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Date: October 4, 2025
Thesis Statement:
Constant data collection and algorithmic surveillance most negatively affect marginalized groups—particularly low-income communities and minorities—by reinforcing existing social, economic, and institutional inequalities through biased systems in policing, employment, healthcare, and digital services.

I. Introduction

A. Hook:
In today's digital world, nearly every click, purchase, and movement is tracked. What many see as harmless data collection often serves as the foundation of systems that quietly decide who gets a job, a loan, or even a fair trial.

B. Background Context:
Algorithmic surveillance—data-driven systems that monitor behavior and make predictions—has become central to policing, hiring, and healthcare. While these technologies promise objectivity and efficiency, numerous studies have shown that they often reproduce or intensify social bias.

C. Revised Thesis:
Constant data collection and algorithmic surveillance deepen inequality by embedding existing racial and class biases into supposedly "neutral" systems, disproportionately harming low-income and minority communities across multiple sectors.

II. Algorithmic Surveillance in Policing and Criminal Justice

A. Topic Sentence:
Predictive policing and risk assessment algorithms replicate racial discrimination under the guise of objectivity.

B. Supporting Evidence:

1. ProPublica's *Machine Bias* investigation exposed how the COMPAS algorithm rated Black defendants as "high risk" nearly twice as often as white defendants with similar records (Angwin et al., 2016).

2. The AI Now Report shows how policing algorithms often operate without public oversight, deepening systemic inequalities in law enforcement (Whittaker & Crawford, 2018).

C. Analysis:
These findings demonstrate how surveillance tools rely on historical policing data that already reflect racial bias, turning discrimination into data-driven "evidence."

III. Economic Disparities in Algorithmic Decision-Making

A. Topic Sentence:
Corporate algorithms in platforms and marketplaces often exploit data in ways that economically disadvantage marginalized groups.

B. Supporting Evidence:

1. Pandey et al. (2021) found that ride-hailing algorithms charge higher prices and offer longer wait times to low-income and minority neighborhoods.

2. Data collection and profiling in retail and banking use purchasing history to target or exclude customers from deals and credit offers.

C. Analysis:
Algorithmic systems amplify existing class divisions, embedding digital redlining into modern commerce. What appears to be "efficient pricing" becomes structural economic discrimination.

IV. Algorithmic Bias in Employment and Hiring

A. Topic Sentence:
AI-based recruitment tools perpetuate workplace inequality by reflecting the biases in their training data.

B. Supporting Evidence:

1. Chen et al. (2023) show how AI hiring software often filters out applicants from underrepresented backgrounds due to biased data inputs.

2. The systems evaluate language patterns, names, or schools attended—factors tied to race or socioeconomic class.

C. Analysis:
Algorithmic hiring transforms social prejudice into quantifiable “fit scores,” reducing diversity and reinforcing occupational stratification.

V. Health Disparities in Algorithmic Surveillance

A. Topic Sentence:
AI in healthcare reproduces bias when trained on datasets that underrepresent certain populations.

B. Supporting Evidence:

1. Agarwal et al. (2023) show medical AI models often predict worse health outcomes for minorities due to skewed training data.

2. Misdiagnosis and unequal access to care emerge when algorithms assume “universal” data that excludes vulnerable communities.

C. Analysis:
Health-related surveillance systems illustrate that algorithmic inequality has physical consequences—biased data literally shape who gets care and who doesn’t.

VI. Counterarguments and Rebuttals

A. Opposing Viewpoint:
Some argue that algorithmic systems are neutral tools and that bias arises from human misuse, not the technology itself.

B. Rebuttal:
However, Grother et al. (2019) demonstrate measurable demographic disparities in face recognition accuracy, proving bias exists within the technology’s design itself.
Additionally, the AI Now Report (Whittaker & Crawford, 2018) argues that neutrality is impossible without structural accountability and diverse input.

C. Analysis:
While human oversight can reduce bias, true neutrality requires systemic reform in data collection, model design, and regulation—not blind faith in algorithms.

VII. Conclusion

A. Summary of Key Points:
Algorithmic surveillance in policing, commerce, hiring, and healthcare disproportionately harms marginalized groups by embedding structural bias into automated systems.

B. Proposed Solutions or Calls to Action:

1. Implement stronger transparency and auditing requirements for algorithmic systems.
2. Mandate public accountability and diverse data inclusion.
3. Support interdisciplinary research on equitable algorithm design.

C. Broader Implications:
Without reform, algorithmic surveillance risks becoming the invisible architecture of modern discrimination—one where inequality is coded into the very systems that claim to be objective.

Works Cited (used in-text)

- Whittaker, M., Crawford, K., & AI Now Institute. (2018). *AI Now Report 2018.*
- Angwin, J., Larson, J., Mattu, S., & Kirchner, L. (2016). *Machine Bias.* ProPublica.
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- Chen, Z., et al. (2023). *Ethics and Discrimination in Artificial Intelligence-Enabled Recruitment. Humanities and Social Sciences Communications*, 10(1), 79.
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