‘Affordances’ for Machine Learning

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ABSTRACT

The field of machine learning (ML) has long struggled with a principles-to-practice gap, whereby careful codes and commitments dissipate on their way to practical application. The present work bridges this gap through an applied affordance framework. ‘Affordances’ are how the features of a technology shape, but do not determine, the functions and effects of that technology. Here, I demonstrate the value of an affordance framework as applied to ML, considering ML systems through the prism of design studies. Specifically, I apply the mechanisms and conditions framework of affordances, which models the way technologies request, demand, encourage, discourage, refuse, and allow technical and social outcomes. Illustrated through three case examples across work, policing, and housing justice, the mechanisms and conditions framework reveals the social nature of technical choices, clarifying how and for whom those choices manifest. This approach displaces vagaries and general claims with the particularities of systems in context, empowering critically minded practitioners while holding power—and the systems power relations produce—to account. More broadly, this work pairs the design studies tradition with the ML domain, setting a foundation for deliberate and considered (re)making of sociotechnical futures.

CCS CONCEPTS

• **Human-centered computing** → Interaction design; Interaction design process and methods.

KEYWORDS

Affordances, Machine Learning, Design Studies, Mechanisms and Conditions Framework, AI Alignment, Principles-to-Practice

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1 INTRODUCTION

Much has been written about the specifications and effects of machine learning (ML) systems, variously assessing, critiquing, and/or hyping their technical and social significance. Less attention, however, has been dedicated to ML technologies as objects of design—implements with technical features that could be otherwise, fabricated through subjective and creative choices. This omission is notable, as ML technologies are integral across major institutions, implicated in consequential decisions, and interwoven with the paces and practices of everyday life. How these systems are designed, matters. Considered attention from the design studies tradition is thus a generative intervention in the production and understanding of ML systems, and the task to which this paper is set. In particular, I apply a central construct from design studies—affordances—to the ML domain, mobilizing an operational framework from which to evaluate, build, and reimagine ML applications. This move scaffolds a bridge between ideals and execution, alleviating the perennial principles-to-practice gap that has long plagued AI and ML fields [1-3].

The design of technological systems is the design of social systems, deriving from and shaping both culture and practice. As a discipline, design studies is premised on the notion that human behaviors and experiences are affected by the contours and levers of designed objects. This base postulate has long circulated through myriad professional sectors such as user experience (UX) research [4, 5], law [6-8] hardware and software development [9-12], human-computer-interaction (HCI) [13, 14], robotics [15, 16], engineering [17, 18], architecture [19-21], and education [22-24] via a common conceptual tool: technological affordances. In its simplest sense affordances are the ways technical features enable and constrain for socially situated subjects [9, 25-30]. Assessing and in-building particular affordances through combined feature sets has been a central practice across spheres of technological design. Here, I extend affordances to ML through the *mechanisms and conditions framework* [25, 31], an operationalization attending to dynamism in both subjects and structure.

I begin by motivating the argument with two fundamental assumptions, before delving into a concise overview of affordances in technological design, including a summative description of the mechanisms and conditions framework. I then explicate how the framework applies to the domain of ML and highlight the relevance of an ML-affordance pairing. With this foundation set, three case examples exhibit the utility of affordances for ML and demonstrate how practitioners can apply the mechanisms and conditions framework for targeted ends of analysis and (re)design.

1.1 Two Ground Truths

The argument for *why* and demonstration of *how* affordances apply to ML grows from the roots of two interrelated ground truths: (1) technologies are social, political and power infused, and (2) the diffusion of ML has reproduced and amplified inequality. These base assumptions sit at the intersection of the social and technical, merging sociological insights with empirical patterns wrought by technological deployments.

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Point one is the fundamental notion that technologies—broadly conceived— are imbued with human values that shape our social worlds. These materialized values reflect and affect political interests and power relations, embodying society and constructing it in turn [32-34].This may be intentional and in service of an agenda, like installing protruding bars across public benches to prevent people from sleeping on them and thus dissuading occupation by those who are unhoused [35], or a digital interface that makes privacy settings opt-in (rather than opt-out) so that platform owners can optimize data extraction [36]. The politics and power of technology may also be implicit, like the use of White women as proxies for various forms of image calibration (e.g., Shirley cards, the Lena image, and Jennifer in Paradise for film, digital processing, and Photoshop, respectively), embedding a default Whiteness that continues to persist [37, 38]. In short, the design of material artifacts reflect and affect human subjects and their social worlds, as encompassed in the maxim 'design designs' [39].

Recognizing the social in the technical is a vital task for scholars and practitioners engaged with sociotechnical objects, including (perhaps *especially*), ML technologies. ML systems, by definition, learn, develop, and change. Their effects snowball and self-perpetuate, reflecting, intensifying, and codifying the social worlds in which they operate [40-43]. They project objectivity, promise efficiency, build momentum, and govern in ways difficult to pinpoint and cumbersome to undo. These conditions set the stage for a second ground truth, that the diffusion of ML in contemporary societies has amplified inequality [43-47]. The reasons for this are many and complex, but distil into a simple fact: ML relies on data derived from a world that is unjust. ML outputs thus default towards an inequitable status quo, serving power and fortifying the margins [41, 48-50]. In practice, that has resulted in a veritable game of Whac-a-Mole—ML systems emerge, cause alarm and rebuke, retreat, and then resurface with old promises wrapped in new garb.

Together, these ground truths convey a field site at once troublesome and hopeful. The social nature of technologies may entrench extant inequalities and legitimize privilege through ML applications. Yet this same sociality reveals an inherent malleability. Technologies, and the worlds they build, need not be as they are and can instead, be otherwise [32, 51-53]. With the rise of ML and its embedding across institutional and organizational spheres, we face a sociotechnical landscape in need of, and ripe for, considered attention. This is a task for which design studies is well suited, mobilized here through an affordance approach.

2 AFFORDANCES

2.1 Definition and Background

Affordances are how the features of a technology affect that technology's uses and functions for socially situated subjects. This refers to direct utilities—what one can or cannot do with a technology—and flow on social effects. The concept originates with the ecological psychologist JJ Gibson in his study of military pilots and their aircraft, capturing the mutually constitutive relationship between human subjects (pilots) and technological objects (aircraft) [30]. In the 1980's and 1990's Don Norman brought affordances to the field of design, imploring designers to consider how their design choices would communicate with, and condition the behaviors and experiences of, those who encountered the designed object [9, 54]. Norman's classic example is of a door indicating whether it is to be pushed or pulled based on the shape and placement of its handle. With Norman, and as an outgrowth of his work, affordances became a conceptual mainstay in hardware and software design and UX research. The concept has since expanded across myriad disciplines and subfields—communication studies, disability studies, educational technology, engineering, architecture [27, 28, 55-63]—with ascending relevance as scholars attempt to understand rapid technological developments and the effects of these developments upon interpersonal and structural realities.

Affordance's conceptual value for technology studies is twofold. First, it conveys a dynamic interplay between humans and technologies rather than a static separation of the two. Second, and relatedly, affordance strikes a balance between technological determinism and radical constructivism, attending to the ways people and things co-constitute each other. This dual conceptual value underpins the use of affordance as a guiding construct across scholarly disciplines and applied fields. However, two persistent weaknesses have undermined the concept's efficacy and threatened its endurance: a binary application and presumed universal subject. Although affordances are theorized as dynamic and relational, they have been historically conveyed as either present or absent—something either affords or does not—missing the nuanced ways affordances push, pull, enable, and constrain with varying degrees of intensity. In turn, scholars and practitioners often describe affordances through the persona of an unspecified universal subject, as though the technology and its features operate the same way for all people, in all places, at all times, despite contrary assumptions in affordance theory's fundamental formulation [25, 27, 31, 64-66] (and demonstrated unequivocally by scholars of disability and affordance [62]). The subsequent section describes a recently developed framework that resolves these critiques by shifting the orienting question from *what* technologies afford to *how* technologies afford, *for whom and under what circumstances?* This is the framework I pair with ML.

2.2 The Mechanisms and Conditions Framework of Affordances

The mechanisms and conditions framework of affordances (M&C framework) transforms a singular concept into an operational model, attending to the dynamism and diversity of human-technology relations [25, 31]. This framework has two parts: the mechanisms and the conditions. The mechanisms address *how* technologies afford, while the conditions address variation across subjects and circumstances (see Table 1).

The mechanisms of affordance correct for the concept's binary application by resisting claims about what a technology affords (or does not afford), instead specifying how technologies *request, demand, encourage, discourage, refuse,* and *allow* social action. Requests and demands refer to the ways a technology initiates some action or set of actions, while encourage, discourage, and refuse refer to the ways a technology responds to activities users seek to enact. Allow is neutral in intensity and applies to bids placed by both the technology itself and the human subjects engaging it. For example, mobile phone push notifications *request* a user's

Table 1: Mechanisms & Conditions Framework of Affordances

Mechanisms of Affordance (*How artifacts afford*)	**Conditions of Affordance (*For whom and under what circumstances?*)**
Bids Placed by the Artifact	*Perception*
Request	
Demand	
Responses from the Artifact	*Dexterity*
Encourage	
Discourage	
Neutral Intensity	*Cultural & Institutional Legitimacy*
Allow	

Derived from Davis and Chouinard (2016) and Davis (2020).

attention but do not *demand* it. Should the user wish to ignore the notifications, this will be *discouraged* but not *refused.* The user is *allowed* to change their phone settings and silence notifications, reducing the *request* for attention and *encouraging* focus on the people and things in physical proximity. These mechanisms are not mutually exclusive, but represent a porous continuum fastened by analytic hooks, such that debates may ensue about whether the technology *requests* versus *demands; allows* versus *discourages*; *discourages* versus *refuses* and so forth.

The conditions of affordance correct for the presumed universal subject that often operates in affordance analyses, attending instead to a diversity of human-technology relations. The mechanisms of affordance are conditioned on three interrelated dimensions: *perception, dexterity,* and *cultural and institutional legitimacy. Perception* is what a person knows (i.e., perceives) about a technology’s functions. *Dexterity* refers to how skilled and able a person is in operating that technology. *Cultural and institutional legitimacy* refers to the degree of support (or lack of support) one has in a technology’s operation. For example, to silence phone notifications a user must be aware that the option is available (*perception*), be able to find and activate the option (*dexterity*), and the action must be condoned in the context of the phone’s use for this particular person (*cultural and institutional legitimacy*). Without this knowledge, skill, and social support, what would be *allowed* is instead, *discouraged* or *refused.*

2.3 Affordances for Machine Learning

The mechanisms and conditions framework, in its simple yet specifying language, makes technological systems observable, and thus responsible for what they are and what they do. It operationalizes the way design decisions materialize the social—in both origin and effect. This undermines ambiguity and plausible deniability, fostering accountability in their place. Towards such ends, the mechanisms and conditions framework is a tool of both analysis and design, with the capacity to scrutinize and reimagine the infrastructures, platforms, models, and outputs operating through the range of ML applications that increasingly infiltrate, organize, and govern social life.

Analysts, those interested in auditing systems from within and/or from without, can lay bare in clear terms how the system and its component parts *request* a particular type of subject, and how that subject ought to behave; what opportunities are opened and foreclosed; and thus, who and what are *encouraged* vs *refused,* interrogating how these sociotechnical relations reflect, reinforce, or alternatively, upend existing patterns of power, privilege, dominance, and deference.

The mechanisms and conditions framework is also operative at the foundations of development and design. As a systems approach, the framework begins at the end and begins with the social—how do we want these data, algorithms, inputs and outputs to function? Do we want them, for example, to *demand* equity, *refuse* intersectional ‘isms,’ *request* inclusivity, and *allow* a plurality of voices, perhaps *encouraging,* especially, those from the margins [48, 52, 67-70]? How will this correspond to the interrelated elements of data sources, interfaces, cleaning protocols, benchmarks, agentic humans, legal policies, and institutional practices that make, and are made by, ML systems?

3 CASE EXAMPLES

Summarizing the argument to this point, I have said that (1) technologies are social and thus design matters; (2) ML applications by default, reinforce and amplify inequality, prompting sociotechnical repair; (3) yet there remains a gap between the principles by which to do so and the practices of implementation; (4) an affordance approach, using the M&C framework, can serve as a principles-to-practice bridge, making legible the ways ML systems and their constituent parts *request, demand, encourage, discourage, refuse,* and *allow* across subjects and circumstances, attending to direct human-technology encounters as well as the broader social effects that eventuate therein. In this section, the argument grounds and animates through three case examples, demonstrating the M&C framework as a tool of both analysis and (re)design. The examples represent varied uses and outcomes of the framework in relation to ML applications, illustrating the reconfiguration of ML systems (Example 1), dismantling ML systems (Example 2), and the capacity of ML tools to expose and amend the affordances of institutionalized social systems (Example 3). These are anchored in case studies of Amazon’s data-driven warehouse work, inferential policing through genetic phenotyping, and housing justice, respectively. The technical implements of each case are presented as embedded objects, entangling computation within complex political economies.

Table 2: Amazon Fulfillment Center Affordance Analysis

Feature(s)	Mechanism of Affordance	Outcomes	For Whom (Subject)
ID badge scanners and individualized product scanners	*Demand*	Surveillance	Of workers
Time rates	*Request*	Speed over safety	From workers
	Discourage	Advanced age, disability, ailment, fatigue	For workers
	Encourage	Optimal labor extraction	From workers/For corporate
	Encourage	Rapid delivery	For customers
Movement sensors + product trackers + automated warehouse navigation systems	*Request*	Discretization	Of worker & management tasks
	Refuse	Intercession	From workers & management
	Encourage	Replaceability	Of workers
Real-time scheduling algorithms	*Encourage*	Optimal logistic efficiency	For corporate
	Demand	Workplace tethering	For workers
Ubiquitous tracking + Precarity	*Discourage*	Collective action	For workers

Conditions of affordance (*perception, dexterity, cultural & institutional legitimacy*) are sensitizing constructs.

3.1 Redesign with Affordances: Data Driven Warehouse Work

3.1.1 Warehouse Standards. Example 1 focuses on the conditions of labor and work at a company that is active in setting a global standard, and with which many of us are implicated through everyday practices of consumption: Amazon fulfillment centers. These are sites about which Alessandro Delfanti notes there is an entire genre of journalism, with a growing corpus of activist and academic attention [71-74]. It is from this this documentation—by journalists, activists, and academics—that a depiction of warehouse work emerges.

Workers in Amazon fulfillment centers do two main things: stock products to be picked and pick products to be shipped. Warehouse processes are billed as 'smart' and 'efficient,' driven by always-learning systems that advance and govern based on data from consumer purchases, employees' bodily movements, time sensors, heat sensors, video monitors, product scanners, curated employee feedback, targeted employee monitoring, customer feedback, delivery feedback, and managements' evaluations calibrated to corporate-designated metrics. These data produce algorithms that hire and fire, that set and display countdown timers for increasingly granular tasks, that extend or shorten shifts, dictate how when and where employees move within the warehouse, and that punish employees who are out of synch, too slow, too stagnant, dissatisfied, or union-inclined. The warehouse also pairs workers with automated systems in an extractive relationship, whereby workers train the synthetic forms designed for human displacement.

In a general sense, then, we observe a form of data-based and mechanized governance that deskills and denigrates. *How* and *for whom* is clarified with an operationalized affordance lens. For example, these data driven systems *demand* discretization and automation of warehouse tasks, making knowledge and experience irrelevant, even a liability, thus *allowing* management to not only monitor, but also easily discipline and replace workers, while *requesting* workers move and use their bodies within tightly prescribed choreographies—*discouraging* (or *refusing*) embodiments that are ill, disabled, aged, or tired. Management, too, become replaceable and acquiescent, moored to systems that *demand* attention to metrics, *discourage* and in some cases *refuse* skilled and subjective decision making, and *request,* at multiple levels, service to corporate goals, even when those goals conflict with workers' and managers' labor (and human) interests. Moreover, neither managers nor workers have *the cultural and institutional legitimacy*, a condition of affordance, to alter, reprogram, or recalibrate system properties, thus *refusing* agentic input over the very infrastructures that mandate bodily and temporal compliance. Table 2 displays the affordance analysis by which these contentions derive.

3.1.2 Reconfiguring Warehouse Standards. To be sure, there are acts of resistance to the mechanized control occurring within Amazon's warehouses. Recall that affordances *shape* but do not determine, social and behavioral outcomes. Workers ignore their countdown timers, place objects in unfindable slots, choose not to scan items, and engage in union organizing. This comes at a cost, but it is not entirely *refused.* That is, the affordances of the fulfillment center *request* and *encourage* compliance and control, but with fracture points that *allow* labor pushback. Even with these flashes of resistance, however, the default remains exploitative and dehumanizing.

From a design perspective, the challenge of addressing the Amazon model is thus in altering its defaults, creating instead a workplace that supports and insists on human dignity [75-77]—reconfiguring socio-material conditions to respect, compensate, and value the bodies, lives, and labor of workers. The mechanisms and conditions framework can help with this task, too. Here I suggest three specific proposals that align with calls from labor organizers[1]. These proposals reimagine the data-driven warehouse system in efforts to detach the surveillant lens, loosen temporal constraints, and enhance worker autonomy in ways that acknowledge and respect employees as whole human beings. Proposals and their relevant affordances are depicted in Table 3

One proposal is to depersonalize tracking within the warehouse, shifting the surveillant lens onto items exclusively, rather than people. At present, each worker is electronically logged upon entering the warehouse for a shift, followed through the warehouse by sensors that attach to employee badges with unique identifiers, and then further tracked when signing into a handheld scanner which stays with them throughout the shift. This scanner is how employees document the products they stock, pick, and pack, but it is also how management tracks and communicates with individual employees while on site. Workers are monitored throughout the warehouse, into the breakroom, the restroom, the corridors, and the parking lot, with accumulated data about how they do each task and the summative time they spend 'off task'. Such a system *refuses* worker privacy, *demands* surveillance, *encourages* real-time correction and related punitive measures, and thus *requests* worker passivity and compliance, while *discouraging* basic human needs like bathroom breaks and sitting. An alternative configuration might untie tracking from individual employees, dismantling badge readers and altering scanner sign-ins to a generic employee ID. Data would thus pertain to the collective rather than the individual, monitoring product flows but not monitoring people. This alternative, generalized mode of tracking would *refuse* individualized micro-surveillance and attendant micro-management, *encouraging* logistic efficiency without *demanding* dehumanizing control.

A second proposal is the removal of time rates altogether, or recalculation of rates to inbuild excess time, rather than trimming to its strictest edge. Rates dictate how quickly each item should be stocked, picked, and/or packed, and correspond to an ever-restarting countdown clock flashing at workers from handheld scanners. These clocks *demand* attention to pace, *encourage* speed over safety, and are automated in a way that *refuses* shutdown, slowdown, or adjustment by those judged and governed by temporal displays and the urgency these displays communicate. Such affordances are especially onerous for workers with elder bodies, ill bodies, disabled bodies, injured bodies, tired bodies, and those on temporary contracts whose livelihood can be cut if too many countdown clocks time out. Removing (or revamping) these rates, and the clocks that express them, would instead *allow* for variation in speed of movement that aligns with the diversity of bodies who do warehouse work, *encouraging* safety and the occasional friendly workplace conversation in lieu of anxious and tightly monitored temporal parameters.

The third proposal is simple: reconfigure scheduling algorithms to set employee timetables two-weeks out and require human intervention from management plus a non-punitive approval process from employees if these timetables change. The company could also pool and centralize hours so that employees can pick up, drop, and trade shifts, as suits. Amazon currently uses automated scheduling tools that predict customer demand and related staffing needs. These tools continue to update in real-time, cutting shifts or adding hours with little notice and no meaningful employee recourse. This system thus *discourages* a work-life balance for employees, *requesting* an always-on, always available relationship to the workplace, while *allowing* management to practice 'just in time' staffing. The alternative proposal *requests* a degree of stability and commitment from management in the scheduling protocol by creating friction to its alteration, while *encouraging* empowered employees who can attend to and adjust for their own scheduling preferences and income needs. This alternative system *refuses* rigid asymmetries between management and workers and *demands* respect for workers as whole human beings with lives beyond the warehouse walls.

Note that these proposals boil down to *not* collecting data, collecting less data, or collecting different data and using it more respectfully. I am therefore not suggesting complex models or elegant algorithms, but simple adjustments derived from the labor movements bubbling within Amazon's warehouse sector, operationalized here through an affordance lens. These proposals are of course aspirational. Amazon, and Big Capital in general, are programmed to extract. But imagining what could be, in concrete terms, sets a standard for debate. This serves the efforts of collective resistance, articulating a version of reality that corporate interests and the legislators who regulate them, must contend with and contest. In other words, to build the worlds we ought, first we must conceive of them and render those worlds legible.

3.2 Dismantling with Affordances: Genetic Phenotyping in Policing

The second case example places an affordance lens on Massively Parallel Sequencing (MPS), a genetic sequencing instrument with processing capacities exponentially greater than extant methods [78, 79]. Though originating as a medical tool for research and treatment of genetic disease [80], MPS has now been repurposed by law enforcement as a tool of inferential phenotyping [81]. In its carceral application, MPS uses genetic markers to infer biogenetic ancestry, gender, and eye color of a suspect based on DNA found at a crime scene. MPS is presently utilized by the Australian Federal Police, whose lead scientist promises near-future developments that expand inferences to include 'distance between the eyes, eye, nose and ear shape, lip fullness, and cheek structure'[2,3].

MPS constructs a suspect when one is unknown. It uses nucleotide sequences mapped into genetic data libraries produced through procedures that amplify small amounts of DNA into much larger amounts, treated with ML models that transform the data into a set of identifiable traits [80]. This process generates a suspect pool tied to, and inextricable from, existing groups of surveilled and policed subjects, crystalizing these subjects into targets of distrust and incrimination. MPS has been the subject of public controversy in Australia, including an open letter and petition for a moratorium[4]. The use of facial classifiers fixes MPS to the logics and practices of racial eugenics and phrenology [83, 84], while its carceral applications

[1]https://www.amazonlaborunion.org/

[2]As quoted in a 2021 AFP media release https://www.afp.gov.au/news-media/media-releases/advanced-technology-allows-afp-predict-criminal-profiles-dna

[3]Of note, and for context, Australia currently has no legislative framework for inferential DNA phenotyping, and representatives from the Australian Federal Police wrote a peer-reviewed article in 2019 advocating for strategies that will keep regulation at bay [82]

[4]Open letter linked here. To date, the AFP have not responded https://docs.google.com/forms/d/e/1FAIpQLSfR2ese1242KxVJI7DOkTF0AudP2vU0P2CvkiUhMLY8MBupog/viewform

Table 3: Amazon Fulfillment Center Affordance Redesign

Original Feature(s)	**Original Affordances & Outcomes Summary**	**Feature Adjustment**	**New Mechanisms ofAffordance**	**New Outcomes**	**For Whom(Subject)**
ID badge scanners and individualized product scanners	*Demand* worker break surveillance	Centralized scanner data, break un-trackable ID badges	*Discourage*	Surveillance	Of workers/By management
			Allow	Product tracking	By management
			Demand	Recognition of humanity	For workers
Time rates	*Request* speed over safety break for workers; breakDiscourage workers break of age and with ailments; *Encourage* optimal labor extraction for breakcorporate and rapid delivery for customers	Remove time rates or set for the slowest quartile of workers	*Encourage*	Bodily diversity	For workers
			Encourage	Sociality	For workers
			Allow	Bio-breaks	For workers
Real-time scheduling algorithms	*Demand* workers tether themselves to workplace; *Encourage* optimal break personnel efficiency break for corporate actors	Stabilized scheduling algorithms break with built-in human friction and worker participation functions	*Allow*	Life planning	For workers
			Discourage	Work-life overreach	From corporate

Conditions of affordance (*perception, dexterity, cultural & institutional legitimacy*) are sensitizing constructs.

Table 4: MPS Affordance Analysis

Feature(s)	Mechanisms of Affordance	Outcome(s)	For Whom (Subject)
DNA libraries	*Demand*	Connection between physicality and criminality	By police/For targeted citizens
	Request	Return of phrenology	For intelligence professionals/Towards targeted citizens/Within scientific communities
Objectified outputs	*Discourage*	Contestation	By targets of suspicion
Proprietary data and algorithms + complex technical processes	*Refuse*	Intercession	By suspects or criminal-judicial actors

Conditions of affordance (*perception, dexterity, cultural & institutional legitimacy*) are sensitizing constructs.

join MPS with a battery of algorithmic policing tools that consistently and systematically re-entrench punitive control over minoritized populations [52, 85, 86]. In MPS, we find a technology that requires dismantle. An affordance analysis puts this in clear terms (see Table 4).

Articulated through the mechanisms of affordance, MPS *demands* integration between physical characteristics and character assessment, *requesting* and *encouraging* correspondence between physiology and criminality, tied to existing patterns of policing in which suspicion begets criminalization, which begets suspicion and so forth. MPS also *discourages* contestation and intercession from affected communities, for once criminalization is established, the burden of proof shifts to suspected individuals and to those with now suspicious bodies. Yet the accused and the surveilled lack the *cultural and institutional legitimacy* to call such decisions into question, nor do most people, including officers, judges, and other criminal-judicial actors, have the *dexterity*, or skills and knowledge, to interrogate these systems and evaluate their veracity. In Example 1 (data driven warehouse work) we reconfigured the system to align with human-centered goals of dignity, diversity, and autonomy. In contrast, MPS in policing has no space for reimagining, as the analysis lays bare the tool's fundamentally troubled character.

3.3 Affordances of Social Systems: ML Models as Vectors of Change

The third case example shifts the target of focus. Examples 1 & 2 apply affordance framing to ML applications. Here instead, the analytic target is a social system, with affordances that can be identified and transformed through ML models. This move requires a reading of institutions (and their policies and practices) as artifacts of human making—implements that can be scrutinized and (re)designed in much the same way as material technologies. With this reading, institutions are subject to an affordance lens, while ML acts as a both a reflective mirror and constructive tool for social change. Specifically, the mechanisms and conditions framework can pair with ML outputs to collaboratively reveal, and thus diagnose and amend, structural social patterns.

A burgeoning argument contends that for purposes of addressing inequality and human bias, ML is more effective at diagnosis and redress than prediction and decision making [47, 87]. This has been demonstrated across various spheres, in which ML decision systems consistently exacerbate inequality, yet also reveal the historical and ingrained circumstances that

Table 5: Machine Learning as Vector of Social Change

Features	Mechanisms of Affordance	Outcome(s)	For Whom (Subject)
Redlining	*Demands*	Neighborhood racial segregation	For homeowners and their families
	Encourages	Access to valuable properties	For White home buyers
	Refuses	Access to valuable properties	For Black home buyers
Property grading (Grades A-D given to properties based upon ostensible quality and thus break value of the property)	*Encourages*	Extractive insurance rates	By mortgage insurers/ Towards lower income home buyers of color
	Discourages	Wealth accumulation	For homeowners in low-grade properties
	Encourages	Wealth accumulation	For homeowners in high-grade properties
Subprime mortgages (Mortgage plans that reduce or waive down payment requirements in exchange for disadvantageous interest rates)	*Encourage*	Predatory inclusion	By banks/ Towards home buyers without existing wealth to make a down payment
Credit scores as loan indices	*Demand*	Interlinking of multiple institutional determinants of wealth	For borrowers
	Encourage	Differential loan conditions and legitimated loan rejection	By banks/ Towards borrowers
Reparative legislation (as presently proposed)	*Encourages*	Remediation	By the state/For Black residents
	Refuses	Full compensation	By the state/For Black residents

Conditions of affordance (*perception, dexterity, cultural & institutional legitimacy*) are sensitizing constructs.

make inequality endemic. Here, I draw out one such instance: housing justice and related wealth disparities as studied by So and colleagues out of the MIT Data Feminism Lab [88]. Using a combination of causal inference methods and ML, these researchers estimated the racial wealth gaps caused by generations of disparate access to home ownership and differential property values, calculating the reparations required to redress for these enduring imbalances and comparing that figure to an extant reparations program. Their analyses of housing maps, census data, and economic indicators of return on investment (ROI) reveal significant wealth costs to borrowers of color due to institutional features such as redlining, subprime mortgages, and property grading that concentrate Black homeowners into poorly valued areas while devaluing the homes and neighborhoods where Black people live. They then devised an ML algorithm which calculates the amount necessary to remediate racial wealth gaps[5], comparing this calculation to a real reparations program in Evanston, Ill. Their findings show that the compensation levels of this reparations program are under-funded, requiring greater down payment assistance and reconfigured debt-to-income ratios.

Conveyed with an affordance framing in Table 5, we can thus say that institutionalized lending practices have historically *encouraged* banks to deny Black borrowers, *requested* disproportionate White wealth, and *discouraged* (perhaps *refused*) racial equity and neighborhood integration, while existing reparative measures *encourage* remediation, but in their present form, *refuse* full compensation. Of note, ML is not necessary to recognize the intergenerational economic (and social) consequences of institutionalized wealth inequities tied to housing, loan, and insurance access. Nor do we need computational models to understand the validity of economic reparations. However, in the pairing of affordances with ML, these realities obtain not only clear articulation, but also weight and precision.

ML-enabled indicators lay bare *how* social systems afford privilege and disadvantage, for whom, and to what effect. This sets the stage for interventions of both policy and practice. Such interventions are vital, lest we fall into *datafied injustice*, repeatedly quantifying a problem as though it is not already obvious [51]. In this vein, Barabas and colleagues point to ML as a useful tool in hypothesis formation for causal inference procedures that enable randomized controlled trials of risk-needs interventions in the criminal justice system [87], while So et al., in the example from this section, use ML methods to not just evince racial wealth disparities in the US, but also to evaluate policies aimed at redress [88]. For each, the point is to shift institutional arrangements that *encouraged* housing, wealth, and freedom for White people disproportionately, to those that *request* recompense for these historically rooted circumstances and *demand* equity across racial groups.

4 CONCLUSIONS AND TAKEAWAYS

Based in design studies, theories of affordance have long been central to understanding and intervening in the development and analysis of technological systems, yet ML has remained outside of the design studies purview.

[5]Based on quantifying the amount of money needed for Black borrowers who were rejected from prime loans to reverse that decision.

This is perhaps a function of ML as data driven, and thus less obviously conceived as an object of design. As I have demonstrated, however, ML systems and the models on which they run are subject to myriad design decisions which both reflect and shape the social worlds in which these systems operate. The present work thus extends affordances to ML, anchored by the M&C framework. Through three case examples across work, policing, and housing justice, I show how the M&C framework can illuminate the ways both technological and social systems afford across subjects and circumstances. Not only does this bring affordances (and design studies more broadly) to the field of ML, but also shows by example how to mobilize the M&C framework as a critical tool of both revelation and (re)making, scaffolding a path between principles and practice. Beyond this core contribution, I conclude with four key takeaways to guide affordance studies of ML systems going forward.

The first point is that analysis and design are intertwined. Though presented distinctly across the case examples herein, analysis and design are inextricable and reciprocally connected. Analyses should be done with an aim towards remaking, while objects remain always in process and under analytic scrutiny, subject to adaptation and dismantle. This reciprocal relation is especially relevant to objects that develop through machine learning as they are never complete and always responsive to the data of a dynamic social world that has, and continues to, reflect, perpetuate, and intensify patterns of social order.

Point two builds on yet also complicates the first: though analysis and design are intertwined and ongoing, front-end planning should take precedence. Once a system is built, it runs on its own inertia. Adjustments and retrofits overlaid upon a faulty core may alleviate some harms, but remain tied to a basic set of parameters from which deviations are necessarily limited and alternative pathways preemptively foreclosed. Moreover, as Ehsan and colleagues point out, ML applications can leave imprints upon the people and institutions through which these systems are implemented, such that effects endure even after an ML system discontinues [89].

Point three goes back to the socio-structural character of technological systems, and the ways these systems are always and inevitably embedded within political economies of interests and power. Those working at the intersection of affordances, technology, and the law are especially instructive here, reckoning with the ways policies and regulation materialize with and through hardware, software, and code [6-8]. This is a vital point when considering the case examples presented above—each of which contend with institutional actors backed by corporate and/or state authority. Put plainly, one cannot expect such institutions to redesign if they do not perceive it in their interests to do so. However, ML standards *can* be compelled through interrelated efforts of collective action, organizational policies, and legislative interventions which together, focus social, regulatory, and legal attention upon sociotechnical configurations. Such efforts can be aided by, developed through, and implemented with the M&C framework.

Finally, identifying affordances—as they are in analysis and how they ought to be, in design—is contingent on the people in the proverbial room. Everyone has a standpoint that renders some things more observable and others, less. But, if we take seriously the canonical feminist point that those on the margins offer a uniquely valuable perspective for their recognition of realities otherwise clouded by privilege [67, 90], then the White masculinity of computational professions becomes acutely salient. As D'Ignazio and Klein point out, data and computational sciences (broadly conceived) suffer from a 'privilege hazard', by which those who make and evaluate technological systems cannot access, predict, or understand the harms that will ensue for people unlike themselves [42]. An affordance approach and its manifestation through the M&C framework requires sharp social attunement, best deployed through many and diverse hands. This means efforts at design and audit that give access to the outside, that place affected communities at the center, and that approach with humility, honesty, and a readiness to respond when the machines that decide, assist, govern, and predict inevitably learn to reproduce (and regress) the social systems of which they are a part.

The logics and tools of design studies, including affordances, do not solve the troubles wrought by AI, automation, machine learning, or any other technological system, nor do they promise the realization of social good. These logics and tools do, however, draw explicit links between technical choices and their social effects, making these connections observable and thus actionable. Such a linkage is necessary, if not sufficient, for deliberate and considered approaches that hold technological systems and those who make and deploy them to account, and for building technologies that reflect and contribute to renditions of society that we hope to achieve. The M&C framework, in particular, attends to *how, for whom, and under what circumstances* technologies operate, by which a simple vocabulary exposes sociotechnical complexities underneath. As applied to the ML domain, the framework has been shown here as an instrument of analysis, (re)design, dismantle, and critical reflection. It also joins together design studies and machine learning, laying a foundation for this generative pairing.

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