructs extensively until consensus was reached. In the following, we describe each coding technique in greater detail and explain how we iterated among them.

Open coding: During each wave of data analysis (see Figure B1), we began with open coding, defined as "[b]reaking data apart and delineating concepts to stand for interpreted meaning of raw data" (Corbin & Strauss 2015, p. 239). For most empirical materials (e.g., interviews, vlog entries), we manually segmented the data into meaningful excerpts and derived preliminary concepts. For the forum posts included in the topic modeling procedure, however, this segmentation was performed computationally through the grouping of semantically related posts into distinct topics. Our task then became to interpret the emergent topics qualitatively, identify their underlying conceptual meanings, and develop corresponding first-order concepts. In this sense, topic modeling functioned as an automated pre-stage of data fragmentation, while conceptual interpretation remained a manual and inductive process consistent with the principles of open coding. By wave 2 of the analysis, for example, the forum data had already been partitioned into semantically coherent topics generated by the BERTopic model. To derive first-order concepts from these topics, we examined each topic's keywords together with its three most representative forum posts. We identified these posts using the "get_representative_docs()" function implemented in BERTopic (Grootendorst 2024). On this basis, we interpreted each topic and assigned a short descriptive phrase as a conceptual label (see Table D1 for examples).

Table D1. Open coding of topics (examples)

Topic	Keywords	Excerpt of one representative forum post	First-order concept
3	pool, pools, uberpool, requests, rides, ride, you, pax, the, they	*Uber and drivers need to inform these uberpool losers. I will make zero stops on pool…Do not give these pool riders extra service for free. [T]hey think pool is a regular "get your own car ride." IT IS NOT. And drivers taking cheap pool pax to stop at [T]aco [B]ell are losing money and making other drivers look bad for not wanting to stop EXTRA, for these crap pax. No more stops drivers, if you do make stops you are part of the problem.*	Driver rejects unwanted ride requests
11	filter, destination, df, set, home, direction, filters, rides, it, use	*You aren't really limited to two a day with Uber, if you know how to use it properly. I use it many times every day. You are limited to two uses that end up with you getting to the destination while it's still active. All you have to do to avoid that is to turn it off and then go offline when you're a few minutes from the destination.*	Driver strategically turns destination filter on and off to allow for its unlimited use
51	gps, spoofing, spoof, coordinates, cell, apps, spoofer, using, route, phase	*If Uber rolls out the Charlotte surge nationwide, I will roll out my GPS spoofing app nationwide. It runs on a jail broken iPhone. It will simulate a route with the longest route possible while you actually drive the shortest route. The purpose is to milk Uber, not overcharge the passengers.*	Driver engages in GPS spoofing
127	settlement, lawyers, lawsuit, writ, terms, case, objection, oconnor, marianne, mailer	*I would go to uberlawsuit.com. They are the ones handling the lawsuit in California. Shoot them an email and ask. I'm not sure how your being in Canada changes anything. I know that being here in the [U.S.] they will still represent you on a case by case basis as an individual, even if you are beyond the 30 day window. If they are not representing Canadian drivers, they may be able to suggest someone who is. Send them an email then come back and let us know so others from Canada can learn from your situation.*	Driver joins lawsuit against Uber

134	timer, cancellation, drive, fee, ride, cancel, location, wait, immediately, pickup	*I love when I get a phone call that the pickup location is different for whatever reason. Free money is awesome. Cancel and no-show them into oblivion. If you really want to be clutch, turn off your location at the pickup location in [the app], drive to where the person said they are really at, see if you can find them standing outside from a safe distance looking at their phone like a moron, then cancel no-show at [the] 5 min mark and enjoy the show.*	Driver hides from passenger and cancels ride request after five minutes ('no-show') to collect cancellation fee

Similarly, we worked through our remaining textual materials and highlighted excerpts that triggered analytical ideas or insights, again assigning short descriptive phrases to them (Gioia et al. 2012). Throughout the process, we constantly compared newly identified concepts with existing first-order concepts (ibid). We either mapped new concepts onto existing ones when substantial overlap became apparent or generated additional first-order concepts when meaningful differences emerged. For instance, in wave 2, the final BERTopic model yielded 151 topics, 38 of which were unrelated to our phenomenon of interest, leaving 113 topics for analysis. These topics and the interview transcripts resulted in 45 and 22 distinct first-order concepts, respectively. Table D2 illustrates how we consolidated these two sets by retaining distinct concepts derived from either the topic-modeling outputs or the interview transcripts (see the first two examples) and merging conceptually overlapping ones (see the third example).

Table D2. Retaining and merging first-order concepts from topics and interviews (examples)

#	Data type	Excerpt of coded data	First-order concept
1	Topic	<u>Keywords of topic 141</u>: wade, geofenced, ping, stacked, navigation, app, preferences, chrome, delivery, switch <u>Excerpt from the most representative post for topic 141</u>: "*It looks like Uber is trying to force their navigation on you. I'm using the switch-off method of working around it. Just running an app (such as Waze or Google Maps) over the Uber app."* (Forum Member 7)	Driver uses other navigation apps
2	Interview transcript	*"What we're doing right now is, we're engaged in a data study, where we are using an app that's created by a cooperative called Driver's Seat Cooperative. Through that app, drivers are able to extract the data that Uber is extracting from them. This is ongoing…but we're hopefully going to be able to see exactly where drivers are driving, how much they're earning, and prove exactly how exploited they are through that process."* (Interviewee 4)	Driver develops app that collects the same data as the Uber app to disclose unfair AM practices

3	Topic	<u>Keywords of topic 26</u>: acceptance, rate, accept, requests, accepting, trips, rides, low, you, uber <u>Excerpt from the most representative post for topic 26</u>: "*You can reject any ride you want, and your acceptance can suck. You'll get intimidating emails from Uber, but you likely won't get deactivated without an additional reason tacked on—like a low rating or an accusation of trying to 'game' their system.*" (Forum Member 15)	Driver declines undesirable ride requests
	Interview transcript	*"If I see a pick-up at a specific bar location that I know has horrible, terrible people that come out of there, I won't accept it."* (Interviewee 10)	

At this stage, the open coding process had yielded a set of first-order concepts. Figure D3 illustrates a subset of these concepts (cf. Chatterjee et al. 2024) identified during wave 1 of our data analysis.

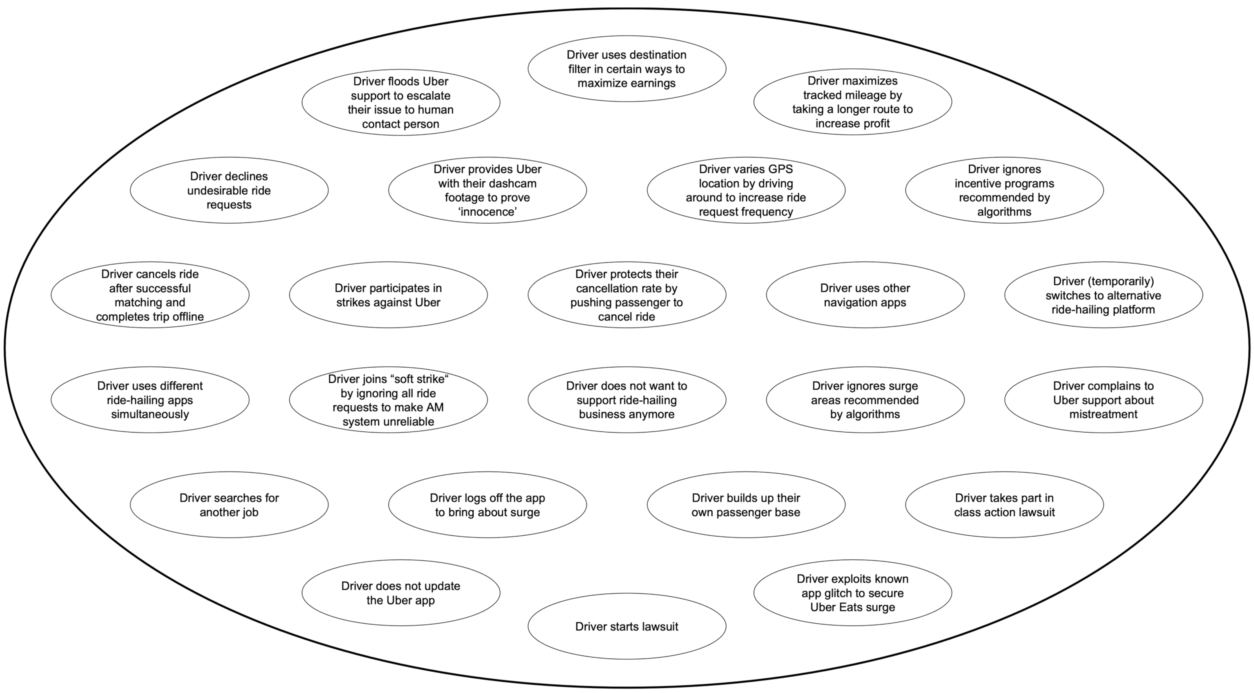

Figure D3. Illustrative subset of first-order concepts (wave 1)

We then moved to a subsequent phase of open coding focused on structuring and consolidating first-order concepts into more abstract second-order themes (Gioia et al. 2012). During this phase, we revisited both the raw data and the previously developed first-order concepts with a more refined analytical focus. The resulting concepts were systematically compared for similarities and differences, and conceptually related concepts were grouped into second-order themes; that is, higher-level categories capturing broader patterns and relationships within the data. Figure D4 illustrates how a subset of first-order concepts was grouped into second-order themes during this early and still preliminary stage of the analysis.

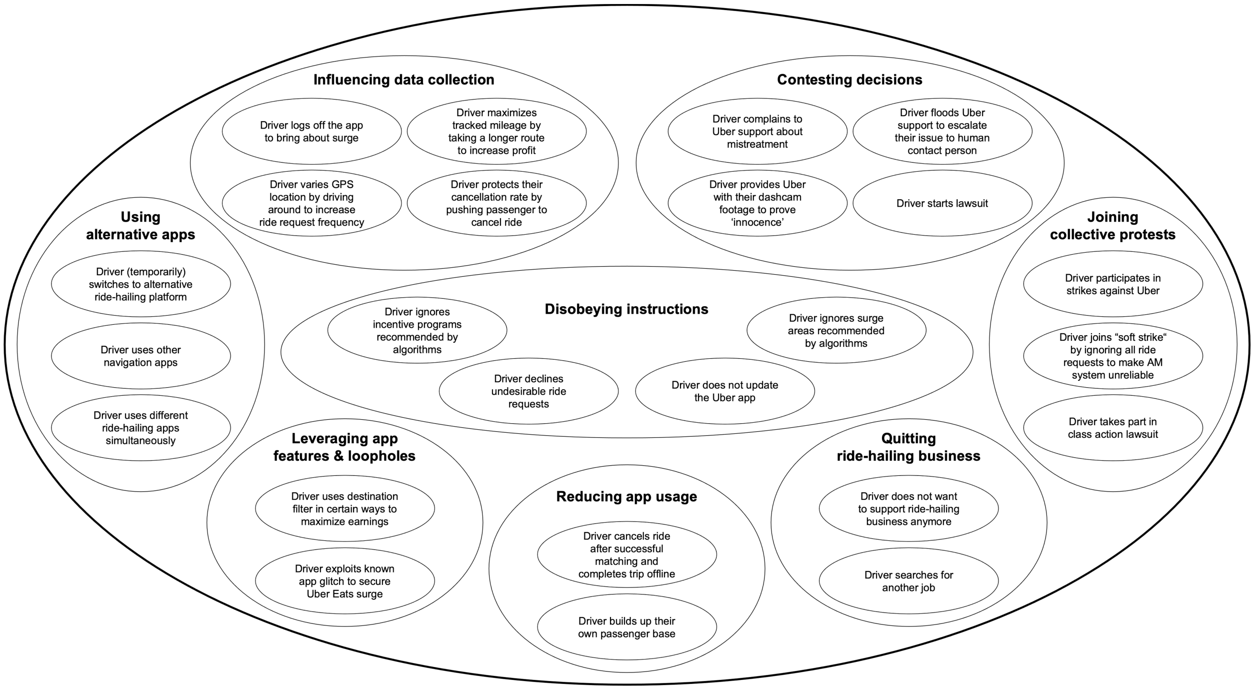

Figure D4. Grouping of first-order concepts into second-order themes (wave 1)

Axial coding: During axial coding, we examined the previously developed hierarchical relationships between first-order concepts and second-order themes in greater detail and checked them against the empirical data to refine and consolidate the emerging theoretical structure (Corbin & Strauss 1990). We also continually compared second-order themes for similarities and differences. To validate these themes and their relationships to the underlying first-order concepts, we repeatedly returned to the empirical materials. In some cases, this process prompted additional rounds of open coding and the emergence of new first-order concepts. Once a stable set of second-order themes had emerged, we grouped these themes into aggregate constructs (Gioia et al. 2012). We then returned to the data to assess the broader applicability of these constructs and refined them where necessary. Throughout the analysis, we relied on the general data structure recommended by Gioia et al. (2012), continually updating it to document and organize our evolving coding results (see Figure D5 as an example from wave 1). The resulting aggregate constructs ultimately formed the basis for the third and final coding procedure: selective coding.

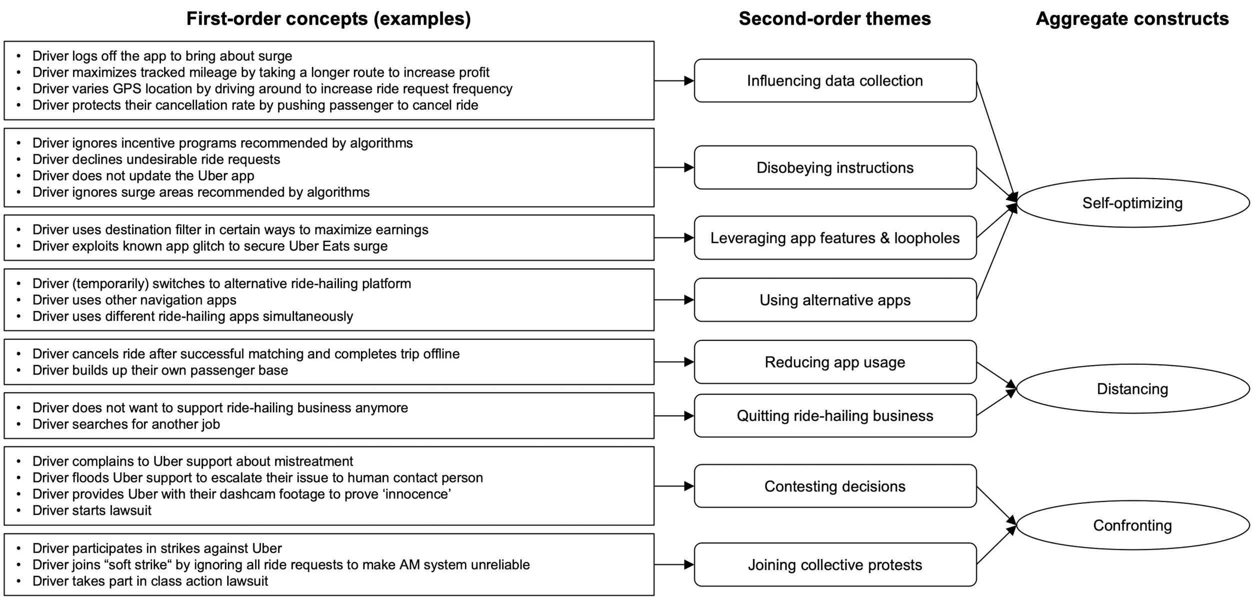

Figure D5. Preliminary data structure (wave 1)

Selective coding: We employed selective coding during waves 2 and 3 of the analysis (again, see Figure B1) to consolidate the results of the previous coding stages into an overarching and coherent theoretical narrative (Strauss & Corbin 1998). The focus of this phase was on tracing the cyclical relationships among the aggregate constructs in order to iteratively develop a process-theoretical model of how platform workers navigate the contested terrain of AM to (re)gain greater control over their working conditions. To achieve this, we reflected on the aggregate constructs and their underlying second-order themes, repeatedly returned to the empirical data, and wrote analytical memos to develop process narratives for individual drivers we had interviewed. Table D6 presents an illustrative example of such a narrative.

Table D6. Selective coding based on analytical memos (example)

Step	Quote	Memo
Summary memo: Indicative of a cyclical pattern, this Uber driver's algoactivism unfolded as follows: Perceived terrain loss → *Successful* algorithm resourcing → Self-optimizing → Perceived terrain gain → Perceived terrain loss → *Failed* algorithm resourcing → Perceived terrain loss → Exit.		
1	*In the very beginning, you were given no information. You were just given information about where you were picking someone up, but you had no idea where you were going. It supposedly didn't matter because you were getting paid a certain amount of money that was enough, and it was fine. And now the prices went all the way down…I was becoming more frustrated and making less money for the same amount of work.*	Initially, Interviewee 15 did not object to being unable to see the destination of ride requests; however, this changed after Uber reduced fares. → **Perceived terrain loss** (Getting the lay of the terrain)

2	*You accepted the fact that [Uber] didn't have your best interest at heart. And you were on your own…You have to take responsibility for yourself.* *Then, I was in a forum where I saw so many people were making money. And I said, how did [they] do that? But they couldn't talk about it in the forum because all the companies would have people in those forums…You had to go to private [Facebook] groups [or the like].*	Interviewee 15 noticed that other drivers were still earning money and turned to online forums and chat groups to seek their advice. → **Algorithm resourcing** (*successful*)
3	*You would have to strategically plan to be in an area at a certain time where you knew a surge would start and then you would turn on your application and take advantage of it.*	Interviewee 15 strategically adjusted his work behavior to capitalize on surge pricing. → **Self-optimizing** (Manipulating data capture)
4	*So [with self-optimizing] you can actually just make a decent amount of money that's requisite for your work.*	Interviewee 15 was successful in enacting this algoactivistic practice, which enabled him to increase his earnings. → **Perceived terrain gain** (Getting the lay of the terrain)
5	*There aren't as many algorithmic 'games' [left]…Everybody was like don't turn on [the app] until you get there, things like that, and they drive up a surge and take advantage of that. And these things work in small periods of time until the algorithm adjusts. And then it doesn't quite work. You would see all of a sudden, the result wouldn't be the same…You wouldn't be able to sign on. Or if you were waiting…the surge wouldn't happen or you wouldn't see it…[Uber] changed it very quickly…They're not going to show you real time information. So, you don't have that opportunity to manipulate anything.*	Interviewee 15 realized that his self-optimizing practice was no longer effective because Uber had reconfigured its AM system to prevent drivers from manipulating data. → **Perceived terrain loss** (Getting the lay of the terrain)
6	*There is not enough surge, nor does surge actually mean enough for a volume of drivers to be manipulated.*	After realizing that chasing surge fares was no longer an effective strategy, Interviewee 15 struggled to identify alternative strategies. → **Algorithm resourcing** (*failed*)
7	*For the most part, it's just not worth it anymore. And those drivers who are smart have all left. And they have other professions because they were all driven out.*	Interviewee 15 came to view working as an Uber driver as no longer worthwhile. → **Perceived terrain loss** (Getting the lay of the terrain)
8	*I started training to get another job. I don't think it's meant to be a full-time profession…It is grueling, and it takes a wear and tear on you and your car…It's not even commensurate to that math. I stopped driving, really.*	Interviewee 15 ultimately stopped driving for Uber. → **Exit**

Building on these memos, we visually mapped temporally ordered relationships among the second-order themes (see Figure D7 for an example). This process enabled us to trace how these themes evolved and interacted over time, thereby providing a structured representation of the dynamics observed in the data.

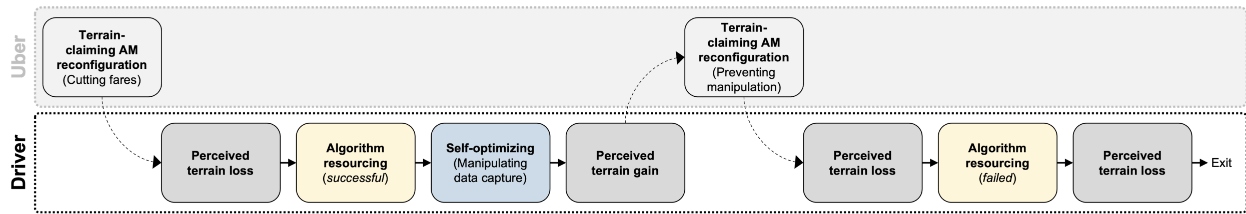

Figure D7. Temporal mapping of aggregate constructs and second-order themes (example)

Drawing on these visualizations, we abstracted recurrent empirical patterns to identify overarching relationships among key concepts and inform the development of our theoretical model. Figure D8 illustrates this abstraction by synthesizing instances documented in Table D6 and Figure D7. Overall, selective coding revealed three recurring process dynamics through which ride-hailing drivers contest AM: (1) *reassessing terrain*, (2) *exploring opportunities for terrain contestation*, and (3) *contesting terrain through algoactivistic practices*. Whereas selective coding in wave 2 yielded an initial process-theoretical model, wave 3 focused on its further refinement and culminated in the final model presented in Figure 3 of the main text.

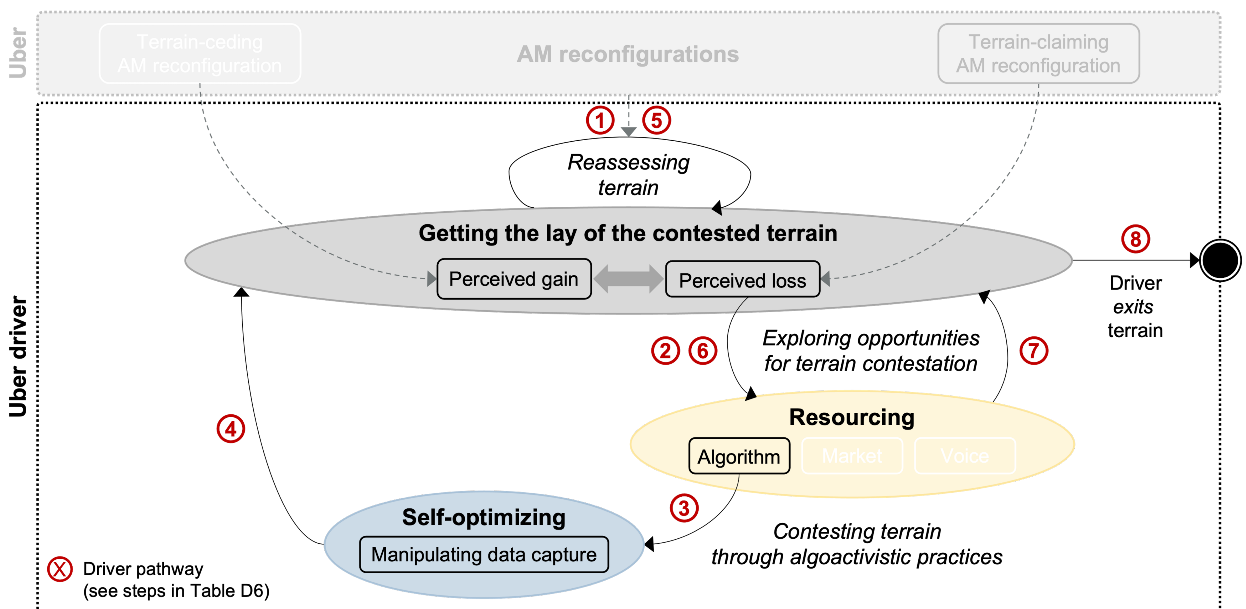

Figure D8. Abstracted empirical patterns based on temporal mapping (example)

References

Blei DM, Ng AY, Jordan MI (2003) Latent dirichlet allocation. *Journal of Machine Learning Research* 3:993-1022.

Cameron LD (2024) The making of the "good bad" job: How algorithmic management manufactures consent through constant and confined choices. *Administrative Science Quarterly* 69(2):458-514.

Cameron LD, Rahman H (2022) Expanding the locus of resistance: Understanding the co-constitution of control and resistance in the gig economy. *Organization Science* 33(1):38-58.

Carlsen HB, Ralund S (2022) Computational grounded theory revisited: From computer-led to computer-assisted text analysis. *Big Data & Society* 9(1):1-16.

Chatterjee S, Chakraborty S, Fulk H K, Lowry P B (2024) The role of dissonant relational multiplexity in information system implementation failures: Insights from a grounded theory approach. *Journal of the Association for Information Systems* 25(5): 1303-1342.

Corbin J, Strauss A (1990) Grounded theory research: Procedures, canons, and evaluative criteria. *Qualitative Sociology* 13(1):3-21.

Corbin J, Strauss A (2015) *Basics of Qualitative Research: Techniques and Procedures for Developing Grounded Theory*, 4th ed. (Sage Publications, Thousand Oaks, CA).

Curchod C, Patriotta G, Cohen L, Neysen N (2020) Working for an algorithm: Power asymmetries and agency in online work settings. *Administrative Science Quarterly* 65(3):644-676.

Debortoli S, Müller O, Junglas I, Brocke J (2016) Text mining for information systems researchers: An annotated topic modeling tutorial. *Communications of the Ass. for Information Systems* 39(7):110-135.

Distante E (2022) BERTopic: Topic modeling as you have never seen it before. *Medium* (October 20). https://medium.com/data-reply-it-datatech/bertopic-topic-modeling-as-you-have-never-seen-it-before-abb48bbab2b2

Egger R, Yu J (2022) A topic modeling comparison between LDA, NMF, Top2Vec, and BERTopic to demystify Twitter posts. *Frontiers in Sociology* 7.

Gioia DA, Corley KG, Hamilton AL (2012) Seeking qualitative rigor in inductive research: Notes on the Gioia methodology. *Organizational Research Methods* 16(1):15-31.

Grootendorst M (2022) BERTopic: Neural topic modeling with a class-based TF-IDF procedure. *ArXiv* (March 11). https://doi.org/10.48550/arXiv.2203.05794

Grootendorst M (2024) *BERTopic.* https://maartengr.github.io/BERTopic/

Hannigan TR, Haans RF, Vakili K, Tchalian H, Glaser VL, Wang MS, Kaplan S, Jennings PD (2019) Topic modeling in management research: Rendering new theory from textual data. *Academy of Management Annals* 13(2):586-632.

iPa4Fun (2024) *Uber Driver 4.487.10000 for iPhone and iPad.* https://www.ipa4fun.com/ipa/88485/

Kellogg KC, Valentine M, Christin A (2020) Algorithms at work: The new contested terrain of control. *Academy of Management Annals* 14(1):366-410.

Klein HK, Myers MD (1999) A set of principles for conducting and evaluating interpretive field studies in information systems. *MIS Quarterly* 23(1):67-93.

Kulkarni M, Mantere S, Vaara E, van den Broek E, Pachidi S, Glaser VL, Gehman J, … (2024) The future of research in an artificial intelligence-driven World. *Journal of Management Inquiry* 33(3):207-229.

McDaid E, Andon P, Free C (2023) Algorithmic management and the politics of demand: Control and resistance at Uber. *Accounting, Organizations and Society* 109:101465.

Meijerink J, Bondarouk T (2023) The duality of algorithmic management: Toward a research agenda on HRM algorithms, autonomy and value creation. *Human Resource Manag. Review* 33(1):100876.

Mimno D, Wallach H, Talley E, Leenders M, McCallum A (2011) Optimizing semantic coherence in topic models. *Proceedings of the Conference on Empirical Methods in Natural Language Processing.*

Miranda S, Berente N., Seidel S., Safadi H, Burton-Jones A (2022). Editor's comments: Computationally Intensive Theory Construction: A Primer for Authors and Reviewers. *MIS Quarterly* 46(2): iii–xviii.

Möhlmann M, Zalmanson L, Henfridsson O, Gregory RW (2021) Algorithmic management of work on online labor platforms: When matching meets control. *MIS Quarterly* 45(4):1999-2022.

Nelson LK (2020) Computational grounded theory: A methodological framework. *Sociological Methods & Research* 49(1):3-42.

Rahman HA (2021) The invisible cage: Workers' reactivity to opaque algorithmic evaluations. *Administrative Science Quarterly* 66(4):945-988.

Rideshare Drivers United (2024) *We're Uber & Lyft drivers uniting for a fair, dignified, and sustainable rideshare industry.* https://www.drivers-united.org

Schmiedel T, Müller O, vom Brocke J (2019) Topic modeling as a strategy of inquiry in organizational research: A tutorial with an application example on organizational culture. *Organizational Research Methods* 22(4):941-968.

Strauss A, Corbin J (1998) *Basics of Qualitative Research: Grounded Theory Procedures and Techniques*, 2nd ed. (Sage Publications, Thousand Oaks, CA).

The Rideshare Guy (2025) *The Rideshare Guy: Make money driving for Uber, Lyft, DoorDash, Instacart, Uber Eats and more!* https://www.youtube.com/@Therideshareguy/about

UberPeople (2023) *About us.* https://www.uberpeople.net/about/

Weber M, Remus U, Geiger M, Cram WA (2025) Between proactive and reactive coping: How food delivery workers cope with algorithmic management threats. *European Journal of Inf. Sys.*, forthcoming.

Wiesche M, Jurisch MC, Yetton PW, Krcmar H (2017) Grounded theory methodology in information systems research. *MIS Quarterly* 41(3):685-701.