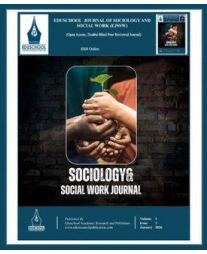
EDUSCHOOL JOURNAL OF SOCIOLOGY AND SOCIAL WORK (EJSSW)

(Open Access, Double-Blind Peer Reviewed Journal)

ISSN Online: 3139-4701



Artificial Intelligence in Child Welfare Decision-Making: Ethical Frameworks and Practice Implications

Vidya N

Research Assistant, Nitte University, Manglore, India.

Article information

Received: 13th February 2026
Received in revised form: 3rd March 2026
Accepted: 22nd April 2026
Available online: 27th May 2026

Volume:1
Issue: 2
DOI: https://doi.org/10.63090/EJSSW/3139.4701.0006

Abstract

The rapid integration of artificial intelligence (AI) into child welfare systems has transformed how risk is assessed, resources are allocated, and decisions are made about vulnerable families. This paper examines the ethical frameworks and practice implications surrounding the deployment of predictive analytics, algorithmic risk-assessment instruments, and machine-learning decision-support tools in statutory child protection services. Through a comprehensive literature review and theoretical synthesis, this study investigates the intersection of social work values, algorithmic governance, and the lived realities of children and families who become objects of computational scrutiny. Findings indicate that while AI tools promise improved consistency, earlier identification of risk, and more efficient use of scarce caseworker time, they simultaneously raise serious concerns regarding algorithmic bias, due process, transparency, and the erosion of professional discretion. The paper proposes a seven-step ethical decision-making framework specific to AI-augmented child welfare practice and identifies critical practice strategies including human-in-the-loop case review, family-engaged algorithmic literacy, bias-auditing protocols, and structured rights-based explanation procedures. Implications for social work education, agency policy, and regulatory reform are discussed, with particular emphasis on the urgent need for algorithmic accountability standards and culturally responsive design that aligns with the profession's commitment to social justice.

Keywords:- Artificial Intelligence, Child Welfare, Algorithmic Bias, Predictive Risk Modelling, Social Work Ethics, Decision-Support Systems.

Introduction

The application of artificial intelligence to public child welfare has accelerated dramatically over the past decade, with predictive risk-modelling tools now deployed or piloted in jurisdictions across the United States, United Kingdom, Australia, New Zealand, and parts of Europe (Saxena et al. 2020). These systems draw on administrative records prior referrals, parental criminal history, public-benefits receipt, neighbourhood indicators, and family-court data to generate probabilistic estimates of future maltreatment, screen-in decisions, or out-of-home placement. Proponents argue that algorithmic decision-support reduces the variability of human judgement, identifies at-risk families earlier, and channels scarce investigative resources where harm is most likely (Vaithianathan et al. 2017). Critics counter that such tools encode and amplify the structural inequalities already baked into the administrative data on which they are trained, disproportionately surveilling poor families and families of colour (Eubanks 2018; Noble 2018).

Social workers occupy a uniquely contested position within these socio-technical assemblages. They are simultaneously the end-users of algorithmic recommendations, the gatekeepers through whom predictions are translated into interventions, and the professionals ethically responsible for the welfare of the children and families involved (Gillingham 2019). Existing professional guidance including the National Association of Social Workers (NASW) Code of Ethics and the joint NASW/ASWB/CSWE/CSWA technology standards predates the most consequential generation of AI tools and offers limited guidance on how practitioners should weigh, contest, or supplement algorithmic outputs in everyday decision-making (NASW 2017; Reamer 2018).

This paper addresses the following question: How can child welfare social workers practise ethically and effectively in an environment increasingly mediated by algorithmic decision-support, while upholding professional standards and protecting client rights?

The research objectives are threefold:

- To synthesise existing literature on AI applications, algorithmic ethics, and digital decision-making in child welfare;
- To develop an ethical decision-making framework tailored to AI-augmented child protection practice; and
- To identify evidence-informed practice strategies that preserve professional judgement, family voice, and social justice commitments.

This inquiry is especially urgent given that, by some estimates, predictive instruments now inform initial screening or risk classification for several million child-maltreatment referrals annually in the United States alone (Saxena et al. 2020), with comparable expansion underway internationally.

Literature Review

Artificial Intelligence Tools in Child Welfare

The application of AI to child welfare has progressed rapidly from rules-based screening algorithms to sophisticated machine-learning models. Early instruments such as Structured Decision Making (SDM) were essentially actuarial checklists, but the present generation exemplified by the Allegheny Family Screening Tool (AFST) in Pennsylvania uses regression and ensemble methods trained on hundreds of administrative variables to produce a numerical risk score at the point of hotline call screening (Vaithianathan et al. 2017). A formal impact evaluation of the AFST concluded that the tool modestly improved the consistency of screening decisions and reduced racial disparities in case-opening rates, although effects on downstream child outcomes were inconclusive (Goldhaber-Fiebert and Prince 2019).

Beyond intake screening, predictive analytics is being applied to placement stability, reunification likelihood, and youth-at-risk identification (Church and Fairchild 2017). Natural-language processing has been used to mine case-note narratives for indicators of escalating risk, and computer-vision applications have been piloted for the assessment of physical injury (Saxena et al. 2020). Despite this proliferation, comparative effectiveness research is sparse, and methodological critiques highlight problems of construct validity, target-population drift, and the conflation of substantiated maltreatment with future referral as the prediction target (Keddell 2015).

Ethical Concerns in Algorithmic Decision-Making

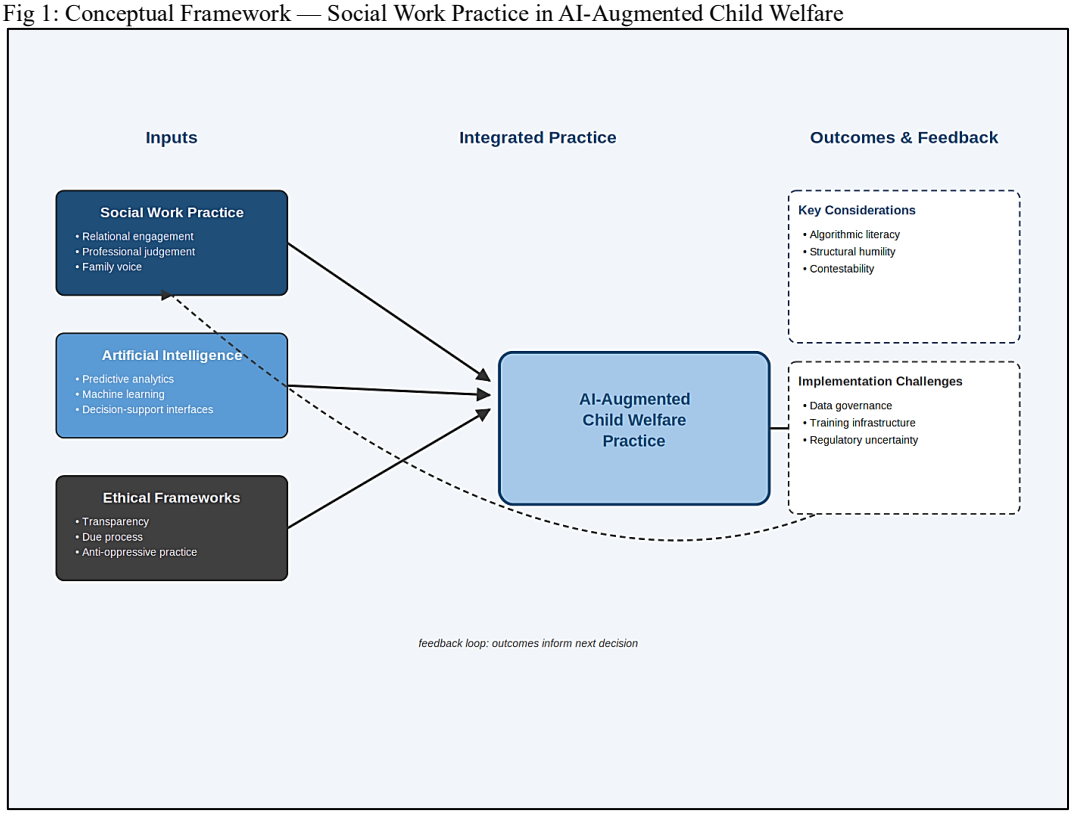
The ethical literature on algorithmic decision-support in public services centres on four interrelated concerns: bias, transparency, accountability, and due process. Eubanks (2018) documented in ethnographic detail how poverty becomes recoded as risk within child welfare algorithms because the administrative datasets used for training over-represent families who have contact with public systems a feedback loop she characterises as the digital poorhouse. Noble (2018) and O'Neil (2016) have demonstrated that algorithmic systems can reproduce and amplify racial, gendered, and class-based inequities precisely because they appear technically neutral.

Brown and colleagues (2019), in a participatory study with affected families and frontline staff in Allegheny County, found that even when an algorithm reduces aggregate disparity it may still feel arbitrary or stigmatising to those subjected to it, particularly when the rationale for a high-risk score is not explained. Gillingham (2019) argues that the opacity of many proprietary tools is fundamentally incompatible with the procedural-justice obligations of statutory social work, since neither the practitioner nor the family can meaningfully interrogate the basis for a recommendation. Recent regulatory developments including the European Union's AI Act and emerging state-level legislation in the United States have begun to codify obligations of explainability, human oversight, and impact assessment for high-risk public-sector AI (European Commission 2024).

Social Work Values and Algorithmic Governance

The translation of core social work values service, social justice, dignity and worth of the person, importance of human relationships, integrity, and competence into AI-mediated practice is contested. Boddy, Dominelli, and Gupta (2020) caution that digital technologies in social work too often reproduce a managerialist logic of efficiency at the expense of relational practice. Reamer (2018) frames ethical AI use as fundamentally a question of competence and informed consent, while Keddell (2015) places the burden squarely on the profession to interrogate the political choices embedded in predictive modelling. There is broad consensus that algorithmic governance must be subject to the same anti-oppressive scrutiny applied to other instruments of state power over vulnerable families.

Fig 1: Conceptual Framework — Social Work Practice in AI-Augmented Child Welfare



Theoretical Framework

This analysis draws on three theoretical perspectives,

- Ecological systems theory
- Critical race theory and structural social work
- Procedural justice and virtue ethics.

Bronfenbrenner's ecological systems theory situates the child within nested layers of influence microsystem,mesosystem, exosystem, macrosystem and thereby foregrounds the institutional, political, and technological structures that condition family well-being (Bronfenbrenner 1979). In AI-augmented child welfare, the algorithm itself functions as an emergent feature of the exosystem: it shapes what practitioners see, what they investigate, and what counts as risk, even when neither the child nor the worker directly interacts with the model's internals.

Critical race theory and structural social work extend this analysis by insisting that the administrative data underwriting any predictive model is the product of historically racialised and class-stratified state practices. As Roberts (2022) and Eubanks (2018) have demonstrated, contact with the child welfare system is itself unequally distributed, so a model trained on prior referrals will inevitably treat Black, Indigenous, and low-income families as inherently riskier. A structural lens therefore reframes algorithmic accuracy as politically secondary to the question of whose vulnerability the algorithm renders visible and whose it conceals.

Procedural justice and virtue ethics together address the normative core of practice under algorithmic conditions. Procedural-justice scholarship demonstrates that people who interact with public systems care intensely about whether they were treated respectfully, allowed voice, and given comprehensible reasons independent of the substantive outcome (Tyler 2006). Virtue ethics, as articulated for the social-work context by Banks and Gallagher (2009), shifts attention from rule-compliance to the formation of practitioner character practical wisdom, courage, justice, and integrity qualities that are arguably most needed precisely when an algorithm produces a recommendation a worker has reason to doubt.

Figure 1 illustrates the synthesised conceptual framework. Social work practice principles, AI technological affordances, and ethical frameworks intersect at the centre on AI-augmented child welfare practice, which must continuously negotiate implementation challenges (data governance, training infrastructure, regulatory uncertainty) and key practice considerations (algorithmic literacy, structural humility, contestability) unique to algorithmic contexts.

Methodological Approach

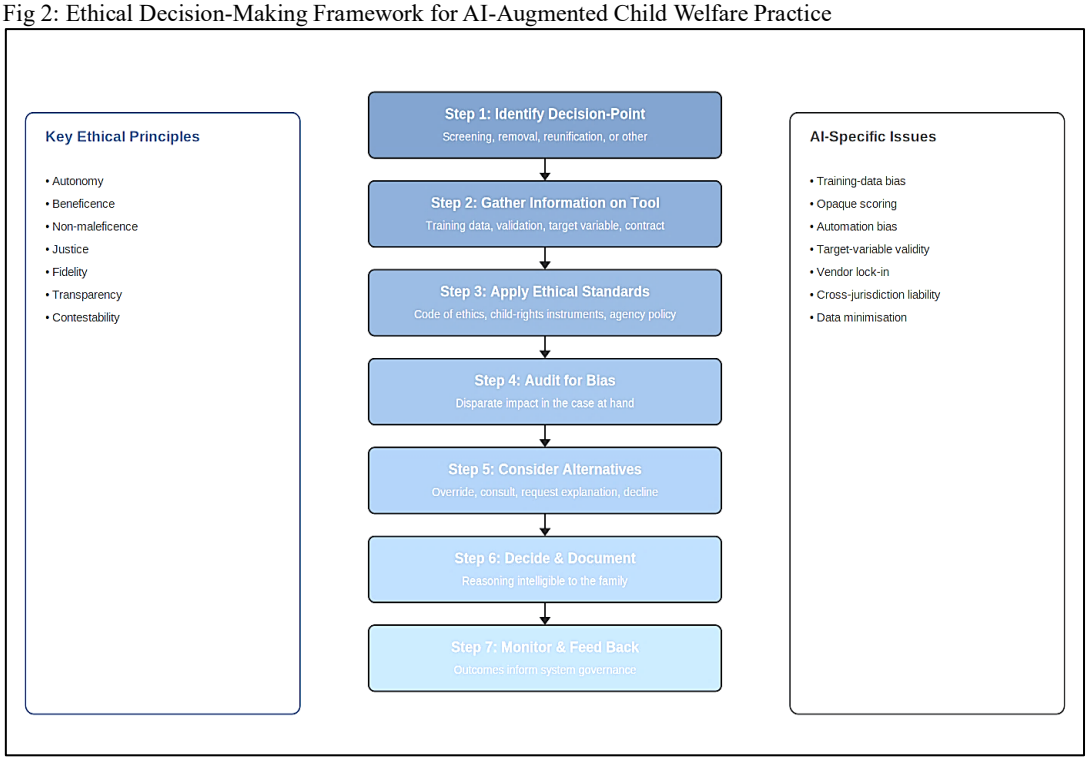
This study employs a theoretical synthesis methodology, integrating interdisciplinary literature from social work, science and technology studies, public administration, computer science, and law. A systematic literature search was conducted across Social Work Abstracts, PsycINFO, Web of Science, ACM Digital Library, and SSRN, covering publications from 2015 to 2025. Search terms combined: 'child welfare,' 'child protection,' 'predictive analytics,' 'algorithmic decision-making,' 'artificial intelligence,' 'machine learning,' 'algorithmic bias,' 'social work ethics,' and 'decision-support.' Inclusion criteria required peer-reviewed empirical studies, theoretical analyses, evaluation reports of deployed tools, or authoritative professional and regulatory guidance.

The analysis followed a thematic synthesis approach, identifying recurring themes around algorithmic bias, transparency, due process, professional discretion, and family voice. Critical discourse analysis was applied to surface assumptions embedded in technical and policy texts regarding what counts as risk, evidence, and good practice. The proposed ethical decision-making framework and practice strategies were developed through iterative refinement, ensuring alignment with the NASW Code of Ethics, international human-rights instruments for children, and emerging AI-governance standards.

Ethical Framework for AI-Augmented Child Welfare Practice

Based on the literature synthesis and theoretical analysis, a seven-step ethical decision-making framework specific to AI-augmented child welfare practice is proposed (Figure 2). This framework extends established bioethical and social-work decision-making models to incorporate algorithm-specific considerations while maintaining consistency with social work ethical principles.

Fig 2: Ethical Decision-Making Framework for AI-Augmented Child Welfare Practice



Key Ethical Principles Extended to AI-Augmented Practice

Informed Consent and the Right to Explanation

Traditional informed-consent doctrine assumes that a client can be apprised of the nature, purpose, and risks of an intervention. In statutory child welfare, where contact is rarely voluntary, the consent burden falls instead on transparency and due process. Families subjected to algorithmic risk-scoring should be told that a tool has been used, what categories of data informed the score, what the score is taken to mean, and how they can request human review or contest the outcome. Practitioners must develop the literacy to explain these matters in plain language, and agencies must ensure that explanations are not merely formal but substantively responsive to the family's situation.

Transparency and Algorithmic Accountability

The opacity of proprietary models is a foundational ethical problem. Where vendor agreements preclude inspection of model internals, social workers should at minimum demand access to model cards, validation studies, demographic performance breakdowns, and disparate-impact audits (Brown et al. 2019). Agency-level accountability requires standing review boards with community representation, periodic re-validation against current populations, and public reporting of outcomes disaggregated by race, ethnicity, disability, and socio-economic status.

Bias, Fairness, and Anti-Oppressive Practice

Bias is not a residual technical flaw but a structural feature of any system trained on data produced by an inequitable institution. Anti-oppressive practice in this context demands that practitioners ask not only whether the model is accurate, but whether the population from which the training data was drawn was justly surveilled in the first place. Mitigation strategies include excluding variables that proxy for race or poverty, raising the threshold for algorithmically-prompted intervention, and pairing every high-risk score with a structural-humility checklist that prompts the worker to consider material supports before coercive measures.

Professional Discretion and Automation Bias

A robust empirical literature on automation bias documents the tendency of human decision-makers to over-weight algorithmic recommendations, particularly under time pressure or when accountability is diffuse (Skitka, Mosier, and Burdick 2000). Ethical AI-augmented practice therefore requires deliberate structural counter-weights mandatory documentation of independent professional judgement, clear procedures for overriding the model, supervisory case review of cases where the algorithm and the worker disagree, and protection of workers from disciplinary action when good-faith overrides turn out, in retrospect, to have been the right call.

Competence and Algorithmic Literacy

Ethical practice mandates competence across three domains: substantive child welfare practice, basic algorithmic and data literacy, and structural critique of socio-technical systems. Social workers do not need to be data scientists, but they should be able to interrogate a tool's target variable, recognise common failure modes, distinguish correlation from causal mechanism, and articulate the political stakes of its deployment. Continuing professional education, supervision frameworks that include the algorithm as an object of reflection, and accessible community-of-practice forums are essential.

Table 1. Ethical Challenges and Mitigation Strategies in AI-Augmented Child Welfare

Ethical Challenge	AI-Specific Risks	Mitigation Strategy
Algorithmic Bias	Training data reflects historical over-surveillance of Black, Indigenous, and low-income families; proxy variables encode race and poverty.	Audit disparate impact across protected characteristics; exclude or transform proxy variables; raise intervention thresholds; pair scores with structural-humility prompts.
Opacity and Lack of Explanation	Proprietary models prevent inspection of internals; families and workers cannot interrogate the basis of a recommendation.	Require model cards, validation studies, and demographic performance reports as a condition of procurement; provide plain-language explanations and a documented right of contestation.
Automation Bias and Erosion of Discretion	Workers over-defer to algorithmic scores under time and accountability pressure; professional judgement atrophies.	Mandate documented independent reasoning; require supervisor sign-off on algorithm-worker disagreement; protect good-faith overrides from punitive review.

Due Process and Family Voice	Families are scored without notice, lack a meaningful right to challenge inputs, and may not know an algorithm was involved at all.	Provide written notice of algorithmic use; establish an accessible challenge procedure; permit families to inspect and correct administrative data used as input.
Data Governance and Privacy	Wide cross-agency data integration; risk of secondary use, breach, and surveillance of non-clinical aspects of family life.	Apply data-minimisation principles; conduct privacy and human-rights impact assessments; restrict secondary use; align with international child-rights instruments.
Practitioner Competence	Workers deploy tools they have not been trained to interrogate; supervisors lack frameworks for algorithmic case discussion.	Embed algorithmic literacy in social work curricula; develop continuing-education modules; integrate algorithmic reflection into supervision; build community-of-practice forums.

Note. This table synthesises key ethical challenges identified in the literature review with proposed mitigationstrategies aligned with NASW ethical standards and emerging AI-governance frameworks.

Practice Strategies for AI-Augmented Child Welfare

Drawing from the evidence base and the proposed ethical framework, several practice strategies emerge as particularly well suited to AI-augmented child welfare. These strategies leverage the legitimate capacities of predictive tools pattern recognition across high volumes of administrative data, support for consistency of decision-making while preserving the relational, structural, and rights-based commitments that distinguish social work from purely actuarial practice.

Human-in-the-Loop Case Review

Algorithms in child welfare should function as decision-support, not decision-substitute. A human-in-the-loop model treats the algorithmic score as one input among many, requires the practitioner to articulate independent reasoning before consulting the score, and reserves consequential decisions particularly the removal of a child from the home to the documented judgement of qualified professionals. Implementation requires interface design that does not anchor practitioners to the score, supervisory review of all algorithm-driven escalations, and routine retrospective audits comparing algorithmic recommendations with case outcomes.

Family-Engaged Algorithmic Literacy

Where algorithms are used, families have a right to understand. Practice strategies include providing accessible written and oral explanations at the point of algorithmic contact, walking families through the categories of administrative data that informed the assessment, supporting their ability to correct inaccurate records, and explicitly inviting them to add context that the data cannot capture. Co-designed practice tools developed with parents who have prior child-welfare involvement improve both family voice and the quality of the information feeding back into the system.

Bias-Auditing and Equity Monitoring

Routine, public, and disaggregated auditing of algorithmic performance should be a non-negotiable feature of any deployment. Audits should examine differential calibration, false-positive and false-negative rates across racial, ethnic, gender, disability, and socio-economic strata, and the geographic distribution of high-risk classifications. Practice-level equity monitoring complements technical audits by tracking the lived consequences of algorithm-driven decisions disproportionality in case opening, in court filings, and in removals and by feeding these findings to community-representative oversight bodies.

Rights-Based Explanation and Contestation Procedures

A structured contestation procedure operationalises procedural justice. Families should be informed that an algorithm was used, given a written summary of relevant inputs and the resulting categorisation, offered the opportunity to respond, and entitled to seek independent human review by a worker not involved in the original screening. Where contestation reveals data errors or misclassification, agencies should commit to timely correction of the underlying administrative record, not merely the present case.

Strengths-Based and Structural-Support Pairing

Finally, ethical practice resists the drift from prediction toward coercive intervention. Where an algorithm flags elevated risk, the default response should be the offer of voluntary, strengths-based, material support housing, child-care, mental-health services, income assistance not investigation. Pairing every high-risk classification with

a structural-support menu shifts the orientation of the system from surveillance to provision, in keeping with the profession's social-justice mandate.

Discussion

This analysis reveals both the promise and the considerable risk of AI-augmented child welfare practice. Predictive tools can, in principle, support more consistent decision-making and earlier identification of children whose situations would otherwise escalate (Vaithianathan et al. 2017). Yet realising this promise requires a level of institutional commitment to transparency, equity auditing, professional discretion, and family voice that very few jurisdictions currently demonstrate.

The proposed ethical decision-making framework emphasises systematic engagement with algorithm-specific risks training-data bias, automation bias, opacity, target-variable validity, and the political economy of vendor relationships while remaining grounded in core social work values. Key implications include the urgent need for procurement standards that condition the purchase of any algorithmic tool on demonstrable bias auditing and explainability, agency policy that protects practitioner discretion to override, and statutory recognition of a family's right to know, to access, and to contest.

Implementation must also confront equity concerns that extend beyond the algorithm itself. Disparities in administrative data availability across jurisdictions, uneven digital infrastructure in tribal and rural welfare systems, and the global concentration of AI-vendor capacity in a small number of firms in the Global North all shape who is scored, how, and by whose model. Social work's commitment to social justice demands that these structural questions be treated as central, not peripheral.

Professional competence is perhaps the most pressing immediate concern. Current social work education programmes rarely prepare graduates to read a confusion matrix, interrogate a target variable, or recognise the difference between a calibration disparity and a base-rate problem. Curricular reform, continuing-education infrastructure, and supervision models that take the algorithm seriously as an object of reflection are urgently required. Professional organisations must move quickly to update ethical guidelines, accreditation standards, and risk-management protocols that address the realities of AI-augmented practice.

Limitations and Future Directions

This theoretical analysis is limited by the rapidly evolving state of AI deployment in child welfare; empirical evidence on long-run outcomes remains thin, and most published evaluations come from a small number of well-resourced jurisdictions whose findings may not generalise. The proposed framework requires empirical validation through case studies, practitioner surveys, and outcomes research in diverse welfare systems. The accelerating pace of foundation-model development further implies that recommendations will require regular revision.

Future research should examine the comparative effectiveness of AI-augmented versus algorithm-free decision-making for specific decision-points and populations; the lived experiences of families subjected to algorithmic scoring, particularly in racially and economically marginalised communities; optimal training and supervision models for developing practitioner competence; and the institutional conditions under which contestation procedures are actually exercised. Participatory research with parents, kin caregivers, and youth with care experience would strengthen both the legitimacy and the practical utility of any framework that aspires to govern these tools.

Conclusion

Artificial intelligence is not arriving in child welfare; it has arrived. The question facing the profession is no longer whether to engage but how and on whose terms. This paper has argued that ethical AI-augmented practice is possible only when algorithmic decision-support is structurally subordinated to social work values, family voice, and a clear-eyed analysis of the structural inequities that algorithms otherwise risk laundering as objectivity.

Core social work values service, social justice, dignity and worth of persons, the importance of relationships, integrity, and competence remain foundational. The challenge lies in translating them into a practice environment where decisions are increasingly mediated, often invisibly, by machine-learning systems whose construction is shaped by interests other than the family's. The frameworks and strategies proposed here are an opening contribution, not a settled answer.

As social workers, educators, researchers, and regulators take up these questions, the imperative is clear: the profession must insist that the families it serves are not reduced to data points, that practitioners are not reduced

to score-confirmers, and that the algorithm is recognised for what it is a powerful but partial tool that must be governed by the ethical standards of the profession it claims to support.

References

Banks, Sarah, and Anne Gallagher. Ethics in Professional Life: Virtues for Health and Social Care. London: Palgrave Macmillan, 2009.

Boddy, Janet, Lena Dominelli, and Anna Gupta. "Social Work Values and Ethics in the Era of Digital Mental Health." British Journal of Social Work 50, no. 6 (2020): 1910–1928.

Bronfenbrenner, Urie. The Ecology of Human Development: Experiments by Nature and Design. Cambridge, MA: Harvard University Press, 1979.

Brown, Anna, Alexandra Chouldechova, Emily Putnam-Hornstein, Andrew Tobin, and Rhema Vaithianathan. "Toward Algorithmic Accountability in Public Services: A Qualitative Study of Affected Community Perspectives on Algorithmic Decision-Making in Child Welfare Services." In Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems, 1–12. New York: ACM, 2019. https://doi.org/10.1145/3290605.3300271.

Church, Christopher E., and Amanda J. Fairchild. "In Search of a Silver Bullet: Child Welfare's Embrace of Predictive Analytics." Juvenile and Family Court Journal 68, no. 1 (2017): 67–81. https://doi.org/10.1111/jfcj.12086.

Eubanks, Virginia. Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor. New York: St. Martin's Press, 2018.

European Commission. Regulation (EU) 2024/1689 of the European Parliament and of the Council Laying Down Harmonised Rules on Artificial Intelligence (Artificial Intelligence Act). Brussels: Official Journal of the European Union, 2024.

Gillingham, Philip. "Decision Support Systems, Social Justice and Algorithmic Accountability in Social Work: A New Challenge." Practice 31, no. 4 (2019): 277–290. https://doi.org/10.1080/09503153.2019.1575954.

Goldhaber-Fiebert, Jeremy D., and Lea Prince. Impact Evaluation of a Predictive Risk Modeling Tool for Allegheny County's Child Welfare Office. Pittsburgh, PA: Allegheny County Department of Human Services, 2019.

Keddell, Emily. "The Ethics of Predictive Risk Modelling in the Aotearoa/New Zealand Child Welfare Context: Child Abuse Prevention or Neo-Liberal Tool?" Critical Social Policy 35, no. 1 (2015): 69–88. https://doi.org/10.1177/0261018314543224.

National Association of Social Workers. NASW, ASWB, CSWE, and CSWA Standards for Technology in Social Work Practice. Washington, DC: NASW, 2017.

Noble, Safiya Umoja. Algorithms of Oppression: How Search Engines Reinforce Racism. New York: New York University Press, 2018.

O'Neil, Cathy. Weapons of Math Destruction: How Big Data Increases Inequality and Threatens Democracy. New York: Crown, 2016.

Reamer, Frederic G. "Evolving Ethical Standards in the Digital Age." Australian Social Work 71, no. 2 (2018): 148–159. https://doi.org/10.1080/0312407X.2017.1416652.

Roberts, Dorothy E. Torn Apart: How the Child Welfare System Destroys Black Families—and How Abolition Can Build a Safer World. New York: Basic Books, 2022.

Saxena, Devansh, Karla Badillo-Urquiola, Pamela J. Wisniewski, and Shion Guha. "A Human-Centered Review of Algorithms Used within the U.S. Child Welfare System." In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems, 1–15. New York: ACM, 2020. https://doi.org/10.1145/3313831.3376229.

Skitka, Linda J., Kathleen L. Mosier, and Mark Burdick. "Accountability and Automation Bias." International Journal of Human-Computer Studies 52, no. 4 (2000): 701–717. https://doi.org/10.1006/ijhc.1999.0349.

Tyler, Tom R. Why People Obey the Law. 2nd ed. Princeton, NJ: Princeton University Press, 2006.

Vaithianathan, Rhema, Emily Putnam-Hornstein, Nan Jiang, Parma Nand, and Tim Maloney. Developing Predictive Risk Models to Support Child Maltreatment Hotline Screening Decisions: Allegheny County Methodology and Implementation. Auckland: Centre for Social Data Analytics, Auckland University of Technology, 2017