Democratizing Algorithm Development: Rethinking the Design of Complex Hybrid Decision-Making Systems

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Abstract. Algorithm development is traditionally approached as a technical optimization task. Yet this process often unfolds within complex sociotechnical systems of engineers, developers, domain experts, policymakers, and others. This paper develops a theoretical framework for democratizing algorithm design, and framed as a network reconfiguration problem. By integrating conjoint analysis and human-in-the-loop (HITL) methods, I propose a rethinking of how development of algorithms is approached, and specifically the mechanisms that contribute to influence within the network. Namely, new edges are created between peripheral stakeholders and central developer hubs, while iterative feedback loops re-balance flows of authority and trust. This theoretical advance in modeling sociotechnical systems as adaptive networks is premised on the notion that for algorithms in consequential settings to have a chance at deployment at scale, they must be viewed as reliable. And reliability is heavily informed by end-user attitudes toward the system. To illustrate, I present a case study in healthcare, where algorithm-aided hybrid decision-making tools assist physicians/providers in consequential settings. The case focuses on how conjoint experiments help to reveal tradeoffs in human preferences and priorities, and then how HITL allows these preferences to be embedded into the evolving system design.

Keywords: complex systems · adaptive networks · algorithm development · human-in-the-loop · conjoint design

1 Introduction

Artificial intelligence (AI) and complex systems are embedded within many different sociotechnical contexts that connect developers, institutions, end-users, and decision-makers. These networks are complex, in that they are heterogeneous [8,25], adaptive [16], and characterized by emergent behaviors [4,19]. This complexity is especially visible in healthcare settings, where hybrid decision-making systems, such as physicians making decisions supported by algorithmic

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tools, have become common [9,10,23]. Diagnostic support systems, risk calculators, and triage algorithms all represent algorithmic nodes interacting with human nodes, with consequences that directly affect patient outcomes.

Despite this networked reality, algorithm development often ignores the distributed nature of decision-making. Developers occupy central positions, while decision-makers and other end-users remain peripheral when it comes to design decisions and architecture. The result is a skewed topology of influence, where algorithms are optimized within technical contexts, but the perspectives of those affected are not structurally integrated into the development process or factored into the decision decisions. This imbalance undermines legitimacy and creates risks of mismatch between technical performance and social expectations [7].

This paper introduces a framework for democratizing algorithm development that explicitly treats a hybrid decision-making algorithm as a complex network problem. The contribution is first a theoretical model framing democratized algorithm development as adaptive network reconfiguration, where conjoint analysis and human-in-the-loop (HITL; [12]) methods serve as rewiring tools; and second, a case study in hybrid decision-making in healthcare illustrates how conjoint analysis elicits preferences from clinicians (decision-makers) and patients (impacted end-users), while HITL ensures iterative embedding of these preferences in system design.

2 Algorithms as Complex Networks

2.1 Sociotechnical Networks

Rather than existing in isolation, algorithms are embedded within sociotechnical systems composed of developers, institutions, regulators, end-users, and the broader public. Within these systems, we can think of them as networks where nodes represent heterogeneous actors with distinct roles and resources, while edges represent flows of information, authority, and influence [15]. Algorithmic systems can therefore be understood as both technical artifacts and relational entities, constantly interacting with social structures and institutions (e.g., [11]).

From such a perspective, when new algorithmic tools are introduced, they add nodes and reconfigure edges across the sociotechnical system. For example, the adoption of a recommender system in a media platform reconfigures relationships between users, advertisers, and content creators by altering flows of attention and visibility [1,3]. Similarly, the perception of hybrid decision support algorithms in criminal sentencing is attenuated by the biases [22] and even personalities [21] of those assessing them. In each case, algorithms are not simply tools but active participants in complex systems, redistributing influence and shaping decision-making processes at many levels.

2.2 Structural Imbalances

Despite their embeddedness, algorithms are often developed as if they were isolated technical objects. That is, development tends to occur within clusters of experts e.g., software engineers and technical managers, who form densely connected hubs within the system or network. Meanwhile, those most affected by algorithmic outputs remain weakly connected or peripheral nodes, with little direct input into system design.

From a network perspective, such an asymmetry creates structural imbalances: some groups exercise disproportionate influence on how algorithms are designed and evaluated, while others are excluded from shaping the criteria that directly impact them. These imbalances could manifest as, e.g., structural holes, bottlenecks, or power asymmetries that distort flows of information or even trust [24]. The result is not only bias in outputs but also erosion of legitimacy, accountability, and long-term adoption, where trust in these types of consequential hybrid decision-making systems is required for maintaining long term legitimacy, support, and deployment [7]. Yet, when only a narrow set of actors impact and engage in algorithmic design, the system becomes fragile to shocks, resistant to oversight, and misaligned with diverse societal expectations.

2.3 Democratization via Rewiring

Democratizing algorithm development, whereby human influence is more explicitly embedded into the system design, can thus be framed as a network rewiring process. Rather than leaving peripheral nodes disconnected, democratization seeks to create new edges that directly connect end-users, stakeholders, and affected humans to the development and design processes. Such a step can be achieved through methodological interventions such as conjoint analysis, which provides a statistically rigorous way of eliciting preferences and quantifying tradeoffs across potential design choices [5,14]. In this sense, conjoint analysis functions as a mechanism for adding new links between non-expert actors and developers, translating heterogeneous preferences into structured inputs.

Formally via [5], the conjoint framework assumes that the overall utility of a given algorithmic design can be expressed as the sum of its attribute-level contributions, or "part-worths":

$$U(\mathbf{x}) \;=\; \alpha \;+\; \sum_{k=1}^{K}\sum_{\ell=1}^{L_k} \beta_{k\ell}\, d_{k\ell}(\mathbf{x}), \tag{1}$$

where $U(\mathbf{x})$ is the latent utility of design $\mathbf{x}$, α is a constant term, $d_{k\ell}(\mathbf{x})$ is a dummy indicator taking value 1 if design $\mathbf{x}$ includes level ℓ of attribute k (and 0 otherwise), and $\beta_{k\ell}$ is the estimated part-worth for that attribute level, with one level per attribute normalized for identification [5].

Tradeoffs emerge by comparing utilities across attributes. If two designs differ only on attributes a and b, for example, the difference in utility is

$$\Delta U \;=\; (\beta_{ai} - \beta_{aj}) \;+\; (\beta_{br} - \beta_{bs}). \tag{2}$$

Setting $\Delta U = 0$ yields a compensating tradeoff: the improvement from changing a offsets the loss from changing b. When attributes are coded numerically (e.g., latency, accuracy), the marginal tradeoff simplifies to

$$\left.\frac{dx_b}{dx_a}\right|_{dU=0} = -\frac{\beta_a}{\beta_b}. \tag{3}$$

These constructions allow for quantifying how much of one input or property (e.g., interpretability) humans are willing to give up for another (e.g., accuracy). As a result, we get a structured way to embed human preferences into the network of the algorithmic design process.

Now, human-in-the-loop (HITL) methods extend this rewiring by introducing iterative feedback loops that adjust the network over time. Instead of a one-off interaction with human subjects, for example, HITL mechanisms ensure that human preferences are continuously embedded into the system, strengthening ties, balancing edge weights, and adapting to evolving contexts [13].

Formally, HITL integration of this sort can be expressed as an iterative update rule:

$$\theta^{(t+1)} = \theta^{(t)} + \eta \cdot g\big(\nabla L(\theta^{(t)}), h^{(t)}\big), \tag{4}$$

where $\theta^{(t)}$ denotes the algorithm's parameters at iteration t, $L(\theta)$ is the technical loss function, $h^{(t)}$ represents human feedback at iteration t, η is a learning rate, and $g(\cdot)$ is some sort of aggregation function that adjusts the system *given human input.*

In this setup, the system optimizes for technical performance via $\nabla L(\theta^{(t)})$, while human feedback $h^{(t)}$ modifies or reweights the signal. Over iterations, human preferences are not merely consulted once as in most experimental settings, but rather continuously recorded and embedded, ensuring that the network adapts to both technical and human objectives.

Taken together, conjoint analysis (collecting of human preferences) and HITL (embedding of human preferences) transform algorithm development from a centralized, expert-dominated cluster into a more distributed, adaptive, and resilient sociotechnical network. This reconceptualization highlights democratization as a structural intervention that impacts dynamics of algorithmic system design at its most foundational level.

2.4 Algorithms as Networks of Components and Actors

To see algorithms directly as complex networks, consider that both their technical architecture and their human preference embedding can be represented as *interconnected nodes and weighted edges.* On the technical design side, consider that nodes may represent components such as features, parameters, decision rules, etc., while edges encode flows of information between these components. Then, on the human, social side, nodes represent human actors, such as developers, regulators, end-users, etc., with edges reflecting flows of influence, oversight, and feedback. So, when these are combined, the result is a multilayer network structure whereby technical and social subsystems are able to evolve and adjust together.

Formally, let $G = (V, E, W)$ be a weighted graph. The node set V can be partitioned into V_T (technical components) and V_S (human/social actors). The edge set E captures both *intra*-layer links (e.g., between technical features, or between human actors) and *inter*-layer links (e.g., from a user providing feedback to a model component). Edge weights $W = \{w_{ij}\}$ represent the strength of influence, which may be derived from observed interactions, decision rules, or experimentally elicited preferences. For example, the aforementioned part-worth utilities from conjoint analysis ($\beta_{k\ell}$) can be embedded as weights on edges from stakeholder nodes to the corresponding algorithmic attributes. Likewise, iterative HITL updates can be expressed as, e.g., time-indexed weight adjustments:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \eta \cdot h_{ij}^{(t)}, \tag{5}$$

where $h_{ij}^{(t)}$ encodes human input at iteration t and η controls the rate of adaptation.

This network rendering makes explicit that algorithms are not necessarily static functions but rather dynamic systems of interconnected parts, which when developed carefully, reflect both technical requirements *and* human preferences at a variety of levels. Biases and blind spots can be understood as structural holes or bottlenecks in G [18], while democratization "rewires" the topology by adding new edges and adjusting weights to reflect diverse stakeholder preferences.

In this framing, evaluating algorithms becomes a problem of analyzing network properties such as centrality, modularity, robustness, etc., where highly centralized structures may be efficient but fragile, while more distributed networks may promote fairness, adaptability, and resilience.

3 Case Study: Hybrid Decision-Making Systems in Healthcare

Clinical practice often relies on hybrid decision-making systems in which physicians remain the ultimate authority but their judgments could be shaped by algorithmic tools [23]. For example, systems like risk prediction for heart disease [17], triage in emergency departments [2,20], and diagnosis in radiology [6] are now commonplace. In each of these and the many other similar contexts, the stakes are exceptionally high, where errors could result in misdiagnosis, poor treatment, and/or limited access to care. Thinking of such systems as networks allows for considering how the various actors and components fit together and how democratization of the design of such systems could be operationalized.

A hybrid healthcare decision-making support system can be structured around several core elements. First, consider physicians as central decision nodes, which are connected both to technical components (algorithms, data inputs, model outputs) as well as to patients as the "end-users" of care. Patients then form another class of nodes whose preferences, needs, and attitudes must flow back into the network if the system is to be responsive to these, thereby democratizing the design in the simplest sense. Software developers, hospital administrators, and other relevant decision-makers would also part of this network, in that they contribute design expertise, resources, and also the enforcement of institutional constraints. Without intentional rewiring of these “sub-systems,” it would be reasonable to expect the latter set of actors to form dense clusters of influence, while patients would occupy more peripheral positions, if their voices are heard and accounted for at all.

Conjoint analysis provides a way to rebalance these positions by eliciting structured preferences from both physicians and patients. In practice, experimental settings would present respondents with several alternative versions of algorithmic decision tools that differ in attributes such as accuracy, interpretability, turnaround time, fairness criteria, and even heuristics such as uses of terms like “big data” or the mention of an elite institution in the design of the algorithm. Physicians may reveal, for example, that they are willing to trade a small reduction in predictive accuracy for improved interpretability that allows them to explain results to colleagues or patients. On the other hand, patients may indicate that they prefer transparency in communication or a signal of the legitimacy of the algorithm’s design to enhance trustworthiness of the system, even if it meant longer wait times for results. These signaled tradeoffs are quantified in the conjoint setting as part-worth utilities, which can then be embedded directly as edge weights connecting patient and physician nodes to specific algorithmic features. In this overly-simplistic yet still realistic setting, conjoint analysis functions as a bridge between peripheral actors’ values and the system, where these values become encoded into the architecture of the system.

Then, human-in-the-loop feedback extends this integration beyond a one-time exercise, as is most common in experimental settings. Namely, once attributes have been weighted and prototypes developed, iterative feedback cycles embed stakeholder input into the ongoing refinement of the tool. Early versions of diagnostic support systems can be tested in simulated clinical settings, where physicians provide structured evaluations of how outputs align with clinical decisions. Patients, too, can interact with mock interfaces and evaluate the clarity and fairness of communication, for example. Each round of feedback updates the system’s parameters, effectively adjusting edge weights in the network. Over successive iterations, the algorithm evolves toward balancing the human preferences of stakeholders, with the optimality of the system. This dynamic process strengthens the connections between peripheral and central nodes, continuously adapting the system to shifting expectations and contexts.

4 Concluding Remarks

When viewed from a network perspective, the outcome of such a democratized algorithmic design process is a system with greater connectivity and resilience, imbued with great human trust, and as a result, increased legitimacy. Instead of a highly centralized structure dominated by developers and high-level decision-makers/elites, the network includes stronger ties linking end-users and mid-stream humans (e.g., patients and physicians in the case of the healthcare setting) directly to design attributes and decision rules. The result is a more distributed and adaptive network topology that is less prone to failure when central nodes are misaligned with societal or human preferences and expectations. Returning to the instructive case of healthcare where the legitimacy and trust of patients and clinicians are critical to the adoption and sustainability of the system, such rewiring is essential. By structuring hybrid decision-making in this way, the complex network, whether of healthcare delivery, criminal sentencing, or political redistricting, becomes both robust and accountable, as well as relfective of those who are most affected by the output of the system.

In sum, this paper developed a dual contribution for complex systems and networks research: first, a theoretical framework modeling a democratized algorithm design as adaptive network "rewiring," and second, an applied case study demonstrating the approach in healthcare hybrid decision-making context. By rewiring sociotechnical networks through conjoint experiments and HITL feedback loops, healthcare and all other similarly positioned, consequential algorithms can develop in sustainable and responsonsive ways. These are attributes that are more critical now than ever before, in a world dominated by fast-moving development and deployment of autonomous and AI systems.

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