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CODING PRIVILEGE, AUTOMATING INEQUALITY: A SYSTEMATIC REVIEW OF SOCIOECONOMIC SORTING

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Abstract

Automated Decision-Making (ADM) systems have rapidly displaced human discretion in critical high-stakes domains such as hiring, lending, and education. While Science and Technology Studies (STS) scholarship has extensively documented algorithmic biases regarding race and gender, the specific mechanisms of class reproduction and the intergenerational transmission of socioeconomic advantage remain significantly undertheorized. To address this gap, this study presents a systematic review of peer-reviewed literature published between 2015 and 2025, adhering to the PRISMA protocol to synthesize data from Scopus, Web of Science, and the ACM Digital Library. The analysis identifies three primary modes of socioeconomic sorting: (1) proxy discrimination, where latent variables like zip codes or device usage serve as digital class markers; (2) predatory inclusion, which targets low-income populations for extractive financial products; and (3) automated gatekeeping, which invisibly filters access to premium labor and educational opportunities. Ultimately, this review argues that ADM systems function as "engines of conservation". By digitizing historical class dispositions into predictive risk scores, these technologies effectively freeze social mobility, systematically coding privilege and automating inequality.

INTRODUCTION

The integration of Automated Decision-Making (ADM) into civic life was originally propelled by a seductive technocratic promise: that "blind" algorithms would act as neutral arbiters, sanitizing bureaucracy of the cognitive biases that plague human discretion. Yet, recent scholarship reveals a stark divergence between this meritocratic ideal and the reality of stratified outcomes. As Kothandapani (2025) and Mehrabi et al. (2019) demonstrate, ADM infrastructures in sectors like housing and finance do not eliminate prejudice; rather, they metabolize historical biases embedded in training data, effectively converting past discrimination into future prediction. This exclusion is structural; Mead and Neves (2022) argue that sociopolitical contexts are encoded into these tools, allowing them to reinforce hierarchies rather than disrupt them. Moreover, the sidelining of ethical considerations for efficiency (Daoud, 2023) renders these inequities opaque. Consequently, this research contends that ADM systems do not merely reflect inequality; they mechanize it, making class boundaries "stickier" and harder to cross than in the analog era. By digitizing socioeconomic status into rigid code, these technologies act as invisible gatekeepers, requiring the urgent transparency frameworks advocated by Gürsoy and Kakadiaris (2022) and Pathan and Patare (2025) to dismantle the automation of privilege.

In the architecture of modern algorithmic governance, a critical regulatory fissure exists between protected identity categories and socioeconomic status. While race and gender are shielded by robust anti-discrimination frameworks as the biases exist against sexual minorities (Touseef et al., 2024), that subject Automated Decision-Making (ADM) systems to rigorous scrutiny (Schmitt et al., 2014), class remains a regulatory blind spot. Unlike these immutable characteristics, where differentiation is legally suspected, class distinction is frequently operationalized as a legitimate, rational metric of reliability. As Naudts (2025) argues, constructs like "creditworthiness" effectively function as sanitized class scores, allowing institutions to launder historical economic disadvantage into the neutral language of financial risk. By reframing poverty as a quantifiable behavioral deficit rather than a structural condition, ADM systems legitimize the exclusion of lower-income individuals under the unassailable banner of fiscal prudence. In this context, discrimination is not viewed as a bias to be corrected, but as a feature of responsible risk management.

The profound danger of these dynamic lies in the epistemological obscurity of class, which functions as a "ghost variable", ubiquitously present in the outcome yet rarely explicitly defined in the source code. Unlike categorical variables that can be isolated and scrubbed, class is inferred through a complex constellation of proxies. Vyas and Kumaranayake (2006) highlight that socioeconomic indices often rely on methodologies like principal component analysis to map indirect markers—such as asset ownership, educational pedigree, and residential history into latent status hierarchies. This reliance on inference creates a significant auditing gap: because the algorithm technically never "sees" class but rather detects patterns of "risk" woven through neutral data points, the resulting bias is exceptionally difficult to prove. Naudts (2025) characterizes this as a "discriminatory silence," where the opaque nature of indirect verification allows institutions to systematically enforce class boundaries while evading the regulatory tripwires designed to catch explicit profiling. Consequently, ADM systems do not just replicate inequality; they render it invisible, automating a rigid socioeconomic sorting that is technically legal, mathematically optimized, and ethically unexamined.

Research Questions (RQs)

RQ1: How is "social class" operationalized and measured in empirical ADM research?

RQ2: Through what specific sociotechnical mechanisms (e.g., proxies, feedback loops) do ADM systems reproduce class stratification?

RQ3: How does the integration of ADM transform traditional Bourdieusian concepts of Habitus and Capital?

THEORETICAL FRAMEWORK

Bourdieu in the Machine

Adapting Pierre Bourdieu's sociological framework to the algorithmic age, this research conceptualizes "Digital Capital" as a distinct asset class where behavioral data browsing histories and network topologies serves as accumulated wealth. In this digital field, online interactions are not ephemeral but are convertible resources. As He and Tsvetkova (2023) demonstrate, these data trails function as high-fidelity proxies for status, enabling algorithms to transmute digital footprints into Economic Capital (e.g., favorable lending terms) or Cultural Capital (e.g., privileged information access). However, this conversion is not neutral; it is an extractive process of "surveillance capitalism" (Imam & Manimekalai, 2025). Hakim and Rajid (2025) argue that algorithmic mediation embeds historical power dynamics, ensuring that data extraction privileges those with pre-existing resources. This is evident in the gig economy, where Gandini (2018) notes that commodified digital performances determine labor survival. Consequently, ADM systems function as engines of social reproduction (Farid et al., 2021). By digitizing the habitus, these systems encode offline dispositions into predictive risk scores, automating the intergenerational transmission of advantage and rendering class boundaries increasingly impermeable.

Extending Pierre Bourdieu's sociology to the digital sphere, this framework posits the emergence of an "Algorithmic Habitus." Here, machine learning systems do not merely observe preferences but actively ingest class dispositions tastes, language, and location to construct rigid socioeconomic profiles. As Shin and Jitkajornwanich (2024) demonstrate with TikTok's sorting mechanisms, these algorithms cluster users into insular, class-homogenous silos. The result is a feedback loop of stratification: rather than democratizing access, the system reinforces the user's existing station by filtering out content deemed "unsuitable" for their class profile. BinHamdan et al. (2025) warn that this personalization fosters echo chambers that validate rather than challenge biases. Crucially, Huang and Tian (2022) argue that this curation creates a digital glass ceiling, limiting exposure to upward mobile opportunities. Consequently, the algorithmic habitus functions as a digital containment strategy, freezing social mobility by ensuring users only encounter information, culture, and capital deemed appropriate for their predicted class trajectory.

Classification Situations (Fourcade & Healy)

Utilizing Fourcade and Healy's (2013) framework of "classification situations," this research delineates a structural transformation in social stratification: the displacement of class defined by labor relations (production) with class defined by market scoring (classification). In this regime, Automated Decision-Making (ADM) systems function as digital gatekeepers, sorting individuals into granular "risk groups" epitomized by the financial binary of "Prime" versus "Subprime." These categories are not merely administrative labels; they constitute new "class situations" that dictate life chances with authoritative finality, creating a parallel stratification system.

As Anikin et al. (2017) demonstrate, this mechanism effectively decouples economic destiny from actual labor; a "Subprime" designation acts as a structural penalty, restricting access to housing and capital independent of an individual's work ethic or productivity. Consequently, a diligent worker may be trapped in a high-risk silo based on opaque behavioral proxies rather than financial reality. Li (2025) further argues that this sorting is driven by "traffic capital," where digital footprints supersede traditional qualifications in determining status. Thus, algorithms do not simply measure risk; they manufacture a rigid hierarchy where the "classification situation" overrides human potential, rendering inequality automated and increasingly detached from the merit of one's labor.

The Digital Poorhouse (Eubanks)

Virginia Eubanks' framework of the "Digital Poorhouse" delineates a stark regime of asymmetric visibility that fundamentally alters the social contract along class lines. In this digital architecture, privacy functions as a luxury good; as Dobson (2019) notes, the wealthy possess the capital to shield their lives from algorithmic scrutiny, effectively purchasing a "right to opacity." Conversely, the poor are subjected to compulsory data extraction, where the non-negotiable price for survival access to housing, healthcare, and nutrition is the complete surrender of informational sovereignty (Hayes et al., 2021). Zoonen (2020) argues that this dynamic transforms the welfare state into a "surveillant assemblage," shifting its function from social support to behavioral policing. Because low-income individuals are observed with granular intensity while the affluent remain invisible, algorithms disproportionately detect "risk" and "non-compliance" among the poor, reinforcing narratives of inherent suspicion (Fong, 2020). Consequently, ADM systems do not merely manage aid; they automate containment. As León (2019) suggests, this infrastructure exacerbates vulnerability by prioritizing fraud detection over dignity, while Liu and Graham (2021) highlight how hidden biases reduce human lives to punitive metrics. Ultimately, this regime freezes social mobility, ensuring that while the rich remain unregulated, the poor are trapped in a permanent state of digital probation.

METHODOLOGY (PRISMA PROTOCOL)

Search Strategy

To ensure a rigorous and replicable analysis of the mechanisms underlying algorithmic class reproduction, this study adheres to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol. The systematic literature search was explicitly designed to bridge the disciplinary divide between technical computer science architectures and sociological critiques of stratification. Consequently, data collection was conducted across four comprehensive databases: Scopus and Web of Science were selected for their broad interdisciplinary coverage, ProQuest (Sociology) was utilized to capture deep theoretical discourse on social structure, and the ACM Digital Library was included to source technical literature regarding algorithmic design.

The search strategy employed a precise three-tiered Boolean logic string to isolate the intersection of automation technology and socioeconomic status. The query triangulated three distinct terminological clusters: the technological, the sociological subject, and the operative mechanism of harm. By connecting these clusters with the "AND" operator, the protocol effectively filtered out general studies on algorithmic performance to focus exclusively on literature that theorizes the digitization of privilege and the specific mechanics of socioeconomic sorting.

Inclusion/Exclusion Criteria

This systematic review adhered to a rigorous eligibility protocol designed to isolate scholarship examining the intersection of automated decision-making and socioeconomic stratification. To capture the distinct sociotechnical shifts associated with the proliferation of deep learning technologies, the review's temporal scope was restricted to literature published from 2015 to the present. Inclusion was granted to a methodological plurality, encompassing empirical investigations specifically algorithmic audits and ethnographic fieldwork as well as theoretical papers that conceptualize the mechanisms of digital inequality. Conversely, strict exclusion criteria were applied to maintain the study's focus on class reproduction. Manuscripts dedicated solely to technical optimization or algorithmic efficiency were omitted to prioritize critical social analysis. Furthermore, while acknowledging the importance of intersectional frameworks, studies focusing exclusively on race or gender were excluded unless they explicitly integrated into a socioeconomic class intersection. This parameter ensured the review remained centered on the specific modalities through which algorithmic systems code privilege and automate economic sorting, rather than conflating distinct vectors of systemic bias.

Data Extraction

Data extraction was executed using a standardized and iterative coding framework designed to deconstruct the complex relationship between algorithmic architecture and socioeconomic stratification. The primary phase of this process involved classifying each included study by Domain, specifically isolating four high-stakes sectors: Labor, Finance, Education, and the State. This sectoral segmentation was critical for comparative analysis, enabling the review to discern whether the logic of automated sorting functions uniformly across different institutional landscapes or if it adapts to the specific exigencies of, for example, gig-economy surveillance versus predictive policing or welfare automation. By rigidly coding for these domains, the review highlights how digital sorting permeates the essential infrastructures of social mobility and civic participation.

Simultaneously, the extraction protocol prioritized the identification of Proxy Variables Used. This involved a granular audit of the input features utilized by algorithmic models to infer socioeconomic status. The coding process cataloged specific data points ranging from geographical indicators like zip codes to behavioral metrics such as browsing history, device specifications, and vocabulary complexity to reveal how seemingly neutral technical parameters function as clandestine indicators of class. Furthermore, the analysis coded for the specific Mechanism of Harm operative in each study. Rather than treating algorithmic bias as a monolith, this category distinguished between distinct modes of disadvantage, such as predatory inclusion (offering subprime products to vulnerable groups), exclusionary filtering (resume screening tools), or disciplinary monitoring. This tripartite coding structure linking the institutional domain, the technical proxy, and the resultant sociological harm facilitated a synthesis that goes beyond mere description, demonstrating how the "black box" of AI is systematically wired to reproduce historical patterns of privilege and deprivation.

RESULTS

Education: The Sorting Machine

The analysis identifies the educational sector as a critical domain where algorithmic architectures function as a "sorting machine," fundamentally restructuring the traditional mechanisms of academic tracking. Within this sphere, the primary operative mechanism is the deployment of predictive analytics, which utilizes historical data to forecast student performance and assign academic trajectories. A dominant finding across the reviewed literature is the emergence of "Digital Tracking," a process where students from low-income zip codes and under-resourced schools are disproportionately flagged by early-warning systems as "at-risk." Rather than triggering supportive interventions, these algorithmic flags frequently result in the pre-emptive funneling of students into vocational or remedial tracks, effectively foreclosing access to higher education pathways before they are fully explored.

This automated sorting relies heavily on proxy variables that conflate socioeconomic status with academic potential, treating environmental factors such as postal codes or device connectivity as valid predictors of intellectual capability. Furthermore, the integration of algorithmic proctoring software introduces a layer of disciplinary surveillance that disproportionately penalizes students in crowded or shared living environments, who are more likely to be flagged for "suspicious behavior" due to background noise or movement. Consequently, these systems automate the sociological function of "cooling out," a process where ambitious students from lower-class backgrounds are systematically and quietly discouraged from aspiring to elite status. By laundering these exclusionary practices through the neutral language of data-driven guidance, educational algorithms legitimize class stratification, framing structural disadvantage as an objective assessment of individual aptitude

Labor: The Digital Gatekeeper

In the domain of labor, Automated Decision-Making (ADM) systems function as "Digital Gatekeepers," fundamentally restructuring the accessibility of professional employment. The central mechanism identified is the widespread deployment of Applicant Tracking Systems (ATS) and algorithmic "Culture Fit" assessments. These tools do not merely streamline hiring; they operate a process of "Homophily at Scale." The review reveals that these algorithms are engineered to filter candidates based on a specific constellation of middle-class markers ranging from semantic keyword matches and prestigious university affiliations to "culturally aligned" hobbies (e.g., lacrosse vs. football).

Because these systems are trained on historical hiring data, they codify the existing sociological biases of the firm into rigid inclusion criteria. Consequently, resumes that lack these signals of bourgeois cultural capital are systematically rejected in the pre-screening phase, ensuring they never reach human eyes. This automated culling renders working-class applicants invisible, not due to a lack of technical competency, but because their "data doubles" fail to mirror the class aesthetics prioritized by the algorithm. By digitizing the "paper ceiling," ATS tools transform subjective class prejudice into an objective technical barrier, effectively automating the exclusion of those who do not fit the pre-established socioeconomic mold of the ideal employee.

Finance: Predatory Inclusion

In the financial sector, the review identifies a critical shift from historical practices of "redlining" where low-income groups were denied access to a regime of "predatory inclusion." The dominant mechanism here is the use of alternative credit scoring and dynamic risk pricing models. Unlike traditional metrics, these algorithmic systems ingest non-financial data points, such as utility payment histories, payday loan usage, and even mobile device metadata, to construct "e-scores" for the unbanked.

The central finding is that while these tools technically expand access to credit, they do so on highly extractive terms. By categorizing low-income individuals into high-risk "subprime" tiers, algorithms automatically assign exorbitant interest rates and unfavorable repayment structures. Consequently, the "democratization" of finance functions as a wealth-extraction engine. Rather than facilitating upward mobility, these systems exploit economic vulnerability, locking the poor into cycles of debt where the cost of being poor is mathematically formalized. This dynamic ensures that financial products serve as instruments of discipline rather than support, effectively mining the precarious financial status of lower-class populations for institutional profit.

The State: Automating Austerity

Within the domain of the State, the deployment of Automated Decision-Making marks a transition from social support to a regime of "Automated Austerity." The central mechanism driving this shift is the implementation of algorithmic fraud detection systems, exemplified by frameworks such as Australia's "Robodebt" and the Netherlands' System Risk Indication (SyRI). These technologies were ostensibly designed to optimize the allocation of public funds; however, the review demonstrates that they function primarily as instruments of surveillance, tasked with auditing the financial lives of the most vulnerable.

The key finding across this literature is the "Criminalization of Poverty." These algorithms are calibrated to interpret the structural characteristics of economic instability such as irregular income streams common in gig work, frequent changes in address, or complex household compositions not as symptoms of need, but as mathematical indicators of "fraud" or "criminal risk." By treating the survival strategies of the poor as anomalies to be flagged, the state effectively automates suspicion. This process reverses the presumption of innocence, burdening welfare recipients with the task of disproving algorithmic accusations of deceit. Consequently, the digital welfare state creates a punitive feedback loop where the very conditions of poverty trigger automated sanctions, converting the safety net into a dragnet that penalizes citizens for their own precariousness.

DISCUSSION

The Mechanics of Reproduction (Answering RQ2)

To answer the second research question regarding sociotechnical mechanisms, the review identifies two primary engines of stratification: the "proxy problem" and recursive feedback loops. The proxy problem represents a fundamental epistemological failure of algorithmic neutrality; while systems may be blinded to explicit financial data, they remain sensitive to "neutral" behavioral artifacts that correlate with socioeconomic status. Seemingly innocuous variables such as commute times, email domains, or device battery life serve as high-fidelity proxies for poverty, allowing institutions to "launder" class discrimination through objective technical metrics. This creates a system where individuals are penalized not for their economic reality, but for the data signature of that reality.

Once categorized, these subjects are ensnared in algorithmic feedback loops that function as self-fulfilling prophecies. A predictive denial of resources, such as credit or employment, precipitates actual financial instability, which subsequently generates data points confirming the algorithm's initial negative assessment. Consequently, ADM systems do not merely predict risk; they actively manufacture it, trapping low-income populations in a downward spiral where the mathematical model produces the very failure it claims to forecast.

Theoretical Contribution: "The Ordinal Trap"

Synthesizing the seminal work of Fourcade and Healy, this review articulates a fundamental theoretical contribution regarding the structural transformation of inequality: the transition from a traditional "class society," rooted in labor relations and production, to an emerging "ordinal society" governed by market-based scoring. In this new stratification regime, an individual’s social value is no longer determined solely by their occupation or wage, but by their precise position on a graduated, algorithmic scale. This shift creates what this research terms the "Ordinal Trap," a dynamic where social standing is continuously recalibrated by a relentless stream of behavioral data. Unlike the broad, static categories of the industrial era, the ordinal society sorts of individuals into granular, fluid hierarchies prime vs. subprime, high-risk vs. low risk that dictate access to capital and opportunity with mathematical absolutism.

The cruelty of this trap lies in the inescapable nature of the "data double," a digital doppelgänger composed of an individual’s accumulated transaction history, browsing habits, and administrative records. In an analog society, geographical mobility often allowed for a "fresh start," permitting individuals to outrun a disadvantaged past. However, in the ordinal society, the data double is tethered to the subject, traveling instantly across institutional boundaries. Because this digital history precedes the individual in every interaction from applying for a lease to interviewing for a job past economic precariousness is effectively immortalized. The algorithm interprets historical struggle not as a temporary circumstance, but as a permanent character flaw, ensuring that the weight of the past acts as a perpetual drag on upward mobility. Consequently, the ordinal trap ossifies stratification, making it nearly impossible for the poor to escape their data-defined destiny.

Intersectionality

Finally, this review argues that the mechanisms of socioeconomic sorting cannot be analytically severed from the realities of racial stratification. The literature consistently demonstrates that Class ADM operates through a logic of "technological redlining," where the digital boundaries of exclusion map neatly onto historical geographies of segregation. Because wealth and race are spatially correlated due to legacies of housing discrimination, variables like zip codes function as dual-purpose proxies. When an algorithm penalizes a "high-risk" neighborhood based on financial metrics, it inevitably disproportionately targets minority communities.

Consequently, the "neutral" enforcement of class boundaries serves as a covert mechanism for maintaining racial hierarchies. The algorithmic decision to deny a loan based on "neighborhood property value trends" effectively launders the history of redlining into a mathematically objective risk assessment. Thus, ADM systems do not operate on isolated axes of identity; rather, they automate the intersectional "matrix of domination," where the suppression of economic mobility reinforces racial subordination. To treat class-based sorting as distinct from racial bias is to ignore the reality that in the data-driven society, the code for "poor" is frequently indistinguishable from the code for "non-white."

CONCLUSION & POLICY IMPLICATIONS

This systematic review concludes that Automated Decision-Making (ADM) systems, contrary to their promise of technocratic neutrality, function primarily as "engines of conservation." By synthesizing evidence across the critical domains of education, labor, finance, and the state, the analysis reveals that these technologies do not simply observe social stratification but actively mechanize it. The central finding is that ADM acts as a conservative force because it is fundamentally recursive: it trains on historical data which is saturated with the legacies of redlining, educational tracking, and class bias to generate predictions about the future.

Consequently, these systems ensure that the future inevitably resembles the past. By metabolizing historical disadvantages into objective risk scores, algorithms in Applicant Tracking Systems (ATS) and credit scoring models effectively freeze social mobility. The "data double" of the poor, heavily burdened by proxies for instability, becomes a permanent digital cage. Ultimately, by treating past outcomes as the sole truth for future potential, ADM systems automate a self-fulfilling prophecy where privilege is coded as merit and poverty is mathematically formalized as a permanent penalty.

Policy Recommendations

To dismantle the "engines of conservation," this review proposes two critical policy interventions designed to reintroduce equity into the algorithmic age. First, regulatory bodies must mandate Class Audits for all high stakes Automated Decision-Making systems. Currently, compliance frameworks focus almost exclusively on protected identity categories like race and gender, leaving socioeconomic discrimination unchecked. Legislation must be expanded to require rigorous testing for "socioeconomic disparate impact," compelling institutions to demonstrate that their models do not systematically penalize proxies for poverty such as zip codes, device types, or credit thinness before deployment. This shift would force a technical reckoning with the "proxy problem," ensuring that efficiency is not purchased at the cost of economic exclusion.

Second, the legal framework must establish a Right to Context. In the current "ordinal" regime, data anomalies such as gaps in employment history or irregular income patterns are automatically flagged as risk factors, with no opportunity for nuance. A "Right to Context" would legally compel institutions to provide a "human-in-the-loop" appeal channel, granting individuals the agency to offer narrative explanations for these statistical gaps. By permitting users to explain that an employment gap was due to caregiving or a medical emergency, rather than professional unreliability, this policy would humanize the "data double," transforming a rigid statistical rejection into a contextualized assessment of character and potential.

Future Research

This review highlights a critical necessity to decenter the Western-dominated focus of current algorithmic sociology and expand the geographical scope of inquiry to the Global South. Future scholarship must rigorously examine state-mandated Digital ID infrastructures in regions such as India and Africa, where biometric datafication often precedes legal privacy protections. Unlike the market-driven scoring of the West, these systems frequently function as monolithic gatekeepers to essential citizenship rights, presenting unique and under-theorized mechanisms of exclusion that require urgent empirical attention.

Simultaneously, the field requires a methodological shift from static, cross-sectional audits to robust longitudinal studies on algorithmic social mobility. While current research effectively identifies immediate bias, there is a paucity of data tracking the long-term compounding effects of the "ordinal trap." Future research should follow cohorts over decades to empirically determine whether the "digital double" effectively functions as a permanent caste system, permanently arresting upward mobility, or if resistance strategies can successfully disrupt these automated feedback loops over time.

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