THE NEW ARCHITECTURE OF CONTROL: ALGORITHMIC MANAGEMENT IN THE GIG ECONOMY

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INTRODUCTION

The gig economy continues to occupy a measurable, though methodologically complex, segment of the U.S. labor market. According to the Report on the Economic Well-Being of U.S. Households in 2024 published by the Federal Reserve, 13% of individuals reported earning income from selling goods, and 9% reported earning income from short-term tasks such as ridesharing, food delivery, or other app-mediated services.[1] These figures reflect the normalization of platform-facilitated supplemental income and underscore the growing role of digital intermediaries in shaping household financial strategies.

At the center of this shift is a governance structure commonly described as algorithmic management. This Article examines how algorithmic management structures work within the gig economy. Section II clarifies the foundational concepts of algorithmic management and the gig economy, emphasizing how both terms function as analytical constructs rather than formally codified legal categories. Section III explains the operational architecture of algorithmic management systems by modeling them as a layered decision structure consisting of data, model, decision, and feedback components. Finally, Section IV applies this framework to Uber's ride-hailing platform to illustrate how these systems operate in practice and how they shape worker outcomes, procedural safeguards, and regulatory debates. Together, these sections demonstrate that the defining feature of platform labor markets is not merely flexible work, but the relocation of managerial authority from human supervisors to algorithmic systems.

I. CONCEPTS & TERMINOLOGY

A. ALGORITHMIC MANAGEMENT

The concept of algorithmic management provides the analytical foundation for understanding governance within platform-mediated labor markets. The term was first articulated in scholarly literature in 2015 by Min Kyung Lee, Daniel Kusbit, Evan Metsky, and Laura Dabbish, who studied management systems on ride-hailing platforms such as Uber and Lyft.[2] Their research documented how

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[1] BD. OF GOVERNORS OF THE FED. RSRV. SYS., REPORT ON THE ECONOMIC WELL-BEING OF U.S. HOUSEHOLDS IN 2024 - MAY 2025 (2025).

[2] Min Kyung Lee, Daniel Kusbit, Evan Metsky & Laura Dabbish, *Working with Machines: The Impact of Algorithmic and Data-Driven Management on Human Workers* in PROC. 33RD ANN. ACM CONF. HUM.

software systems were assuming functions traditionally performed by human supervisors, including but not limited to, allocating and assigning work, optimizing labor allocation through real-time data processing, and evaluating worker performance through metrics such as ratings and acceptance rates.[3] This technological substitution enabled companies to coordinate and oversee large, geographically dispersed workforces with minimal direct human managerial oversight.[4]

Subsequent academic work expanded the concept beyond individual platforms. For example, Stark characterizes algorithmic management as a core mechanism of labor control across the platform economy, arguing that platforms govern workers and users through algorithmically mediated feedback systems rather than traditional managerial authority.[5] In his model, platform owners coordinate activity through a triangular relationship among the platform and thus are able to co-opt the actions of both providers and consumers as inputs into management processes.[6]

International institutions have adopted comparable definitions. The ILO defines algorithmic management as the use of computer-programmed systems to direct, evaluate, and shape how work is performed. This includes both purpose-built management software and general digital platforms that effectively influence how workers perform their jobs.[7] An ILO taxonomy further clarifies that such systems assign responsibility for task allocation and decision-making to algorithms that may improve themselves through self-learning processes based on accumulated data.[8]

Importantly, algorithmic management does not depend on *advanced* artificial intelligence. Many systems that meaningfully

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FACTORS COMPUTING SYS. 1603, 1603–12 (2015), https://doi.org/10.1145/2702123.2702548.

[3] *Id.* at 1603 (defining "algorithmic management" as "software algorithms [that] allocate, optimize, and evaluate work" and "assume managerial functions" traditionally performed by human supervisors).

[4] *Id.*

[5] David Stark & Ivana Pais, *Algorithmic Management in the Platform Economy*, 14 SOCIOLOGICA 47, 49 (2021), https://doi.org/10.6092/issn.1971-8853/12221 (arguing that in the platform economy, "algorithmic management involves a peculiar kind of cybernetic control" structured through triangular relations between platform owners, providers, and users).

[6] *Id.*

[7] UMA RANI, ANNAROSA PESOLE & IGNACIO GONZALEZ VAZQUEZ, INT'L LABOR ORG., 4 ALGORITHMIC MANAGEMENT PRACTICES IN REGULAR WORKPLACES: CASE STUDIES IN LOGISTICS AND HEALTHCARE, EUR 31846 EN (2024).

[8] *Id.* at 12.

restructure work operate through relatively simple rule-based architectures: if-then logic that automatically assigns tasks, enforces acceptance thresholds, ranks workers, or triggers deactivation based on preset metrics.[9] These simpler systems follow typical codified decision trees.[10] The system does not "learn" in any meaningful sense. Rather, it executes predetermined performance rules at scale, applying them uniformly and continuously across a dispersed workforce. Other systems, in contrast, incorporate machine learning models that refine predictions over time, e.g. forecasting demand, calibrating surge pricing, or dynamically adjusting compensation in response to behavioral data.[11]

The distinction between rule-based logic and adaptive AI, while technically meaningful, is not salient for purposes of labor control. Both architectures can restructure work in functionally similar ways. A fixed rule may automatically reduce task visibility once a threshold is crossed; a learning model may instead optimize exposure probabilities based on performance data. In the context of labor control, the defining structural feature of algorithmic management is *the displacement of interpersonal supervision*. As a result, questions of control, accountability, and legal classification increasingly turn on the architecture and operation of algorithmic systems rather than on traditional workplace hierarchies.

B. "GIG ECONOMY"

There is no single, universally accepted official definition of the gig economy in governmental or statistical standards. For example, the U.S. Bureau of Labor Statistics (BLS) does not formally define the "gig economy" or "gig workers." It also acknowledges that researchers use multiple, differing definitions when discussing the concept, which can overlap with contingent and alternative work

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[9] Cindy Candrian & Anne Scherer, *How Terminology Affects Users' Responses to System Failures*, 6 HUM. FACTORS 2082, 2083 (2024) ("Rule-based systems…rely on predefined, expert-crafted heuristics . . . cannot improve their forecasts . . . they rely on predefined rules . . . in contrast, AI systems . . . learn patterns and strategies directly from data, adapting and improving performance based on input data and feedback.").

[10] For example, if a worker's acceptance rate falls below X percent, then reduce task visibility; if response time exceeds Y seconds, then lower ranking; if customer rating drops below Z, then initiate suspension.

[11] *See*, *e.g.*, Mingqiong Mike Zhang, Fang Lee Cooke, David Ahlstrom & Nicola McNeil, *The Rise of Algorithmic Management and Implications for Work and Organisations*, 40 NEW TECH., WORK & EMP. 659, 659 (2025), https://doi.org/10.1111/ntwe.12343 (explaining that algorithmic management leverages machine-learning algorithms to automate managerial decision-making and operational optimization).

arrangements without a discrete classification.[12] Academic and policy literature similarly reflects diverse usage: some define gig work as short-term, on-demand work facilitated by digital platforms, while others use the term more broadly to describe independent work without long-term employment relationships.[13] Because of this variability, scholarly and institutional sources commonly define the gig economy in terms of its characteristics (e.g., short-term, task-oriented, digital mediation, and independent contracting) rather than identifying a single official taxonomy.[14]

Because the gig economy is not formally codified in law, it cannot be defined by job title, sector, or worker preference alone. A purely formal approach, such as relying solely on independent contractor status, would collapse gig work into traditional self-employment, while an industry-based definition would either over-include or exclude paradigmatic cases. Worker preference is similarly unstable as a definitional criterion, as subjective flexibility does not alter the underlying economic and technological architecture of the work arrangement. Accordingly, the gig economy is best defined through a functional framework that identifies recurring structural features as necessary but not individually sufficient conditions that, taken together, establish the gig economy as an analytically sustainable concept.[15] Consistent with this

[12] U.S. DEP'T. OF LAB., BUREAU OF LAB. STAT., CONTINGENT AND ALTERNATIVE EMPLOYMENT ARRANGEMENTS SUMMARY, USDL-24-2267 (2024), https://www.bls.gov/news.release/conemp.nr0.htm [https://perma.cc/CP98-2B8C] ("Contingent work and alternative employment arrangements are measured separately. Some workers are both contingent and working in an alternative arrangement, but this is not necessarily the case.").

[13] *See*, *e.g.*, EMILY D. CAMPION, SOC'Y FOR INDUS. & ORG. PSYCH., THE GIG ECONOMY: AN OVERVIEW AND SET OF RECOMMENDATIONS FOR PRACTICE (2019); Emma Charlton, *What Is the Gig Economy and What's the Deal for Gig Workers?*, WORLD ECON. F. (Nov. 22, 2024), https://www.weforum.org/stories/2024/11/what-gig-economy-workers [https://perma.cc/BKB5-58CY].

[14] *See*, *e.g.*, Kelvin Taylor, Pieter Van Dijk, Sharon Newman & Dianne Sheppard, *Physical and Psychological Hazards in the Gig Economy System: A Systematic Review*, 166 SAFETY SCI. 1, 1–17 (2023); Nancy Worth, *Precarious Work*, in INTERNATIONAL ENCYCLOPEDIA OF HUM. GEOGRAPHY 5, 5–10 (2nd ed., 2020); Austin Brown, Hannah Safford & Daniel Sperling, *Historical Perspectives on Managing Automation and Other Disruptions in Transportation*, in EMPOWERING THE NEW MOBILITY WORKFORCE 3, 3–30 (2019).

[15] *See*, *e.g.*, Nikos Koutsimpogiorgos, Jaap van Slageren, Andrea M. Herrmann & Koen Frenken, *Conceptualizing the Gig Economy and Its Regulatory Problems*, 12 POL'Y & INTERNET 525, 525–45 (2020), https://doi.org/10.1002/poi3.237 (conceptualizing the gig economy along

approach, modern literature (while not articulating a single, formal multi-factor test) consistently identifies four core dimensions: 1) short-term, project-based engagements, 2) task-based work, 3) platform mediation, and 4) independent contracting.[16]

First, the gig economy reflects a flexible, market-mediated labor structure characterized by short-term, project-based engagements rather than indefinite employment relationships.[17] The economic unit of exchange is typically the discrete task, project, or service event, not an ongoing employment contract. Work is thus episodic, contingent on demand, and often compensated per task rather than via salary or hourly wage tied to continuous service.

Second, gig work is structured around task-oriented engagements.[18] Labor is disaggregated into measurable, bounded assignments (e.g., rides, deliveries, freelance projects, microtasks) rather than integrated into long-term organizational roles. This fragmentation of labor differentiates gig work from conventional part-time or temporary employment, which may still operate within sustained employer–employee relationships.

Third, the gig economy is marked by platform mediation.[19] Digital applications and online marketplaces perform coordinating functions traditionally carried out by firms or managers: matching supply and demand, setting pricing mechanisms, processing payments, allocating tasks, and in many cases monitoring performance. This technological intermediation is scaled to the scalability of the gig economy itself.

Fourth, gig work typically involves formal independence from traditional employment relationships.[20] Workers are generally classified as independent contractors rather than employees, retain nominal control over when and whether to accept work, and bear responsibility for tools, expenses, and tax obligations.[21] At the same

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four dimensions: 1) online intermediation 2) independent contractors, 3) paid tasks, and 4) services).

[16] *See, e.g.*, *id*; Bolanle Alake-Apata, *Making Sense of Gig Work, LMI Insight Report no*. 45, LMIC (Sept. 2021), https://lmic-cimt.ca/publications-all/lmi-insight-report-no-45-making-sense-of-gig-work/ [https://perma.cc/2FEV-PFDD].

[17] *See*, *e.g.*, Zahid Ali, *Labor Market Dynamics in the Gig Economy: Opportunities, Challenges, and the Future of Work*, 7 J. APPLIED FIN. & ECON. POL'Y 57, 58 (2023), https://doi.org/10.54254/2754-1169/61/20231285.

[18] *See*, *e.g.*, Marc T. Moore, *The Gig Economy: A Hypothetical Contract Analysis*, 39 LEGAL ISSUE 579, 580 (2019), https://doi.org/10.1017/lst.2019.4.

[19] Ali, *supra* note 17, at 58.

[20] *Id.*

[21] *Id.*

time, this classification often limits access to conventional employment protections such as employer-sponsored benefits, unemployment insurance, and collective bargaining rights.[22]

Conceptualizing the gig economy through these overlapping factors provides a useful framework for distinguishing it from adjacent labor arrangements. Under this approach, the gig economy can be understood as a labor arrangement that emerges where these characteristics converge.

II. ARCHITECTURE AND OPERATION

Similarly, algorithmic management is not formally codified by legal or technological institutions. For purposes of analysis, its operational structure can be best understood as a layered system analogous to other AI-driven decision architectures.[23] This layered approach is adopted primarily for analytical clarity. Rather than requiring readers to engage with the technical details of specific machine-learning models or platform architectures, the layered framework isolates the key managerial functions that allows the overall process to be accurately visualized.

The discussion proceeds in two steps. First, it identifies the core functional components that make up an algorithmic management system. Breaking the system into components allows the basic mechanics of platform governance to be described in terms of discrete operational roles. Second, it turns to the architectural principles that structure how those components interact within a larger technological system.

A. COMPONENTS

The system can be modeled as a four-layer stack: data, model, decision, and feedback/adaptation. At the base sits the Data Layer,[24] which functions as the input substrate of the system. This layer collects, aggregates, and preprocesses structured and unstructured work-related data, e.g., timestamps, location traces, acceptance rates, performance metrics, ratings, and demand signals. It performs cleaning, normalization, feature extraction, and integration across

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[22] *See, e.g.*, Fatima Rodriguez, Ashish Sarraju & Mintu P. Turakhia, *The Gig Economy Worker—A New Social Determinant of Health?*, 7 JAMA CARDIOL. 125, 125–26 (2022), https://doi.org/10.1001/jamacardio.2021.5435.

[23] *See generally* Zeynep Engin, Jon Crowcroft, David Hand & Philip Treleaven, *The Algorithmic State Architecture (ASA): An Integrated Framework for AI-Enabled Government* (2025) (unpublished manuscript) (on file with author), https://doi.org/10.48550/arXiv.2503.08725.

[24] *Id.*

heterogeneous sources.[25] The most appropriate metaphor for this layer is that of a refinery where raw, unprocessed inputs from the real world are filtered, sorted, and transformed into a standardized form that can be reliably used downstream.

Above it operates the Model Layer[26], responsible for representation and inference. This layer is similar to a weather forecasting system: using past and present data to generate informed predictions about future conditions, even though those predictions remain probabilistic rather than certain. Here, machine learning or analytic components estimate relationships, forecast outcomes, compute risk or performance scores, cluster worker profiles, or generate predictive signals about demand and supply. This layer transforms input data into probabilistic or latent representations. It may include regression models, reinforcement learning systems, optimization estimators, or scoring engines. In simpler terms, this layer tries to predict internally what is likely to happen.

The Decision Layer[27] translates model outputs into executable actions. A comprehensible analogy is that of an air system controller who coordinates inputs and outputs to give the ultimate direction to all involved parties (as to prevent collision *and* maximize efficiency). In effect, this layer operationalizes control logic. If the model estimates expected outcomes, the decision layer *selects* actions consistent with predefined goals such as minimizing response time, balancing workload, or maximizing throughput. This is the layer with which one as a consumer is most likely to interact: getting assigned a driver, receiving a cost estimate for the order, etc.

Finally, the Feedback and Adaptation Layer closes the loop. It interfaces with all human agents involved in the process (including workers and customers) through notifications, dashboards, automated assignments, or pricing signals. It also *captures* the consequences of decisions: completion times, compliance behavior, acceptance rates, performance outcomes. These outputs become new inputs for the data layer, enabling iterative recalibration. While it does not possess the same “control” over the other layer that sports coaches (sometimes) have over the players, the Feedback and Adaptation Layer functions similarly in its observation of the outcomes and proceeding adjustment of the strategies.

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[25] Cleaning refers to removing errors or inconsistencies in raw data. Normalization refers to standardizing data formats for comparability. Feature extraction refers to identifying relevant variables from raw inputs. Integration refers to combining data from multiple, heterogeneous sources.

[26] Engin et al., *supra* note 23.

[27] *Id.*

B. PRINCIPLES

With the functional layers identified, the structural design principles governing their interaction are similarly important.

First, modularization means that every layer abstracts a distinct operational responsibility (as detailed above).[28] This separation allows components to be developed, optimized, and modified independently without destabilizing the broader system. Modular design also facilitates reuse across contexts, enabling platforms to deploy similar decision architectures across different markets or service categories while adjusting only specific parameters. This principle is perhaps most familiarized through Lego designs: every piece performs its own function so that the overall structure remains stable even if one block is swapped out or upgraded.[29] Relatedly, each Lego piece may be employed in multiple projects.

Relatedly, these systems rely on encapsulation.[30] Decision logic is insulated from direct exposure to raw data streams, preventing leakage, limiting unintended interference between components, and isolating concerns within the architecture. Because the decision models are separated from the mechanisms that collect and store data, changes to databases, sensors, or data pipelines do not require rebuilding the decision system itself. Illustrative of this principle is a restaurant kitchen: the chefs (Decision Layer) prepare dishes based on ingredients delivered to them, but they do not need to know how the ingredients were sourced, stored, or transported. As long as the ingredients arrive in usable form, the kitchen can continue operating even if the supply chain changes.

Central to this architecture is real-time or near-real-time data ingestion.[31] Continuous data flows, including but not limited to tracking demand fluctuations, worker acceptance rates, geographic positioning, performance metrics, or customer ratings, enable dynamic recalibration of decisions. In effect, the system operates like a self-adjusting thermostat: it constantly senses changes in the

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[28] *See generally* LEN BASS, PAUL CLEMENTS & RICK KAZMAN, SOFTWARE ARCHITECTURE IN PRACTICE (3rd. ed. 2012).

[29] *See generally* Ying Wang, Arne Bilberg & Romen Hadar, *Implementation of Reconfigurable Manufacturing Systems, the Case of The LEGO Group* in 4TH WORLD CONF. PROD. & OPERATIONS MGMT. (2012).

[30] *See generally* RICK LUTOWSKI, SOFTWARE REQUIREMENTS 9–17 (2005).

[31] *See, e.g.*, Giyosjon Jumaev & Mirjalol Jonqobilov, *Real Time Decision Making and Information Extraction Algorithms Models and Applications*, PROCS. 8TH INT'L CONF. FUTURE NETWORKS & DISTRIBUTED SYS. 638, 638–41(2024), https://doi.org/10.1145/3726122.3726212

environment and immediately updates its output to maintain a target condition. It might even be argued that it is precisely this heightened sensitivity to environmental variation that distinguishes algorithmic management from traditional supervisory models that operate on delayed or periodic evaluation cycles.

III. CASE STUDY: UBER

Ride-hailing platforms operate through a sequential chain of automated decision systems[32] that begin with a rider's request and continue through dispatch, pricing, performance tracking, and fraud enforcement. The process is initiated when a rider submits a trip request through the app. The request contains origin coordinates, destination, time stamp, and device data. It then enters the platform's dispatch infrastructure as a trigger event. The system constructs a candidate pool of nearby drivers based on GPS location and estimated time to pick up. Within that pool, an allocation model ranks drivers using inputs such as proximity, real-time traffic conditions, predicted trip length, localized supply-demand balance, and historical acceptance behavior.[33] The request is then offered to selected drivers according to this ranking logic.

Once a driver accepts the assignment, the platform executes pricing and compensation calculations. The rider-facing fare is typically computed in advance under an "upfront pricing" model, which estimates distance, duration, and traffic conditions at the time of request and incorporates contemporaneous demand conditions.[34] In markets that retain rate-card structures, fares are derived from per-time and per-distance components.[35] One notable deviation from this set structure is that of surge pricing. Surge pricing refers to an algorithmically applied multiplier activated when rider demand exceeds available driver supply within a defined geographic zone.[36]

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[32] UBER, *Uber Privacy Notice: Drivers and Delivery People* (2026), https://www.uber.com/global/en/privacy-notice-drivers-delivery-people/ [https://perma.cc/T8HU-XXU2].

[33] Yang Liu, Ruo Jia, Jieping Ye & Xiaobo Qu, *How Machine Learning Informs Ride-hailing Services: A Survey*, 2 COMMC'N TRANSP. RSCH., Dec. 2022, at 2–4, https://doi.org/10.48550/arXiv.2303.14646.

[34] UBER, *How Are Fares Calculated?*, https://help.uber.com/riders/article/how-are-fares-calculated-/?nodeId=d2d43bbc-f4bb-4882-b8bb-4bd8acf03a9d [https://perma.cc/8JHP-4YFC].

[35] *Id.*

[36] UBER, *How Uber's Dynamic Pricing Model Works*, https://www.uber.com/en-GB/blog/uber-dynamic-pricing/ [https://perma.cc/Z5BF-EQA9].

Promotional incentives may be layered onto this calculation as additional inputs.

It is analytically important to distinguish the rider's fare from the driver's pay. The platform calculates driver compensation under a separate formula. Prior to dynamic pricing, Uber publicly advertised a fixed commission (initially 20%, later 25%)[37], such that the driver's share was a stable proportion of the fare. After dynamic pricing, the link between passenger price and driver pay was severed. Empirically, this means that higher passenger fares do not necessarily yield higher driver earnings in proportional terms. One study finds that Uber's take rates are not evenly distributed across trips; rather, "the higher the fare charged to the customer, the higher Uber's take rate, and the less drivers earn per minute in absolute terms," with take rates reaching 50% or more on some trips[38]. In other words, as rider fares increase, the platform may capture a larger share of the incremental revenue. The difference between the rider's payment and the driver's compensation ("take rate") therefore fluctuates across trips, such that increases in rider fares do not mechanically translate into proportional increases in driver earnings.

After the trip is completed, the system incorporates the transaction into ongoing performance measurement. The platform tracks metrics such as acceptance rate, cancellation rate[39], trip completion rate, and passenger ratings. These metrics are calculated over defined "lookback windows," meaning rolling periods of recent activity.[40] By structuring evaluation around a rolling window, the platform ensures that it is always acting on the latest and more relevant information. Within this framework, drivers who fall below

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[37] Ellen Huet, *Uber Raises UberX Commission To 25 Percent in Five More Markets*, FORBES (Sept. 11, 2015), https://www.forbes.com/sites/ellenhuet/2015/09/11/uber-raises-uberx-commission-to-25-percent-in-five-more-markets/ [https://perma.cc/9FFN-7LFK].

[38] Reuben Binns, Jake Stein, Siddhartha Datta, Max Van Kleek & Nigel Shadbolt, *Not Even Nice Work If You Can Get It; A Longitudinal Study of Uber's Algorithmic Pay and Pricing* in 2025 ACM CONF. FAIRNESS, ACCOUNTABILITY, & TRANSPARENCY 1484, 1484–97 (2025), https://doi.org/10.1145/3715275.3732099 (finding that "the higher the fare charged to the customer, the higher Uber's take rate, and the less drivers earn per minute in absolute terms").

[39] UBER, *Understanding Acceptance and Cancellation Rates*, https://www.uber.com/en-DO/blog/understanding-acceptance-and-cancellation-rates/ [https://perma.cc/H7VY-HPT5].

[40] UBER, *Introducing the New Uber Eats Pro–Better Service, Better Status, Better Earning*s (May 13, 2025), https://www.uber.com/blog/uber-eats-pro-preferred-deliveries/ [https://perma.cc/MXD8-ZTAZ] (explaining that acceptance rates are calculated over the "lookback window" of the 100 most recent requests).

defined thresholds may experience reduced access to desirable assignments or rewards, while higher-performing drivers may qualify for priority dispatch or bonus programs.[41]

Running in parallel with dispatch, pricing, and performance measurement are fraud and identity controls. Automated detection systems use machine-learning models to analyze large sets of behavioral and device-level signals in real time to flag anomalies such as suspected duplicate accounts or inconsistent identity indicators.[42] When the system detects suspicious patterns, it may automatically restrict or suspend the account pending review. Importantly, this process often includes a human-in-the-loop component: flagged cases can be escalated to human reviewers and affected drivers or riders may appeal account actions through support channels.[43]

Viewed sequentially, the system operates as an integrated automated governance structure: a trip request triggers dispatch; acceptance triggers fare and compensation calculations; completion feeds into rolling performance metrics; and ongoing monitoring enforces identity and fraud compliance. Each stage relies on defined inputs, ranking logic, and feedback loops that shape both economic outcomes and continued access to the platform.

IV. IMPLICATIONS FOR WORKERS AND REGULATION

The impact of algorithmic management on platform workers is best understood by three factors: income predictability, procedural safeguards, and regulatory response. First, income predictability remains limited. Dynamic pricing and individualized pay formulas render earnings volatile and difficult to forecast. Human Rights Watch has documented core concerns regarding opacity in fare calculation criteria, weighting of performance factors, and limited

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[41] Ngai Keung Chan, *The Rating Game: The Discipline of Uber's User-Generated Ratings*, 17 SURVEILLANCE & SOC'Y 183, 183–90 (2019), https://doi.org/10.24908/ss.v17i1/2.12911 (explaining that Uber may issue warnings or deactivate drivers whose average rating over their last 500 rides falls below a location-specific minimum threshold (e.g., 4.6), and that the "Uber Pro" rewards program conditions access to higher-status tiers and associated monetary rewards on maintaining at least a 4.85 rating and low cancellation rates).

[42] UBER, *Risk Entity Watch–Using Anomaly Detection to Fight Fraud* (Sept. 28, 2023), https://www.uber.com/blog/risk-entity-watch/ [https://perma.cc/9H59-3GWN].

[43] UBER, *Fraud Activities*, https://www.uber.com/gb/en/drive/driver-app/fraud-activities/ [https://perma.cc/3PJP-FYX8].

avenues to meaningfully challenge algorithmic determinations.[44] Even where per-time and per-distance components remain, the interaction of multipliers, incentives, and behavioral metrics produces informational asymmetry. Workers often lack visibility into how ratings, acceptance rates, or cancellation rates affect dispatch priority or compensation, constraining their ability to make fully informed labor decisions.

Second, deactivation risk operates as a significant form of discipline, raising concerns about the adequacy of procedural safeguards."[45] Drivers report persistent anxiety about falling below performance thresholds and losing platform access.[46] At the same time, available survey data suggests that a substantial portion of alleged deactivations are later cleared upon review, indicating that error-correction mechanisms do exist but may be unevenly accessible or insufficiently transparent.[47] Due process concerns therefore center less on the existence of review pathways and more on clarity, timeliness, evidentiary standards, and meaningful opportunity to contest automated decisions.

Third, the health and job-quality effects of platform work are context-dependent–underscoring the role of regulatory responses in addressing variability in working conditions. Some workers value scheduling autonomy and flexibility; others experience stress tied to performance monitoring, earnings volatility, and algorithmic evaluation.[48] Empirical findings remain mixed, and impacts vary by market conditions, regulatory environment, and individual dependency on platform income.

Regulatory posture, however, is evolving. The U.S. Department of Labor's 2024 Final Rule, effective March 11, 2024, rearticulates the multi-factor economic realities test under the Fair Labor

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[44] Letter from Lena Simet, Senior Researcher and Advocate, Human Rights Watch, to David Fish, Executive Director, New Jersey Department of Labor and Workforce Development (Aug. 5, 2025) (on file with author).

[45] Lena Simet, *The Platform Economy Runs on Inequality–and Sidesteps Labor Rights*, INEQUITY.ORG (May 28, 2025), https://www.hrw.org/news/2025/05/28/platform-economy-runs-inequality-and-sidesteps-labor-rights [https://perma.cc/66QP-77LC].

[46] *Id.*

[47] HUM. RIGHTS WATCH, THE GIG TRAP: ALGORITHMIC, WAGE AND LABOR EXPLOITATION IN PLATFORM WORK IN THE US (May 2025) (finding that nearly half of workers who experienced platform deactivation were later cleared of wrongdoing).

[48] Emilia F. Vignola, Sherry Baron, Elizabeth Abreu Plasencia, Mustafa Hussein & Nevin Cohen, *Workers' Health under Algorithmic Management: Emerging Findings and Urgent Research Questions*, 20 INT'L. J. ENV'T RSCH. & PUB. HEALTH 1239, 1239–53 (2023).

Standards Act, signaling closer scrutiny of worker classification.[49] The Wage and Hour Division's 2025 Field Assistance Bulletin further clarifies enforcement priorities.[50] At the state level, the California Court of Appeal in *Castellanos v. State of California* (2023) upheld Proposition 22, preserving California's hybrid classification framework for app-based drivers.[51] Internationally, the European Union has moved more aggressively: the EU Platform Work Directive establishes a rebuttable presumption of employment in certain circumstances and mandates algorithmic transparency[52], while the EU AI Act introduces risk-based governance and documentation requirements for high-risk AI systems, including those used in employment contexts.[53]

Taken together, the evidence reflects neither categorical harm nor categorical benefit. Instead, platform work operates within a socio-technical structure that redistributes managerial discretion through algorithms. The key legal and policy question is not whether algorithmic management exists, but how much transparency, procedural protection, and accountability are required to ensure that technological efficiency does not displace fundamental labor standards.

CONCLUSION

Algorithmic management in the gig economy is best understood not as a discrete technological tool, but as a system of workplace governance. By collecting worker and consumer data, processing that information through predictive or rule-based models, translating outputs into assignments, prices, rankings, and account actions, and then feeding those results back into future decisions, platforms relocate core managerial functions into automated systems. The Uber case study illustrates how this structure operates in practice: dispatch, pricing, compensation, performance evaluation, and fraud enforcement are not isolated technical features, but interconnected mechanisms through which the platform organizes labor and controls access to economic opportunity.

This does not mean, however, that platform work is categorically harmful or that algorithmic management should be treated as inherently unlawful. Rather, it is important to simultaneously hold its

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[49] 29 C.F.R. §§ 780, 788, 795.

[50] Memorandum from Donald M. Harrison, III, Acting Administrator, Wage & Hour Div., U.S. Dep't. of Labor, to Regional Administrators & District Directors, Wage & Hour Div., U.S. Dep't. of Labor (Jun. 27, 2025).

[51] Castellanos v. State of California, 89 Cal. App. 5th 131 (2023).

[52] 2024 O.J. (L 2831).

[53] 2024 O.J. (L 1689).

benefits and harms: flexibility, worker autonomy, increased market access; opacity, earnings volatility, informational asymmetry. The central regulatory challenge, therefore, is not whether algorithms should be used in labor markets. They already are. The more important question is how legal systems should allocate responsibility when managerial power is exercised through technical infrastructure rather than human supervision. As platforms continue to mediate work through data-driven decision systems, labor law, employment classification doctrine, and emerging AI governance regimes will have to reshape itself—beyond the depth of which they might be used to—in order to achieve society's desired outcomes within this fluid architecture.