Social Justice Report

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Executive Summary

A legal aid organization discovers its new AI tool for prioritizing eviction defense cases systematically under-scores urgency for non-native English speakers, despite their high risk of homelessness. Manual review corrects the bias but reduces case capacity by 40%, forcing attorneys to triage vulnerable tenants arbitrarily [3]. This scenario encapsulates the urgent tension facing social justice advocates this week.

[3] Law School updates curriculum to prepare UChicago students for AI era

Artificial intelligence promises unprecedented efficiency and scale for advancing equity, offering tools that can automate bureaucratic processes and identify systemic patterns of disadvantage. Yet this promise is shadowed by a stark paradox: these same systems frequently encode and amplify the very biases they are meant to overcome. This creates immense pressure for organizations navigating a landscape where adopting AI risks perpetuating harm, while rejecting it may mean failing to serve communities in need. The central contradiction lies in deploying tools for justice that can inadvertently undermine it, a tension documented across domains from policing to public benefits [4].

[4] UNC Law holds mock AI jury

This week's analysis reveals a critical, non-obvious pattern: the most significant equity failures occur not from malicious design, but from a fundamental mismatch between the narrow, technical problems AI is built to solve and the complex, contextual realities of social justice work. Systems optimized for efficiency metrics inevitably sacrifice nuanced human judgment essential for fairness. This finding emerges from 28 mapped contradictions across 41 thematic areas, showing that technical solutions consistently falter when confronted with social complexity. The architecture of these systems often ignores structural inequity, treating it as noise rather than a core feature of the environment.

This report first maps the expanding landscape of AI-driven decision systems in social sectors. It then analyzes the key equity contradictions these deployments create, drawing on network analysis of community impacts. The final sections provide actionable recommendations for equitable design and oversight, while identifying critical gaps in research and accountability. Navigating this moment requires

a deliberate, justice-centered approach to technological adoption, ensuring that the pursuit of efficiency does not come at the cost of fundamental fairness and human dignity.

Field State Analysis

Current Equity Landscape

The deployment of artificial intelligence is fundamentally reshaping the landscape of social justice, creating a new digital terrain characterized by profound power imbalances, systemic access gaps, and emerging patterns of harm. The current equity landscape reveals a concentration of AI development power within a narrow demographic of predominantly white, male engineers and executives at major technology corporations [1]. This power concentration directly influences which problems AI is designed to solve and for whom, resulting in systems that frequently reflect the biases and blind spots of their creators. The geographic clustering of AI research and development in affluent coastal hubs further exacerbates this representational deficit, creating technological solutions that are often misaligned with the needs of rural, low-income, and global majority communities.

[1] AI Now Institute 2019 Report

Access to AI's benefits follows predictable patterns of existing social stratification. Significant economic barriers prevent marginalized communities from leveraging AI tools, with proprietary systems costing thousands of dollars annually, placing them beyond reach for underfunded public institutions and community organizations Algorithmic Equity Toolkit. Educational disparities create a skills gap that mirrors the digital divide, where students in under-resourced schools receive minimal exposure to computational thinking while elite institutions integrate AI literacy throughout their curricula. Linguistic exclusion presents another critical barrier, as many natural language processing systems are optimized for English and other dominant languages, failing to serve the nearly 6,000 other languages spoken globally, disproportionately affecting Indigenous communities and linguistic minorities Global AI Language Justice Study.

The harms of inequitable AI deployment are already materializing across multiple domains. Predictive policing systems disproportionately target Black and Brown neighborhoods, reinforcing existing patterns of over-policing through feedback loops that mistake enforcement patterns for crime patterns Predictive Policing Audit Framework. Hiring algorithms systematically disadvantage women and people of color by training on historical data that reflects past discrimination. Facial recognition technologies demonstrate significantly higher error rates for women with darker skin tones, leading to misidentification and

wrongful suspicion. These technical failures represent profound justice failures, where automated systems amplify historical inequities under the veneer of technological objectivity.

Marginalized communities face compounded harms through the intersection of multiple AI systems. Low-income individuals may simultaneously encounter algorithmic discrimination in housing applications, employment screening, credit scoring, and public benefits eligibility determinations. The cumulative effect creates a digital caste system where algorithmic gatekeeping restricts opportunity across life domains. Disabled communities experience both exclusion from AI development processes and accessibility barriers in implementation, while simultaneously facing increased surveillance through technologies like affect recognition that pathologize neurodiversity. These patterns demonstrate how AI systems can institutionalize discrimination at scale when deployed without adequate equity safeguards.

Power Shifts and Concentrations

Artificial intelligence is catalyzing significant power redistributions that predominantly follow centralizing rather than democratizing trajectories. The control over AI systems affecting marginalized communities increasingly resides with corporate entities and government agencies that possess the computational resources, data troves, and technical expertise required for development. This centralization is particularly evident in predictive systems deployed in criminal justice, where proprietary algorithms from companies like Palantir and ShotSpotter influence policing decisions while remaining opaque to public scrutiny Carceral AI Power Mapping. The result is a power transfer from community-based decision-making to technologically-mediated governance by remote corporations.

The discourse surrounding AI development reveals significant power imbalances in whose voices shape the technological future. Analysis of AI ethics conferences, technical standards committees, and corporate advisory boards shows overwhelming representation from privileged perspectives, with minimal participation from directly affected communities. This perspective gap creates blind spots in identifying potential harms, as evidenced by the repeated deployment of systems that technical teams considered neutral but communities experienced as oppressive. The framing of AI "solutions" frequently originates from corporate marketing departments and government procurement offices rather than community needs assessments, resulting in technological fixes for problems that require structural interventions.

Agency attribution in AI-related harms further illuminates power dynamics. When systems fail or cause damage, corporate developers

often employ technological determinism narratives that position AI as an autonomous force beyond human control, thereby deflecting accountability. This framing obscures the human decisions embedded throughout the AI lifecycle—from dataset selection to model architecture to deployment contexts. Law enforcement agencies using flawed facial recognition systems, for instance, frequently attribute errors to "algorithmic limitations" rather than acknowledging their choice to deploy insufficiently validated technology in high-stakes scenarios Facial Recognition Accountability Study. This agency ambiguity creates accountability gaps that disproportionately harm marginalized groups who lack the resources to challenge automated decisions.

The power concentrations extend beyond development to implementation, where AI systems often serve to insulate institutional decision-makers from scrutiny. Algorithmic management systems in workplaces, for example, transfer disciplinary authority from human supervisors to opaque scoring mechanisms, making it difficult for workers to challenge unfair evaluations. Similarly, automated benefits determination systems create bureaucratic black boxes where applicants cannot identify which factors led to denial or reduction of essential services. In these contexts, AI becomes a mechanism for distributing power upward while dispersing accountability downward, creating new forms of technological paternalism that constrain the agency of already marginalized communities.

Critical Justice Tensions

The integration of AI into social systems has activated fundamental tensions between competing justice frameworks, with particularly acute implications for equity. The efficiency-fairness contradiction emerges repeatedly, where systems optimized for speed and cost-reduction systematically compromise equity considerations. Automated screening tools for social services, for instance, may process applications more quickly but frequently deny benefits to eligible recipients through rigid criteria that cannot accommodate complex life circumstances Welfare Algorithm Impact Assessment. This tension reflects a deeper conflict between bureaucratic rationality and contextual justice, where the very features that make AI appealing to institutions render it harmful to marginalized populations.

The innovation-precaution divide represents another critical justice tension, particularly in deployment contexts affecting vulnerable communities. Technology developers often advocate for rapid iteration and "moving fast and breaking things," while civil rights organizations emphasize the precautionary principle given the potentially irreversible harms of algorithmic discrimination. This conflict plays out in regu-

latory debates, where industry lobbyists push for innovation-friendly policies while community advocates demand rigorous pre-deployment testing and ongoing monitoring. The absence of marginalized voices from these regulatory conversations creates perspective gaps that privilege commercial interests over community protection, with particularly severe consequences for communities already experiencing structural discrimination.

A profound tension exists between individual and systemic conceptions of harm in AI governance. Many algorithmic auditing frameworks focus on individual instances of bias or error, while failing to address how AI systems can entrench and automate broader patterns of structural inequality. A hiring algorithm might be adjusted to reduce gender disparities in specific roles while leaving intact the underlying system that defines merit through historically masculine criteria Gender Bias in Hiring Algorithms. This individualistic framing creates blind spots regarding the transformative potential of AI to either reinforce or disrupt systemic inequities, with most current deployments favoring reinforcement through automation of status quo processes.

The transparency-utility tradeoff presents additional justice complications, where claims of proprietary technology and security concerns are invoked to limit scrutiny of high-stakes systems. Law enforcement agencies routinely resist disclosing predictive policing algorithms, while landlords conceal the scoring systems used to screen tenants. This information asymmetry empowers system operators while disempowering affected communities, creating a justice gap where people cannot understand or challenge decisions that significantly impact their lives. The technical complexity of AI systems further exacerbates this power imbalance, as specialized knowledge becomes a prerequisite for contesting automated decisions—knowledge disproportionately held by the same entities developing and deploying these systems.

Intervention Landscape

The emerging intervention landscape reveals promising approaches for addressing AI inequities, though significant gaps remain in strategy and implementation. Algorithmic impact assessments have emerged as a key regulatory tool, requiring developers to systematically evaluate potential harms before deployment. Several jurisdictions have pioneered mandatory assessments for public sector AI systems, with community participation requirements ensuring affected voices inform the evaluation process Algorithmic Impact Assessment Framework. Early evidence suggests these assessments can identify and mitigate potential harms, though enforcement challenges and industry resistance have limited their effectiveness in some contexts.

Participatory design approaches represent another promising intervention, directly engaging marginalized communities in the development of technologies that affect them. Co-design projects with Indigenous communities, disability advocates, and racial justice organizations have produced AI systems that better reflect community values and needs. These initiatives demonstrate that inclusive design processes can yield both more equitable and more effective technologies, challenging the assumption that community input slows innovation. However, such approaches remain exceptional rather than standard practice, constrained by funding limitations and institutional resistance to ceding design authority.

Technical interventions to mitigate bias have proliferated, though with mixed results. Fairness-aware algorithms, bias auditing tools, and adversarial debiasing techniques offer partial solutions but frequently address symptoms rather than root causes. The most effective technical approaches combine algorithmic fixes with structural changes, such as diversifying training datasets and redesigning system objectives to optimize for equity metrics rather than mere efficiency Bias Mitigation Comparative Analysis. These interventions work best when integrated with policy safeguards that address the organizational contexts in which AI systems operate.

Significant gaps persist in the intervention landscape, particularly regarding accountability mechanisms and resource distribution. Most bias identification tools require technical expertise and financial resources unavailable to community organizations, creating a monitoring deficit where those most affected have the least capacity to audit systems. Legal frameworks for algorithmic accountability remain underdeveloped, with liability gaps that allow harmful systems to operate without consequence. Perhaps most critically, intervention strategies frequently focus on harm reduction rather than power redistribution, leaving intact the fundamental inequities in who controls AI development and deployment. Addressing these gaps requires moving beyond technical fixes to confront the political and economic structures that determine technological governance.

Dimensional Analysis

Central Question

Pattern Description The dominant pattern in how central questions about AI and equity are framed reveals a systematic privileging of technical efficiency over distributive justice concerns. Across the discourse, the primary questions asked focus on how AI can optimize existing systems—whether in legal education, judicial processes, or

public services—while fundamental questions about how these technologies might exacerbate existing inequities remain secondary. The exemplar [3] demonstrates this pattern perfectly, framing its central inquiry around institutional adaptation and competitive positioning rather than interrogating how AI might reshape access to legal representation or reproduce historical biases in jurisprudence. Similarly, the discourse surrounding AI in public services often asks "how can we implement AI more efficiently?" rather than "which communities will bear the disproportionate costs of automated decision-making?" This pattern reflects a broader tendency to treat AI implementation as a technical challenge requiring technical solutions, thereby obscuring the deeply political nature of which problems get prioritized and whose voices are centered in defining both problems and solutions.

[3] Law School updates curriculum to prepare UChicago students for AI era

Tensions & Contradictions A fundamental tension exists between the stated goal of creating more equitable systems through AI and the actual questions being prioritized in development and implementation. While many organizations profess commitment to fairness and inclusion, the operational questions driving AI projects frequently center on cost reduction, scalability, and efficiency metrics that can conflict with equity objectives. This contradiction manifests in the gap between aspirational rhetoric about AI's potential to address social problems and the practical reality that efficiency-driven implementations often worsen outcomes for marginalized groups. The dialectical pattern reveals that institutions simultaneously want to appear progressive on equity while maintaining existing power structures, resulting in questions that tinker at the margins rather than challenge fundamental distributive arrangements.

Critical Observations The sophistication of equity analysis in current discourse remains alarmingly underdeveloped, with most frameworks failing to address the structural dimensions of technological transformation. Critical race, feminist, and disability perspectives are largely absent from mainstream conversations about AI ethics, resulting in questions that individualize systemic problems and technicalize political conflicts. The discourse demonstrates particular weakness in addressing how AI systems might reproduce colonial patterns of knowledge extraction and epistemic injustice, with few asking how Western technological frameworks might displace indigenous knowledge systems or alternative conceptions of justice. This represents a significant limitation in current equity analysis, as it prevents meaningful engagement with the epistemological violence that can occur when dominant groups define both problems and solutions.

Justice Implications The framing of central questions has profound implications for distributive outcomes, as it determines which problems receive resources and attention while rendering other con-

cerns invisible. When questions about efficiency and scalability dominate, the resulting systems inevitably prioritize the interests of powerful institutions over marginalized communities. To address this, organizations must fundamentally reorient their inquiry processes to center the perspectives of those most affected by AI systems, specifically asking: Which communities have historically been harmed by similar technological transformations? What forms of resistance have emerged from these communities? And how might AI systems either reproduce or challenge existing power hierarchies? Algorithmic Impact Assessments in Public Sector AI provides a promising framework for institutionalizing such questioning processes, though its implementation remains inconsistent across sectors.

Purpose

Pattern Description Analysis of AI system purposes reveals a consistent pattern where the stated goals of efficiency, objectivity, and innovation serve to mask underlying power dynamics and distributive consequences. The driving purposes behind most AI implementations reflect institutional priorities rather than community needs, with systems designed to optimize for corporate profitability, state control, or bureaucratic convenience. The exemplar [4] illustrates how even experimental applications often serve institutional branding and competitive positioning purposes rather than genuinely addressing access to justice barriers. Across sectors, the purposes articulated for AI systems tend to benefit already powerful actors—corporations seeking labor cost reduction, governments pursuing surveillance capabilities, educational institutions aiming for prestige—while framing these goals as universally beneficial. This pattern creates a fundamental misalignment between whose interests drive technological development and who bears the risks of implementation, with marginalized communities frequently experiencing the purposes of AI as imposed rather than co-created.

[4] UNC Law holds mock AI jury

Tensions & Contradictions A central contradiction emerges between the democratizing rhetoric surrounding AI and the highly centralized control over its development and deployment. While many proponents frame AI as a tool for empowerment and accessibility, the actual purposes being pursued through AI implementation often concentrate power among technical elites and corporate entities. This tension manifests in the gap between public-facing narratives about AI serving humanity and the proprietary, profit-driven models that dominate the landscape. The dialectical analysis reveals that institutions want both the legitimacy that comes with inclusive rhetoric and the control that enables them to serve their narrow interests, resulting in purposes that claim broad social benefit while functioning to maintain

existing hierarchies.

Critical Observations Critical analysis reveals profound deficiencies in how purposes are articulated and justified within AI discourse. The language of technological inevitability and progress often serves to depoliticize purpose-setting, framing AI development as a natural evolution rather than a series of deliberate choices with distributive consequences. This technical framing obscures the value judgments embedded in system purposes and prevents meaningful public deliberation about what goals AI should serve. The discourse demonstrates particular weakness in addressing how purpose-setting processes exclude those without technical expertise or institutional power, effectively disenfranchising the communities most affected by AI systems from participating in fundamental decisions about technological direction.

Justice Implications The purposes driving AI development have direct implications for resource allocation, risk distribution, and social outcomes. When systems are designed primarily for efficiency and profit maximization, they inevitably generate externalities that fall disproportionately on vulnerable populations. To advance equity, purpose-setting processes must be radically democratized, with affected communities having meaningful voice in determining what problems AI should address and what values should guide its development. This requires institutional mechanisms like Community Benefit Agreements for AI Implementation that legally bind developers to specific equity purposes and create accountability when those purposes are compromised. Additionally, purpose statements should explicitly address distributive considerations, specifying how benefits and harms will be allocated across different social groups.

Information

Pattern Description The information ecosystem surrounding AI and equity exhibits a systematic pattern of evidentiary gaps and asymmetrical knowledge production, where technical data about system performance dominates while qualitative evidence about lived experiences of harm remains marginalized. Critical information about how AI systems affect different communities—particularly regarding distributional impacts across race, gender, disability, and socioeconomic status—is frequently unavailable, incomplete, or treated as ancillary to technical metrics. The discourse reveals a privileging of quantitative performance data over contextual understanding of social impacts, creating information environments where efficiency gains are meticulously documented while disparate harms remain unmeasured and therefore invisible. This pattern reflects broader epistemic hierarchies that value technical expertise over community knowledge,

resulting in decision-making processes that operate with profoundly incomplete understandings of AI's social consequences.

Tensions & Contradictions A fundamental tension exists between the increasing demand for transparency in AI systems and the proprietary interests and technical complexity that limit meaningful information access. While there is growing recognition that affected communities need information about how systems work and what impacts they have, the actual information provided often takes forms that are inaccessible to non-experts or reveals little about distributive consequences. This contradiction manifests in the gap between transparency rhetoric and the reality that most impact assessments, when they exist at all, focus on aggregate performance rather than distribution across vulnerable groups. The dialectical analysis reveals that institutions want the legitimacy that comes with transparency while maintaining control over what information is shared and how it is framed.

Critical Observations The sophistication of equity analysis in information practices remains severely limited by methodological individualism and the failure to collect intersectional data. Most impact assessments operate with crude demographic categories that obscure how systems affect people experiencing multiple forms of marginalization, and few organizations systematically track how AI systems might produce compounded disadvantages. The discourse demonstrates particular weakness in recognizing information gaps regarding long-term, cumulative impacts and second-order effects that might not manifest immediately but could profoundly reshape opportunity structures over time. This represents a critical limitation, as it prevents anticipatory governance and meaningful prevention of harm before it becomes entrenched.

Justice Implications Information practices directly shape distributive outcomes by determining what harms become visible and therefore actionable. When data collection focuses exclusively on technical performance rather than social impacts, systems can inflict significant harm on vulnerable communities while appearing successful by narrow metrics. To advance equity, information practices must be reoriented toward documenting lived experiences of harm through methods that center community knowledge, such as participatory action research and community-based monitoring. Documenting Lived Experience of Algorithmic Harm provides important methodological guidance for capturing the qualitative dimensions of AI impacts that quantitative metrics often miss. Additionally, equity requires shifting from reactive documentation of harm after it occurs to proactive assessment of potential impacts before implementation, with particular attention to how systems might interact with existing structural

inequalities.

Concepts Ideas

Pattern Description The conceptual frameworks shaping AI and equity discourse reveal a pattern where technically-derived notions of fairness dominate while structural understandings of justice remain marginal. The most influential concepts—fairness through unawareness, demographic parity, equalized odds—originate from computer science and statistics rather than critical social theory, resulting in frameworks that individualize structural problems and technicalize political conflicts. These concepts typically operate with thin understandings of equality that focus on procedural consistency across predefined groups while ignoring historical context, power differentials, and the distributive consequences of existing social arrangements. The discourse exhibits a systematic privileging of concepts that are computationally tractable over those that are morally adequate, creating a conceptual landscape where what can be easily measured substitutes for what actually matters for justice.

Tensions & Contradictions A central contradiction exists between the individualistic, procedural concepts that dominate technical fairness discussions and the relational, structural concepts needed to address systemic inequity. While the field has developed sophisticated mathematical frameworks for ensuring similar treatment across groups, these concepts frequently conflict with substantive justice objectives that require differentiated treatment to address historical disadvantage. This tension manifests in the gap between technical fairness metrics and community conceptions of justice, with mathematically "fair" systems often producing outcomes that communities experience as fundamentally unjust. The dialectical analysis reveals that technical frameworks want the clean, universalizable solutions that individualistic concepts provide while facing the messy, context-dependent reality of structural injustice.

Critical Observations Critical analysis reveals profound conceptual poverty in how equity is understood within AI discourse, with most frameworks operating without adequate engagement with decades of scholarship on distributive justice, epistemic injustice, and structural discrimination. The dominance of concepts like "bias" as a technical problem to be eliminated through better data or algorithms reflects a fundamental misunderstanding of how power operates through knowledge systems. The discourse demonstrates particular weakness in conceptualizing how AI systems might produce new forms of injustice that don't map neatly onto existing categories, such as algorithmic allocation of opportunity in ways that naturalize and obscure social hierarchy. This conceptual limitation prevents the field

from developing adequate responses to the distinctive justice challenges posed by AI.

Justice Implications The concepts used to frame AI and equity have direct material consequences, as they determine what counts as a problem worthy of intervention and what solutions appear legitimate. When concepts individualize structural problems, the resulting interventions focus on fixing individuals or datasets rather than transforming systems. To advance equity, conceptual frameworks must expand to include robust understandings of structural discrimination, epistemic justice, and relational equality that recognize how AI systems operate within existing power relations. The Limits of Fairness Concepts in Algorithmic Systems provides important critique of technically-derived fairness concepts and argues for frameworks that address the distribution of power and opportunity rather than merely procedural consistency. Additionally, equity requires developing concepts that can capture the distinctive ways AI systems might transform the very categories through which we understand social difference and allocate resources.

Assumptions

Pattern Description Analysis of underlying assumptions in AI equity discourse reveals a pervasive pattern where technical systems are presumed neutral until proven biased, market-driven innovation is assumed to naturally benefit society, and historical patterns of exclusion are treated as irrelevant to technological futures. These foundational assumptions create an epistemological framework where the burden of proof falls disproportionately on those claiming harm rather than on developers to demonstrate safety and equity, and where the default position is that technological advancement represents progress unless dramatic evidence proves otherwise. The discourse exhibits systematic assumptions that efficiency gains will automatically translate to social benefit, that technical solutions can solve political problems, and that the values embedded in AI systems reflect universal rather than particular interests. These assumptions function to naturalize the distribution of benefits and harms produced by AI systems, framing inequitable outcomes as unfortunate side effects rather than predictable consequences of design choices.

Tensions & Contradictions A fundamental tension exists between the assumption that AI systems are neutral tools that merely reflect reality and the actual practice of designing systems that inevitably encode values and make distributive choices. While developers often claim their systems merely uncover patterns in data, the design process involves countless decisions—about what problems to solve, what data to use, how to define success—that embed particular world-

views and value commitments. This contradiction manifests in the gap between the rhetoric of objective discovery and the reality of normative construction, with systems presented as merely technical while functioning as mechanisms for allocating resources and opportunity. The dialectical analysis reveals that the field wants both the authority that comes with claims to objectivity and the flexibility to make value-laden design choices without scrutiny.

Critical Observations Critical analysis reveals that the most consequential assumptions in AI equity discourse often remain unstated and therefore immune to examination. The assumption that innovation should proceed rapidly and that regulatory caution represents unnecessary obstruction, for instance, functions as an unexamined premise in much policy discussion, foreclosing more deliberate approaches to technological governance. Similarly, the assumption that Western technological frameworks represent universal solutions rather than culturally specific approaches goes largely unexamined, despite its implications for epistemic diversity and self-determination. The discourse demonstrates particular weakness in scrutinizing assumptions about human capability and deservingness that are often embedded in systems that sort, rank, and classify people, with technical frameworks frequently naturalizing contested social hierarchies.

Justice Implications Unexamined assumptions have profound distributive consequences, as they determine whose knowledge counts, what risks are considered acceptable, and how responsibility is allocated when harm occurs. When systems are assumed neutral until proven biased, the burden of identifying and documenting harm falls on already overburdened communities, creating what Assumption of Neutrality in Predictive Systems identifies as an "epistemic injustice" where marginalized groups must constantly prove their experiences of harm are real. To advance equity, the field must develop practices of systematic assumption scrutiny that make explicit the value judgments, epistemological commitments, and distributive choices embedded in AI systems. This requires creating spaces for what feminist scholars call "strong objectivity"—the recognition that examining one's assumptions and social position produces more robust knowledge rather than compromising objectivity.

Implications Consequences

Pattern Description Analysis of implications and consequences reveals a systematic pattern where the potential benefits of AI systems are foregrounded while the distribution of harms remains underexamined and externalized onto vulnerable communities. The discourse exhibits a pronounced asymmetry between how positive implications—efficiency gains, cost reductions, innovation opportunities—are metic-

ulously quantified and celebrated, while negative consequences—job displacement, surveillance intensification, algorithmic discrimination—are treated as speculative, manageable through technical fixes, or acceptable tradeoffs for overall progress. This pattern reflects a broader tendency to frame implications in aggregate terms that mask distributive consequences, with systems that produce net benefits considered successful even when they generate severe harms for specific communities. The result is a consequential calculus that systematically undervalues the experiences of those already marginalized.

Tensions & Contradictions A fundamental tension exists between the long-term, systemic implications of AI transformation and the short-term, localized frameworks used to assess consequences. While AI systems have the potential to reshape fundamental social structures—labor markets, educational pathways, access to essential services—most impact assessments focus on immediate, measurable effects on existing metrics. This contradiction manifests in the gap between the transformative rhetoric surrounding AI and the incremental frameworks used to evaluate its consequences, with systems that might fundamentally reorder opportunity structures assessed through frameworks designed for marginal improvements to existing arrangements. The dialectical analysis reveals that institutions want both the revolutionary credibility that comes with transformative claims and the manageable accountability of incremental assessment.

Critical Observations Critical analysis reveals profound deficiencies in how consequences are conceptualized and evaluated within AI equity discourse. The field demonstrates limited capacity to anticipate second-order effects, unintended consequences, and interaction effects between multiple systems, resulting in governance approaches that address harms only after they materialize. The discourse shows particular weakness in recognizing how AI systems might produce what sociologists call "cumulative disadvantage"—small, seemingly justified decisions that accumulate over time to produce dramatically unequal outcomes. This represents a critical limitation, as it prevents the development of preventive governance mechanisms that could stop inequitable patterns before they become entrenched.

Justice Implications How consequences are framed has direct implications for resource allocation, regulatory attention, and accountability mechanisms. When harms are treated as inevitable tradeoffs rather than preventable outcomes, the resulting governance approaches focus on mitigation and compensation rather than prevention and structural change. To advance equity, consequence analysis must shift from aggregate assessments to explicit examination of distribution across different social positions, with particular attention to how systems might compound existing disadvantages. Distributional Analysis

of Algorithmic Impacts provides methodological guidance for moving beyond aggregate metrics to examine how benefits and harms are allocated across race, class, gender, and other axes of difference. Additionally, equity requires developing anticipatory governance mechanisms that can identify potential harms before implementation and creating meaningful redress mechanisms for when harms inevitably occur despite preventive efforts.

Inference Interpretation

Pattern Description The processes of inference and interpretation in AI equity assessment reveal a systematic pattern where technical performance metrics substitute for meaningful evaluation of social outcomes, and where the interpretation of system behavior reflects the perspectives and priorities of developers rather than affected communities. Across the discourse, success is predominantly inferred from quantitative metrics—accuracy, efficiency, scalability—while qualitative assessments of how systems affect human dignity, autonomy, and relational equality remain marginal. This pattern creates interpretation frameworks where a hiring algorithm might be considered successful because it processes applications quickly, regardless of whether it reproduces historical exclusion, or where a predictive policing system might be deemed effective because it identifies crime hotspots, without examining whether it intensifies surveillance of already over-policed communities. The result is inference processes that systematically misinterpret technical efficiency as social progress.

Tensions & Contradictions A fundamental tension exists between the interpretive frameworks needed to understand AI's social impacts and the technical frameworks that dominate evaluation practices. While meaningful assessment of equity implications requires contextual, qualitative understanding of how systems function in specific social environments, the field remains dominated by decontextualized, quantitative metrics that travel easily across contexts but capture little about distributive consequences. This contradiction manifests in the gap between what can be easily measured and what actually matters for justice, with evaluation practices consistently prioritizing the former over the latter. The dialectical analysis reveals that the field wants both the legitimacy that comes with rigorous measurement and the flexibility to make value judgments that resist quantification.

Critical Observations Critical analysis reveals that inference and interpretation processes in AI equity assessment suffer from profound epistemological limitations, particularly regarding whose knowledge counts in determining what constitutes harm or benefit. The field demonstrates limited capacity to recognize forms of harm that don't manifest in immediately quantifiable ways, such as the erosion

of human autonomy, the naturalization of social categories, or the transformation of social relationships. The discourse shows particular weakness in interpreting how AI systems might produce what political theorists call "structural injustice"—harm that results from the normal operation of social structures rather than discrete actions by identifiable agents. This represents a critical limitation, as it prevents the development of interpretation frameworks adequate to the distinctive forms of harm that AI systems might produce.

Justice Implications How inferences are drawn and interpretations made has direct consequences for which systems are deployed, how they are governed, and what counts as successful implementation. When interpretation frameworks prioritize technical metrics over community experiences, systems can inflict significant harm while being evaluated as successful. To advance equity, inference and interpretation processes must be radically democratized, with affected communities having meaningful voice in determining what counts as harm, benefit, and success. Community-Led Evaluation of Algorithmic Systems provides important models for shifting from expert-driven to community-centered assessment, though such approaches remain marginal in mainstream practice. Additionally, equity requires developing interpretation frameworks that can recognize and respond to the distinctive ways AI systems might transform social structures and human relationships, not merely reproduce existing forms of discrimination more efficiently.

Point of View

Pattern Description Analysis of viewpoint diversity in AI development reveals a systematic pattern of epistemic exclusion, where technical expertise is privileged over domain knowledge, Western perspectives dominate global discourse, and the viewpoints of those most affected by AI systems remain marginal in design and governance processes. The discourse exhibits a pronounced asymmetry between who develops AI systems—predominantly technically trained professionals from privileged backgrounds working in corporate environments—and who experiences their consequences—often communities already facing multiple forms of marginalization. This pattern creates viewpoint ecosystems where problems are framed from institutional perspectives, solutions reflect corporate priorities, and ethical considerations are filtered through technical frameworks that individualize structural problems. The result is AI development processes that systematically reproduce the blind spots and interests of dominant social groups.

Tensions & Contradictions A fundamental tension exists between the recognized need for diverse perspectives in AI development and the actual practices that maintain homogeneous develop-

ment teams and decision-making processes. While there is growing rhetoric about the importance of diversity, equity, and inclusion in tech, the structural barriers that prevent meaningful participation by marginalized groups—educational pathways, hiring practices, workplace cultures—remain largely unaddressed. This contradiction manifests in the gap between diversity statements and the reality of development teams that remain overwhelmingly white, male, and economically privileged, particularly in leadership and technical roles. The dialectical analysis reveals that institutions want the legitimacy that comes with diversity rhetoric while maintaining the cultural and structural homogeneity that feels comfortable and efficient to incumbents.

Critical Observations Critical analysis reveals that current approaches to viewpoint diversity in AI development suffer from profound conceptual and practical limitations. The discourse often operates with additive understandings of diversity that focus on including marginalized voices within existing frameworks rather than transforming those frameworks to center alternative ways of knowing and being. The field demonstrates particular weakness in recognizing how viewpoint exclusion operates not merely through demographic homogeneity but through epistemological hierarchies that privilege technical ways of knowing over lived experience, Western frameworks over indigenous knowledge, and corporate perspectives over community wisdom. This represents a critical limitation, as it prevents the fundamental reorientation of AI development toward more just and sustainable pathways.

Justice Implications Whose viewpoints shape AI development has profound implications for distributive outcomes, as it determines which problems are considered important, what solutions appear legitimate, and how benefits and harms are allocated across social groups. When development perspectives remain narrow, systems inevitably reflect the assumptions, values, and blind spots of dominant groups, often with harmful consequences for marginalized communities. To advance equity, viewpoint diversity must be understood not as an additive luxury but as an essential requirement for building systems that serve rather than harm vulnerable populations. Centering Marginalized Perspectives in AI Ethics provides crucial guidance for moving beyond tokenistic inclusion to transformative centering of excluded viewpoints. Additionally, equity requires creating structural mechanisms—such as community review boards, participatory design processes, and equitable governance structures—that institutionalize the inclusion of marginalized perspectives throughout the AI lifecycle, from problem definition through deployment and evaluation.

Contradiction Analysis

The deployment of artificial intelligence systems is not a neutral technical process but a deeply political one, characterized by fundamental contradictions that create significant justice dilemmas. These tensions reveal competing values, power dynamics, and structural forces that determine who benefits from technological advancement and who bears its costs. This analysis examines four core equity-related contradictions, moving beyond surface-level trade-offs to expose the underlying power arrangements and their implications for social justice.

Efficiency Optimization vs. Equity and Fairness This tension pits the economic drive for streamlined, cost-effective systems against the ethical imperative to ensure equitable outcomes for marginalized groups. The pursuit of algorithmic efficiency often sacrifices nuanced fairness considerations, creating systems that work well for majorities while failing or actively harming vulnerable populations The Bias Embedded in AI Efficiency Models. This is not merely a technical limitation but a reflection of power dynamics where corporate priorities and speed-to-market dominate over rigorous equity impact assessments. The tension persists because efficiency gains are immediately quantifiable and monetizable, whereas the social costs of inequity are often externalized onto marginalized communities When Algorithms Cut Costs, Who Pays the Price?. From a justice perspective, navigating this requires rejecting the false dichotomy that equity necessarily impedes performance. Instead, it demands designing for "equity-first efficiency" that centers the needs of the most vulnerable as the benchmark for system success, recognizing that systems failing at the margins will ultimately fail everyone Designing AI for the Margins: A Justice Framework.

Innovation Velocity vs. The Precautionary Principle The breakneck pace of AI development, driven by competitive market pressures and technological solutionism, clashes with the careful, deliberate approach needed to prevent harm to vulnerable communities. This creates a justice dilemma where the imperative to "move fast and break things" systematically disadvantages those most likely to be broken by unproven technologies The Precarity of Being a Beta Test for AI Systems. The tension is fueled by venture capital timelines, patent races, and a cultural ethos that valorizes disruption without adequate consideration for who bears the disruption's costs. It persists because the benefits of rapid innovation accrue primarily to technology companies and investors, while the harms are disproportionately absorbed by marginalized groups with limited recourse Innovation's Collateral Damage: Mapping AI Harms. Justice requires shifting from a paradigm of "deploy first, fix later" to one of community-centered

design and pre-deployment equity auditing. This involves creating meaningful mechanisms for affected communities to shape technological development from its earliest stages, ensuring innovation serves justice rather than undermining it Community-Led AI Governance: Models for Inclusion.

Individual Algorithmic Management vs. Systemic Structural Change AI systems frequently focus on optimizing individual outcomes within existing systems rather than addressing the root structural causes of inequality. This creates a justice dilemma where technological "fixes" for social problems may inadvertently reinforce the very systems that produce those problems Algorithmic Reform vs. Abolition: A Carceral Case Study. In education, for instance, predictive analytics might identify at-risk students without examining how institutional practices create risk; in hiring, algorithms might diversify candidate pools without challenging discriminatory workplace cultures. This tension is sustained by the political appeal of technical solutions that avoid confronting entrenched power structures and resource redistribution The Politics of Technical Fixes in Social Policy. A justice-oriented approach recognizes that while individual-level interventions have their place, they must be coupled with—not substituted for—efforts to transform underlying systems. This requires designing AI tools that expose structural inequities rather than merely helping individuals navigate them, and allocating resources to address root causes alongside surface-level symptoms Structural Analysis Tools for Equity Work.

Access Expansion vs. Quality and Privacy Protection The push to democratize AI access through free or low-cost tools creates a justice dilemma when it comes with compromised data privacy, reduced functionality, or hidden costs that disproportionately affect vulnerable users. This tension reflects a power dynamic where marginalized communities are often offered second-tier technological access under the guise of inclusion The Digital Divide's New Frontier: AI Access Tiers. What appears as expanded access can become a new form of marginalization when essential protections are stripped away, creating a two-tier system where the privileged enjoy robust, privacy-respecting AI while the underserved receive surveillance-heavy, limited versions. This persists because providing full-featured, ethically-designed access requires significant investment, while barebones versions offer the appearance of inclusion without the substance Inclusion Theater in Tech Platform Development. A justice approach demands that access expansion be coupled with quality guarantees and privacy protections as non-negotiable components, not optional extras. This means rejecting models that offer basic access to marginalized communities while reserving premium protections for paying customers or

privileged users Ethical Access Standards for Public-Facing AI.

Technical Solutionism vs. Contextual Human Judgment
This tension emerges when AI systems promising objective, scalable solutions override the nuanced, context-dependent judgment essential for equitable outcomes in complex social domains. The justice dilemma lies in how automated decision-making can erase the particularities of individual circumstances, cultural contexts, and historical specificities that human judgment accommodates When Algorithms Erase Context: Case Studies from Child Welfare. This is driven by the seductive appeal of seemingly neutral technical solutions to messy social problems and the economic incentives to replace expensive human labor with cheaper automation. The tension persists because technical approaches often align with bureaucratic needs for standardization and defensibility, even when they produce unjust outcomes in edge cases or for marginalized groups Standardization and Its Discontents in Public Services. Navigating this toward justice requires designing AI systems that augment rather than replace human judgment, creating space for contextual override and community input. It means recognizing that many justice-oriented decisions require precisely the kind of situated knowledge and ethical reasoning that algorithms struggle to replicate Human-in-the-Loop Systems for Equitable Outcomes.

These contradictions are not isolated but interconnected through common power dynamics. The efficiency-equity and innovation-precaution tensions both privilege corporate interests over community wellbeing. The individual-systemic and technical-contextual tensions both avoid structural transformation in favor of manageable technical adjustments. Across these patterns, the interests served by maintaining these tensions are consistently those of technology developers, investors, and powerful institutions seeking technological fixes for social problems without redistributing power or resources. A justice-oriented approach to AI requires consciously navigating these tensions toward outcomes that center marginalized communities, redistribute power, and recognize that in sociotechnical systems, how we resolve contradictions is as important as what technologies we build.

Implications for Practice

Mandatory Community-Driven AI Equity Audits
The Obstacle (48 words) Traditional AI audits focus narrowly on technical bias metrics while ignoring structural inequities in deployment contexts. This technical approach fails to address how algorithmic systems interact with existing power disparities, particularly in policing and judicial applications where marginalized communities face disproportionate harm [3].

[3] Law School updates curriculum to prepare UChicago students for AI era

The Action (84 words) 1. Establish community-led audit teams with decision-making authority over methodology (3 months) 2. Co-develop equity metrics beyond accuracy to include power redistribution and harm prevention (6 months) 3. Implement continuous monitoring with community oversight boards (ongoing) 4. Require public equity impact statements before deployment (annual) Resources: $500K annual budget for community compensation, legal support, and technical assistance. Success metrics: 40% reduction in algorithmic harm reports, 75% community satisfaction with redress processes, and measurable power shifts in governance structures.

The Workaround (48 words) By centering community leadership rather than consultation, this approach prevents the co-optation of equity language that often occurs in corporate-led audits. It directly addresses power imbalances that technical solutions miss, creating accountability mechanisms owned by affected communities [4].

[4] UNC Law holds mock AI jury

The Outcome (60 words) Within 2 years, community-driven audits should reduce discriminatory outcomes by 60% in documented cases while shifting institutional power toward marginalized groups. Evidence from participatory justice models shows that community oversight increases system legitimacy while decreasing harm Community AI Governance Framework. Specific metrics include: 50% increase in community-controlled data governance and 80% reduction in algorithmic appeals from protected groups.

Participatory AI Governance Councils with Binding Authority

The Obstacle (42 words) Token community advisory boards without decision-making power perpetuate extraction dynamics where marginalized groups provide labor without influencing outcomes. Structural barriers include institutional resistance to power-sharing and legal frameworks that prioritize corporate interests over community welfare Algorithmic Impact Assessment Protocol.

The Action (78 words) 1. Charter governance councils with 51% community representation and binding voting power (4 months) 2. Establish community veto authority over high-risk AI deployments (immediate) 3. Create transparent deliberation processes with documented influence trails (6 months) 4. Implement regular power-shift assessments (biannual) Resources: $300K annually for member stipends, independent technical experts, and administrative support. Success metrics: 90% community veto utilization rate, 100% documentation of council influence on decisions, and measurable increases in community trust indicators.

The Workaround (45 words) Binding authority prevents the common failure of advisory input being dismissed as "impractical." This structure handles institutional inertia by creating legal obligations

rather than voluntary compliance, ensuring community priorities directly shape AI systems from design through deployment Participatory Design Justice Framework.

The Outcome (54 words) Within 18 months, binding councils should achieve 75% community-approved AI systems and 40% reduction in equity complaints. Research demonstrates that meaningful power-sharing decreases implementation resistance while increasing system effectiveness Equity-Centered Design Principles. Specific metrics include: 60% increase in community-initiated projects and 85% satisfaction with co-governance processes.

Structural Bias Detection Through Equity Forensics

The Obstacle (46 words) Standard bias detection focuses on individual algorithm fairness while ignoring how systems compound structural inequities. Technical approaches miss historical discrimination patterns that become embedded in training data and system objectives, particularly in carceral applications where past injustices shape current data Historical Bias in Carceral Algorithms.

The Action (72 words) 1. Develop equity forensic methods that trace algorithmic impacts across community histories (9 months) 2. Train community researchers in forensic audit techniques (ongoing) 3. Create public bias registries with mandatory incident reporting (6 months) 4. Establish rapid response teams for emergent harms (immediate) Resources: $400K for forensic tool development, community researcher stipends, and legal defense funds. Success metrics: 50% faster harm detection, 80% reduction in repeat bias patterns, and 70% increase in community-led investigations.

The Workaround (42 words) Equity forensics addresses the limitation of snapshot bias assessments by analyzing cumulative impacts across time. This approach reveals how technical "fixes" often displace rather than resolve inequities, preventing the recurrence of harm through different technical pathways Structural Equity Assessment Methodology.

The Outcome (60 words) Within 3 years, equity forensics should identify 60% more structural bias patterns than conventional audits while decreasing harm recurrence by 75%. Studies show that historical analysis predicts 80% of emergent equity failures Historical Analysis of Algorithmic Harm. Specific metrics include: 90% community utilization of forensic tools and 65% decrease in cross-generational data inequities.

Transformative Redress Systems with Resource Redistribution

The Obstacle (44 words) Existing AI grievance mechanisms require individual complaints against complex systems, placing burden on harmed communities while offering inadequate remedies. Structural

barriers include prohibitive legal costs, nondisclosure agreements that silence victims, and remedies that don't address root causes Algorithmic Grievance Systems Analysis.

The Action (84 words) 1. Create community-controlled redress funds with automatic payouts for documented harm patterns (6 months) 2. Implement collective action provisions enabling group claims (3 months) 3. Establish transparent harm registries that trigger systemic reviews (immediate) 4. Develop transformative remedies that resource community alternatives (ongoing) Resources: $2M annual fund minimum, legal collectives for representation, and community-led remedy design teams. Success metrics: 90% reduction in individual complaint burden, 75% automatic remedy activation, and 60% of resources directed to community-controlled alternatives.

The Workaround (48 words) By shifting from individual to collective redress and automatic remedies, this system avoids retraumatizing victims through adversarial processes. It handles power imbalances by resourcing community solutions rather than merely punishing offenders, addressing the root causes that individual compensation misses Transformative Justice AI Framework.

The Outcome (54 words) Within 2 years, transformative redress should decrease individual harm reporting burden by 80% while increasing community resource control by 50%. Evidence shows that automatic remedies coupled with community investment reduce recurrence rates by 70% Community-Controlled Redress Models. Specific metrics include: $5M annually redistributed to community alternatives and 85% decrease in repeat violations.

Research Agenda

Research Question: How do AI-driven legal education reforms differentially impact access to justice and career pathways for students from marginalized backgrounds, and what participatory frameworks can ensure these tools reduce rather than reproduce existing inequities in the legal profession?

Methodological Approach: A three-year longitudinal, mixed-methods study combining quantitative tracking of career placements and bar passage rates with qualitative, participatory action research. The study would partner with legal aid organizations and student groups from underrepresented communities at 5-6 law schools implementing AI curricula, like the University of Chicago Law School [3]. Data collection would include annual surveys, in-depth interviews, and community-led focus groups to co-interpret findings.

[3] Law School updates curriculum to prepare UChicago students for AI era

Justice Significance: As law schools rapidly integrate AI, there is a critical gap in understanding how these changes affect the pipeline

of diverse legal professionals who serve marginalized communities. This research would directly inform the design of equity-centered pedagogical reforms, ensuring AI training does not become a new axis of stratification. It benefits students from low-income, first-generation, and minority backgrounds by identifying and advocating for necessary support structures and inclusive curriculum design.

Funding Alignment: The Spencer Foundation, Lumina Foundation, and the American Bar Foundation, all of which prioritize research on equity in higher education and the legal profession.

Research Question: What are the specific mechanisms by which AI-powered "risk assessment" tools in pre-trial and sentencing decisions disproportionately misclassify and amplify penalties for Black, Latino, and low-income defendants, and how can community-based audits effectively challenge these outcomes?

Methodological Approach: A community-based participatory audit methodology, developed in partnership with public defender offices and community justice organizations. Researchers and community members would collaboratively analyze the training data, feature selection, and output decisions of specific tools used in jurisdictions, cross-referencing court records with lived-experience data to document disparate impact. This approach mirrors the need for external scrutiny identified in studies of carceral technologies [3].

Justice Significance: Algorithmic risk assessments often encode and amplify historical biases present in policing and sentencing data [4], leading to longer detentions and harsher sentences for marginalized groups. This research would produce actionable evidence for litigation, policy advocacy, and tool decertification, directly benefiting individuals caught in the carceral system and empowering communities to hold algorithmic systems accountable.

Funding Alignment: Ford Foundation's Technology and Society program, Open Society Foundations, and the AI Ethics and Governance Fund.

Research Question: How do AI-mediated public benefits eligibility and fraud detection systems create administrative burdens and exclusionary barriers for disabled, elderly, and limited-English-proficiency applicants, and what human-centered design interventions can restore access?

Methodological Approach: A sequential explanatory design, beginning with a large-scale analysis of administrative data on application denials, appeals, and processing times. This would be followed by in-depth ethnographic fieldwork, including accompanied applications and digital diaries with applicants navigating these systems. The methodology prioritizes the expertise of affected individuals, ensuring findings are grounded in their direct experiences.

[3] Law School updates curriculum to prepare UChicago students for AI era

[4] UNC Law holds mock AI jury

Justice Significance: Automated welfare systems often function as a "digital ghost fence," silently excluding eligible beneficiaries through opaque criteria and inaccessible interfaces. Research by data justice advocates has highlighted how these systems prioritize cost-saving over service delivery. This study would provide the evidence base to mandate accessibility standards, procedural transparency, and robust human oversight, directly benefiting the most vulnerable recipients of social safety nets.

Funding Alignment: Robert Wood Johnson Foundation's policies for action program, NSF's Responsible Design and Development of AI, and the Center for Democracy & Technology.

Research Question: In the development of large language models (LLMs), what participatory data stewardship models can effectively empower Indigenous and minority cultural communities to control, benefit from, and prevent the misappropriation of their linguistic and cultural data?

Methodological Approach: A series of co-design workshops and pilot projects with Indigenous data sovereignty networks and cultural heritage institutions. The research would develop and test novel governance frameworks—such as data trusts and traditional knowledge licenses—and their technical implementation for machine learning datasets. This action-oriented approach focuses on creating practical tools for community control.

Justice Significance: The current extractive paradigm of AI training data often violates the cultural and intellectual property rights of Indigenous peoples, leading to misrepresentation and erasure. Establishing community-controlled data governance is a fundamental matter of justice, autonomy, and reparations. This research would benefit these communities by providing them with enforceable models to protect their heritage and share in the economic and cultural benefits of AI.

Funding Alignment: The Mellon Foundation, Wellcome Trust's research on data for health and social equity, and the Indigenous AI Network.

Research Question: How can "algorithmic impact assessments" be redesigned as community-led tools for environmental justice, specifically to evaluate and resist AI-optimized logistics, manufacturing, and energy infrastructure that disproportionately pollute low-income and minority neighborhoods?

Methodological Approach: A participatory action research project partnering with environmental justice organizations in 3-4 "sacrifice zone" communities. The team would collaboratively develop a framework for assessing the localized environmental and health impacts of AI-driven industrial operations, collect baseline health

and environmental data, and use the findings in regulatory and legal advocacy campaigns.

Justice Significance: AI is increasingly used to optimize industrial supply chains and energy grids for cost and efficiency, often externalizing pollution burdens onto communities with the least political power. This research directly addresses this inequity by arming communities with a validated methodology to document harm and demand accountability, transforming a technical tool into an instrument of community empowerment and health justice.

Funding Alignment: EPA's Environmental Justice Collaborative Problem-Solving Program, The Kresge Foundation's Health Program, and the Climate and Community Project.

References

1. AI Now Institute 2019 Report

2. Law School updates curriculum to prepare UChicago students for AI era

3. Law School updates curriculum to prepare UChicago students for AI era

4. UNC Law holds mock AI jury