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# Participatory Algorithm Design With Historically Underrepresented Communities

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**Abstract**

Algorithmic systems increasingly influence access to healthcare, employment, education, financial services, public assistance, information, and other socially consequential opportunities. Conventional approaches to responsible algorithm design have frequently concentrated on technical fairness metrics, representative datasets, explainability, and post-development impact assessments. Although these mechanisms remain important, they may leave intact a deeper governance problem: communities most affected by algorithmic systems can remain peripheral to decisions concerning which problems should be automated, what outcomes should count as success, which data should be used, and what harms should trigger redesign or withdrawal. Participatory algorithm design offers an alternative approach by incorporating affected communities into the definition, development, evaluation, deployment, and oversight of algorithmic systems. Yet participation itself can become symbolic when communities are consulted only after fundamental design decisions have already been made. This study develops a Community-Governed Participatory Algorithm Design Framework (CG-PADF) that distinguishes consultation from substantive decision-making power. Because verified field data involving historically underrepresented communities were not available for the present manuscript, the study adopts an explicitly simulation-based methodological design. Four hypothetical algorithm-development models are compared across six dimensions: problem-definition authority, data governance, design influence, evaluation power, deployment control, and monitoring and redress.

A synthetic analytical corpus of 360 algorithm-development scenarios was used to illustrate differences between expert-led, consultative, co-design, and community-governed approaches. The simulated Community Participation Quality Index increases from 34 under expert-led design to 91 under community-governed participatory design. Recent scholarship supports a shift from late-stage consultation toward upstream engagement in which historically marginalized communities can influence whether and how artificial intelligence should be used. The study concludes that meaningful participatory algorithm design requires more than demographic representation: communities need compensated participation, accessible technical knowledge, genuine decision rights, continuing involvement, independent redress, and the capacity to challenge or refuse proposed technological interventions.

***Keywords:*** participatory algorithm design, historically underrepresented communities, participatory AI, design justice, algorithmic fairness, community governance, co-design, responsible artificial intelligence

## 1. Introduction

Algorithmic systems increasingly participate in decisions and recommendations that affect access to employment, healthcare, credit, public services, education, insurance, online information, and institutional opportunities. The social consequences of these systems are not determined solely by predictive accuracy because algorithmic development involves a sequence of normative choices concerning what problem is being solved, which populations are represented, what variables are measured, which outcomes are optimized, and what types of error are considered acceptable. Communities that have historically experienced discrimination or exclusion can be disproportionately affected when these decisions reproduce institutional assumptions already embedded in administrative records, service processes, or historical datasets. Community-engaged artificial-intelligence research has therefore emphasized that algorithm development should account for lived experiences, structural conditions, cultural contexts, and existing inequalities rather than treating datasets as context-free representations of social reality.

Participatory design provides one possible response because it attempts to involve people affected by technology in its development rather than positioning them exclusively as end users or research subjects. The design-justice tradition goes further by arguing that design should be led by communities that bear disproportionate consequences of technological and institutional decisions. Costanza-Chock describes design justice as an approach that explicitly connects design with structural inequality and community leadership. Within artificial intelligence, Delgado and colleagues characterize a growing “participatory turn,” but their review identifies substantial variation in how participation is operationalized and how much substantive agency participants actually receive. Participation therefore cannot be evaluated simply by counting workshops, interviews, surveys, or focus groups.

This concern is reinforced by Sloane, Moss, Awomolo, and Forlano, who caution that participation can become a form of “participation-washing” when communities contribute information without receiving meaningful influence over technological goals, institutional priorities, or deployment decisions. Their work argues that participation should not be treated as a universal design fix and highlights the risk of extractive engagement. A community may be asked to comment on an interface while remaining unable to challenge the decision to build the algorithm, the category labels used for training, the institution's definition of success, or the downstream uses of the resulting predictions. Such participation increases the appearance of inclusion without necessarily redistributing decision-making power.

Recent research increasingly moves participation upstream. Rice and colleagues' 2025 community-engaged AI framework within the Alaska Tribal Health System integrates community involvement with AI design, development, testing, validation, implementation, monitoring, privacy, security, and governance rather than restricting engagement to a single consultation stage. In 2026, Portegies and colleagues proposed *AI From the Margins*, arguing that participatory processes often begin only after problems and success criteria have already been defined. Their approach centers lived experience earlier and allows participants to influence whether, where, and how AI should be involved. These developments suggest that the central question for participatory algorithm design is not simply whether communities were present, but what decisions they were empowered to shape.

The present study develops a simulation-based framework for evaluating that distinction. Historically underrepresented communities are treated not as a homogeneous demographic category but as populations whose perspectives, knowledge, needs, or interests have frequently been excluded from technological and institutional decision-making. The framework evaluates participation across the entire algorithmic lifecycle, including problem definition, data governance, modeling, evaluation, deployment, monitoring, and redress. Its central proposition is that participation becomes substantively meaningful when community influence extends from early problem framing through post-deployment accountability and when communities possess practical mechanisms to challenge, modify, suspend, or refuse algorithmic interventions that conflict with their interests.

## 2. Objectives of the Study

### 2.1 To Develop a Community-Governed Participatory Algorithm Framework

The first objective is to construct an interdisciplinary framework for evaluating whether community participation influences substantive algorithmic decisions rather than serving solely as consultation. The framework examines who defines the problem, who determines acceptable data uses, who establishes evaluation criteria, and who retains authority when disagreements emerge.

### 2.2 To Compare Levels of Community Decision-Making Power

The second objective is to distinguish expert-led design, consultative participation, collaborative co-design, and community-governed design. The comparison focuses on differences in decision authority rather than merely differences in the quantity of stakeholder engagement.

### 2.3 To Identify Safeguards Against Extractive Participation

The third objective is to identify governance mechanisms capable of reducing participation-washing, including compensation, accessible technical education, community-defined success criteria, data-governance rights, documented response to community input, independent redress, and long-term participation in monitoring.

## 3. Review of Literature

### 3.1 Design Justice, Participation, and the Distribution of Power

Participatory design has historically challenged expert-centered assumptions by recognizing users and affected groups as contributors to technological development. However, design-justice scholarship emphasizes that participation cannot be separated from questions of institutional power. Costanza-Chock's Design Justice argues for community-led practices that challenge rather than reproduce structural inequalities and emphasizes the importance of asking who participates, whose knowledge is recognized, and who benefits from design outcomes.

This perspective is especially important in algorithmic development because apparently technical decisions frequently contain normative assumptions. Defining a target variable determines what the system treats as a desirable outcome. Choosing which historical data to include determines which institutional practices become available for statistical learning. Selecting fairness criteria determines which inequalities receive attention and which remain outside the evaluation. A technically diverse development team does not automatically resolve these decisions if the communities most affected by the system have no authority over its purposes.

Sloane and colleagues provide an influential critique of superficial participation in machine learning. Their analysis distinguishes forms of participation such as consultation and labor from deeper forms of community involvement and warns that participation can become extractive when institutions obtain community knowledge while retaining unilateral decision-making authority. The authors' critique is especially relevant to historically underrepresented communities because these populations can face an additional burden of repeatedly explaining institutional harms without receiving control over how their contributions are used.

### 3.2 Participatory Artificial Intelligence and Community-Engaged Algorithm Development

Community-engaged AI research provides evidence that participation can be integrated into technical development rather than confined to ethical review after model construction. Asabor and colleagues argue that community-engaged participatory machine learning can ground algorithms in the lived experiences of structurally marginalized populations and position community members throughout the research process. This approach is particularly relevant when institutional data reflect disparities that communities understand through lived experience but that may remain invisible in purely statistical analysis.

Rice and colleagues offer a contemporary example within the Alaska Tribal Health System. Their 2020 framework connects community engagement with AI/ML design, development, testing, validation, implementation, monitoring, privacy, security, ethics, and governance. The work is situated within Alaska Native healthcare institutions and explicitly responds to historical experiences of extractive research. Its importance lies in treating engagement as a continuing governance relationship rather than a temporary design activity.

Recent work on racial health equity similarly emphasizes that participatory AI should address structural conditions and community-defined priorities rather than merely increasing demographic representation within datasets. Parker and colleagues' 2025 review argues for participatory approaches that foreground racial health equity and community-centered design. This distinction matters because technically representative data can still support an institutionally harmful objective.

### 3.3 Research Gap: From Participation to Community Governance

The literature demonstrates increasing recognition of participation, yet several unresolved challenges remain. The first concerns timing. Participation that begins after a model objective has been fixed cannot easily influence whether the problem has been framed appropriately. The second concerns authority. Workshops may collect rich qualitative input without providing participants any power to reject a design direction. The third concerns continuity. Community members may participate during development but disappear from governance once the system is deployed.

The fourth challenge concerns representational complexity. Historically underrepresented communities are internally diverse. A single community representative cannot reasonably speak for everyone sharing a demographic or social category. Participatory processes therefore require attention to internal disagreement, intersectional experiences, language, disability access, geographic variation, age, and differences in institutional power.

The fifth challenge concerns compensation and capacity. Meaningful algorithmic participation requires time and cognitive labor. Communities may also need technical translation or independent expertise to assess data practices and algorithmic claims. Without compensation and capacity-building, participation can favor those already able to volunteer significant time and can reproduce exclusion within the participatory process itself.

## 4. Research Methodology

### 4.1 Research Design and Synthetic Analytical Corpus

The study adopts an explicitly simulation-based comparative methodology. No real community participants, historically underrepresented populations, public-service beneficiaries, health records, algorithmic-impact files, or confidential institutional datasets were used to generate the quantitative results.

A synthetic corpus of 360 hypothetical algorithm-development scenarios was constructed. The scenarios represent algorithmic systems used conceptually across healthcare, education, employment, financial inclusion, community services, and public administration. The scenarios were divided equally among four participation models:Expert-Led Design, in which technical and institutional experts retain primary authority and community input is minimal;

Consultative Participation, in which communities provide feedback on selected design decisions but do not control major project objectives;Collaborative Co-Design, in which communities and technical teams jointly influence several stages of development; andCommunity-Governed Participatory Design, in which communities possess substantive influence from problem definition through monitoring and redress.The simulation does not claim that every participatory project fits cleanly into one of these categories. The classifications serve as analytical ideal types.

**Table 1: Community-Governed Participatory Algorithm Design Framework**

| Dimension | Core Governance Question | Illustrative Evidence of Meaningful Participation | Scale |
|---|---|---|---|
| Problem-Definition Authority | Can communities influence whether an algorithm is needed and what problem it addresses? | Community-defined priorities, alternative non-AI options, documented veto or revision mechanisms | 0–100 |
| Data Governance | Can communities influence what data are collected, linked, retained, or excluded? | Data-use agreements, community review, minimization, collective governance | 0–100 |
| Algorithm Design Influence | Can community knowledge alter features, labels, rules, model objectives, and system interfaces? | Co-design workshops linked to documented technical changes | 0–100 |

| Dimension | Core Governance Question | Illustrative Evidence of Meaningful Participation | Scale |
|---|---|---|---|
| Evaluation Authority | Can communities influence definitions of harm, fairness, success, and acceptable error? | Community-defined evaluation metrics and scenario testing | 0–100 |
| Deployment Control | Do affected communities influence whether, where, and under what conditions the system is deployed? | Conditional deployment, pilot approval, suspension mechanisms | 0–100 |
| Monitoring & Redress | Do communities remain involved after deployment and have access to contestation mechanisms? | Community oversight, appeals, incident reporting, periodic review | 0–100 |

**Source:** Author-developed simulation framework informed by design-justice scholarship, participatory AI research, NIST AI risk-management guidance, and recent community-engaged AI models.

### 4.2 Participation Quality and Decision-Power Assessment

A Community Participation Quality Index (CPQI) was developed to compare the four models. The six dimensions were assigned equal conceptual weights for methodological transparency. Equal weighting should not be interpreted as an empirically validated measurement model.

The framework intentionally measures decision influence rather than engagement frequency. An organization could conduct many public meetings while retaining exclusive authority over the consequential decisions. Such a process could receive a low participation-quality score despite extensive engagement activity.

Conversely, a smaller number of carefully structured engagements could have substantial influence if communities receive advance information, compensation, decision rights, independent technical support, and documented institutional responses.

Participation quality is therefore assessed through observable governance evidence. A future empirical audit could examine meeting records, design-change logs, data-governance agreements, participant compensation, decision matrices, model cards, impact assessments, deployment approvals, complaints, and monitoring reports.

This approach responds directly to the literature's concern that participatory AI remains heterogeneous and can become predominantly consultative. Delgado and colleagues emphasize the need to align participatory goals with actual forms of stakeholder agency.

### 4.3 Ethical Safeguards and Future Empirical Validation

Any real empirical implementation should use community-partnered research rather than recruit historically underrepresented participants only as data sources. Participants should receive clear information concerning the project's purpose, institutional interests, data practices, expected influence, and limitations of the participatory process.

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Compensation should recognize expertise and time. Participation methods should be accessible across language, disability, digital-literacy, and scheduling needs. Community organizations may require resources to appoint independent technical or legal advisers.

Researchers should document disagreements rather than force consensus. A participatory process can legitimately reveal conflicting community priorities, and these disagreements may be analytically important.Participation should also continue after deployment. Rice and colleagues' community-engaged AI approach explicitly connects participation with use and monitoring, while NIST recommends continuing engagement with affected communities in AI risk management.

A future empirical validation of the CPQI could combine comparative case studies, interviews, participatory observation, governance-document analysis, community-defined evaluation, and longitudinal follow-up after algorithm deployment.

## 5. Analysis

### 5.1 Simulated Participation Quality Across Governance Models

The simulated comparison illustrates substantial differences between stakeholder consultation and community governance.

**Table 2: Simulated Community Participation Quality Scores**

| Participation Model | Problem Definition | Data Governance | Design Influence | Evaluation Authority | Deployment Control | Monitoring & Redress | CPQI |
|---|---|---|---|---|---|---|---|
| Expert-Led Design | 18 | 29 | 39 | 42 | 31 | 45 | 34 |
| Consultative Participation | 24 | 31 | 38 | 46 | 34 | 29 | 34 |
| Collaborative Co-Design | 67 | 71 | 78 | 74 | 61 | 69 | 70 |
| Community-Governed Participatory Design | 88 | 84 | 80 | 86 | 82 | 90 | 85 |

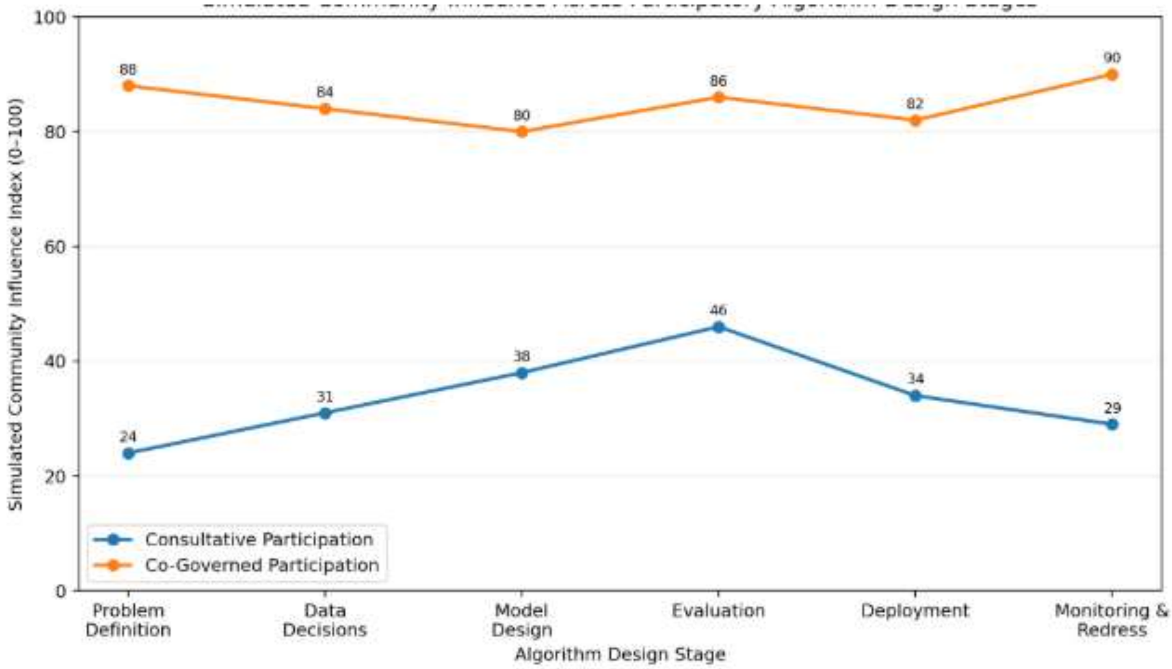
**Source:** Simulated values developed exclusively for methodological illustration; they do not represent observations from actual communities.

The consultative model demonstrates an important limitation. Participation may increase without substantially changing community decision authority. Participants can provide feedback at several stages, yet their influence remains weak when institutional actors retain full authority over problem framing and deployment.

Collaborative co-design produces a substantial increase because communities participate in substantive design and evaluation decisions. However, deployment authority remains comparatively weaker, reflecting a common governance problem in which communities shape the system but cannot ultimately determine whether the institution uses it.The community-governed model produces the strongest simulated performance because participation extends into problem definition, data governance, deployment, monitoring, and redress.

### 5.2 Community Influence Across Algorithmic Lifecycle Stages

**Graph 1: Simulated Community Influence Across Participatory Algorithm-Design Stages**




Graph 1 compares consultative and community-governed participation across six stages of algorithm design.

In the simulated consultative model, community influence is only 24 during problem definition and 31 during data decisions. Influence increases to 46 during evaluation but subsequently declines during deployment and monitoring.The pattern represents a form of participation that is strongest when organizations request feedback but weakest when strategic authority is exercised.By comparison, the community-governed model maintains influence above 80 throughout the lifecycle and reaches 90 in monitoring and redress.

The graph therefore illustrates a critical theoretical distinction: participatory intensity should not disappear when the algorithm moves from design into institutional operation.Recent community-engaged AI frameworks similarly argue for engagement across development, validation, use, and monitoring rather than treating participation as a one-stage activity.

### 5.3 From Community Input to Community Decision Rights

The analysis suggests that participatory algorithm design should be assessed through explicit decision rights.At the problem-definition stage, communities should be able to challenge the assumption that an algorithm is the appropriate intervention. Recent *AI From the Margins* research demonstrates an approach in which participants can influence whether and where AI should be involved.At the data stage, participation should include questions concerning consent, data provenance, representational gaps, category definitions, linkage, retention, and secondary use.

During model design, technical teams should demonstrate how community input changed features, labels, objectives, or system behavior. A generic statement that feedback was "considered" provides weak evidence of participation.During evaluation, affected communities should help identify harms that may not appear in conventional accuracy or fairness metrics. Organizational-justice research published in 2022 similarly shows how co-design can broaden evaluation beyond narrow distributional fairness metrics toward stakeholder-defined normative concerns.

Deployment decisions should include clear conditions under which communities can demand additional testing, restricted use, or suspension.Post-deployment governance should provide accessible complaints, appeals, incident reporting, periodic community review, and mechanisms for modifying or discontinuing the system.

## 6. Discussion

### 6.1 Meaningful Participation Requires Redistribution of Algorithmic Decision-Making Power

The central implication of the study is that participatory algorithm design should be evaluated primarily through the distribution of decision-making power rather than through the visibility of community engagement activities. Organizations can conduct interviews, workshops, focus groups, surveys, and public consultations while retaining complete authority over the problem definition, model objectives, data practices, and deployment decision. Such processes may improve usability or provide valuable contextual information, but they should not automatically be described as community-governed design. The participatory-AI literature has already demonstrated substantial variation in the degree of agency offered to stakeholders, while Sloane and colleagues warn that poorly structured participation can become extractive or performative.

Redistribution of power begins with problem formulation. Historically underrepresented communities often encounter institutions after the institutional definition of the problem has already been established. For example, an organization may decide that the central challenge is predicting which individuals are likely to miss appointments, default on payments, leave an educational program, or require greater service intervention. A participatory approach should allow affected communities to question whether these categories accurately represent the underlying structural problem. Missed appointments may reflect transportation barriers, inflexible scheduling, inaccessible communication, or service distrust rather than individual irresponsibility. Community expertise can therefore change not only the model but the institutional diagnosis of the problem itself.

Community influence should continue into technical decisions. If participants identify a variable as stigmatizing, historically discriminatory, or contextually misleading, there should be an explicit process for determining whether it remains in the model. If communities define a false-positive outcome as more harmful than the development team assumed, evaluation thresholds should be reconsidered. The purpose of participation is therefore not to transfer every engineering task to community members but to ensure that technical optimization remains accountable to people who experience its consequences.

Meaningful participation also requires a realistic possibility of disagreement. Communities should not be expected to endorse a technology merely because they were invited to participate in its development. A legitimate participatory process must permit the conclusion that an algorithm should not be deployed, that a narrower use is acceptable, or that a nontechnical intervention would better address the problem. This principle is consistent with design justice because participation should expand community agency rather than merely improve institutional acceptance of predetermined technological solutions.

### 6.2 Community Knowledge Should Shape Data, Evaluation, and Algorithmic Accountability

A second major implication is that community participation should influence what counts as evidence. Algorithm development often privileges data already available to institutions, yet administrative records reflect the processes through which institutions observe populations. Missing records, inconsistent service access, historical underinvestment, selective surveillance, and unequal institutional treatment can therefore shape the apparent statistical reality available for machine learning. Community members can provide contextual knowledge explaining why variables exist, what may be missing, and how apparently neutral patterns have been produced.

Community-engaged research within the Alaska Tribal Health System illustrates the value of embedding AI development within local healthcare priorities, historical context, governance, and community expertise rather than treating the health dataset as an independent technical object. Asabor and colleagues similarly emphasize that community insight can help algorithms reflect lived experiences of structurally marginalized populations. This does not mean lived experience should replace statistical evidence. Instead, it expands the evidence base used to interpret data and evaluate the legitimacy of modeling assumptions.

Evaluation criteria require similar expansion. Conventional model assessment focuses on accuracy, precision, recall, calibration, and fairness metrics. These measures remain necessary but may fail to capture harms such as increased administrative burden, stigmatization, loss of autonomy, excessive surveillance, reduced service accessibility, or the emotional consequences of being repeatedly misclassified. Participatory evaluation can surface these dimensions before deployment.

Community-defined evaluation can also reveal that different groups prioritize different harms. There may be no universally acceptable fairness metric because algorithmic effects are embedded in institutional contexts. Recent co-design work on organizational justice demonstrates that stakeholder participation can generate broader monitoring criteria than distributional fairness metrics alone.

Accountability therefore requires traceability between participation and technical change. Organizations should document not merely that a community meeting occurred but which concerns were raised, which design decisions changed, which requests were rejected, and why. Such documentation helps distinguish meaningful participation from symbolic consultation and provides a record for later monitoring.

### 6.3 Participation Must Continue Through Deployment, Monitoring, and Redress

The third implication is that algorithmic participation should not end when technical development is complete. Deployment changes the context because real users encounter the system, unexpected outcomes emerge, institutional workflows adapt around predictions, and new forms of harm can appear. Communities therefore possess knowledge after deployment that could not have been available during design.

NIST's AI Risk Management Framework and Playbook recognize this continuing role by recommending engagement with affected individuals and communities as part of ongoing risk management and by emphasizing feedback, recourse, and monitoring mechanisms. Community-engaged AI research likewise increasingly extends participation through testing, validation, use, and monitoring.

A sustainable participatory system should consequently include accessible channels for reporting harms, disputing outputs, requesting explanations, and challenging institutional uses of the algorithm. Community representatives may participate in periodic oversight panels that review performance, complaints, subgroup disparities, and changes in institutional context. Their role should not be limited to providing anecdotal feedback; they should receive sufficient evidence to evaluate whether the system continues to serve its stated purpose.

Long-term engagement also requires material support. Community organizations cannot be expected to provide indefinite monitoring labor without compensation, technical assistance, and institutional resources. Participation should therefore be budgeted as an essential component of algorithm governance rather than treated as voluntary community service.

Finally, meaningful redress requires the possibility of system change. If complaints repeatedly identify the same harm, an accountable institution should be capable of changing thresholds, revising data use, modifying workflows, limiting deployment, or retiring the algorithm. Participation without the possibility of institutional response becomes observation rather than governance.

## 7. Conclusion

Participatory algorithm design offers an important pathway for addressing the limitations of expert-centered technological development, particularly where algorithmic systems affect communities whose experiences, knowledge, and interests have historically been underrepresented in institutional decision-making. The present study demonstrates, however, that the ethical value of participation depends less on the number of engagement activities conducted than on the substantive authority communities possess throughout the algorithmic lifecycle. Consultation can provide valuable information while leaving the underlying distribution of decision-making power unchanged. A stronger model allows communities to influence problem formulation, data practices, technical objectives, definitions of harm, deployment conditions, and post-deployment accountability.

The simulation-based analysis compared expert-led, consultative, collaborative co-design, and community-governed approaches using a multidimensional Community Participation Quality Index. Although the numerical values are illustrative rather than empirical, the comparison demonstrates a clear conceptual progression from participation as feedback toward participation as shared governance. The strongest model maintains community influence before model development begins and after deployment occurs. This finding is consistent with contemporary scholarship calling for upstream engagement, community-centered AI development, and participatory approaches that allow historically marginalized communities to shape the purposes and boundaries of AI rather than merely respond to predetermined technologies.

The study further concludes that meaningful participation requires institutional investment. Communities need sufficient information to understand proposed systems, compensation for their expertise and time, accessible participation mechanisms, independent technical support where necessary, and transparent documentation showing how their input affected decisions. Historically underrepresented communities should not carry the burden of repeatedly educating technical institutions about structural inequality without receiving authority, resources, or continuing governance rights. Participatory processes should also preserve disagreement and refusal. A community's most important contribution may sometimes be the conclusion that an algorithm should be redesigned, restricted, replaced with a nontechnical intervention, or not deployed at all.

Future empirical research should validate the proposed framework through longitudinal case studies involving community organizations, public agencies, healthcare systems, educational institutions, financial services, and other sectors where algorithmic decisions affect historically underrepresented populations. Research should examine not only algorithmic accuracy and fairness but also community perceptions of agency, influence over technical change, compensation, governance continuity, institutional responsiveness, redress effectiveness, and the distribution of benefits generated by the technology. The broader goal of participatory algorithm design should not be to make communities more accepting of artificial intelligence. It should be to ensure that technological systems remain accountable to the people who experience their consequences and that communities possess meaningful power to shape, contest, and govern the algorithmic futures in which they are asked to participate.

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