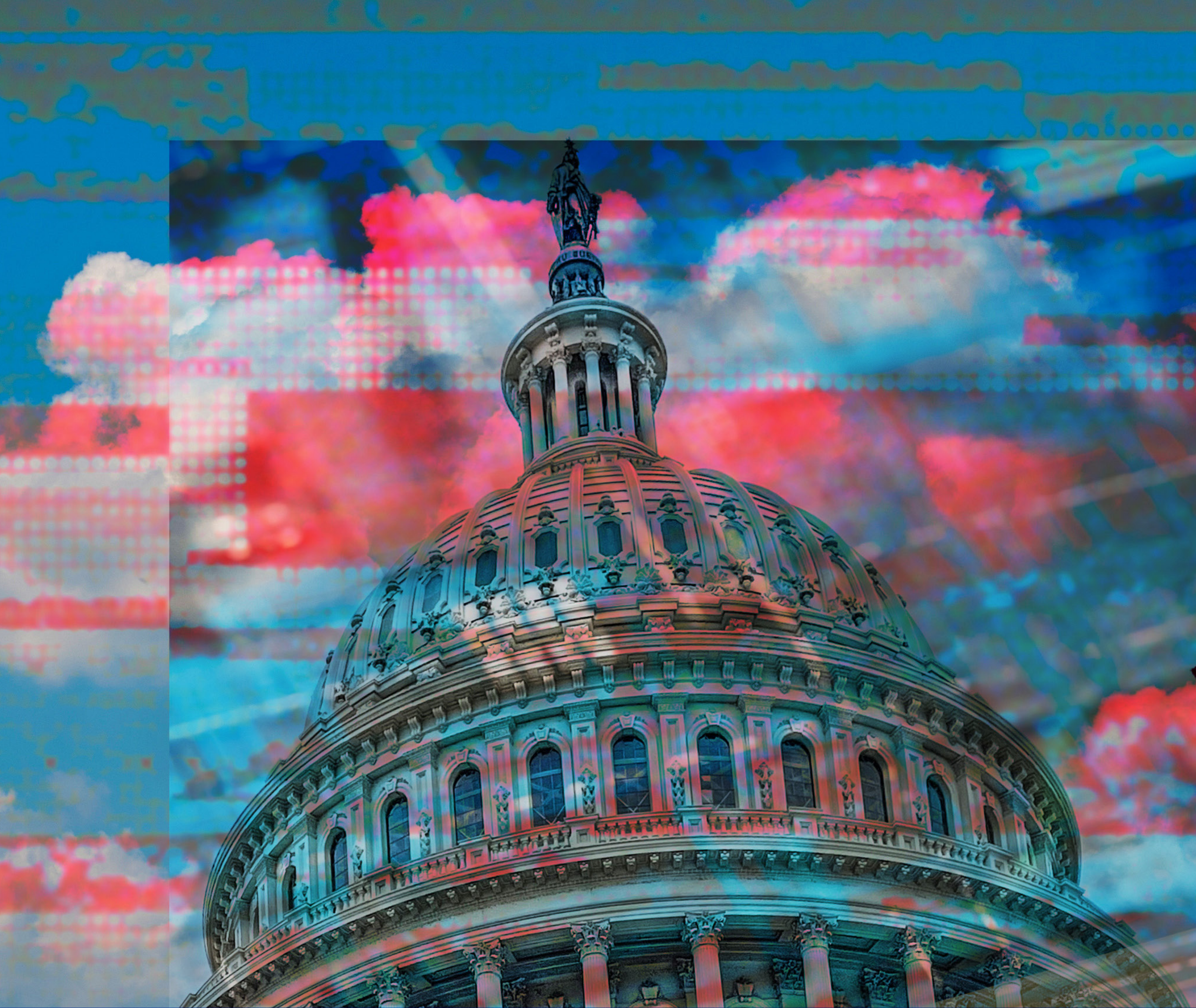

Building Fairer Futures

The Role of AI in Equitable Government Decision-Making

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The Growing Role of AI in Public Decision-Making

In a landscape of tightening budgets and growing demands, governments face increasing pressure to ensure that limited public resources reach the communities that need them most. Given this, policymakers are increasingly developing or, more commonly, procuring Artificial Intelligence (AI) systems from a growing array of tech companies to help make key decisions that have profound implications for equity and fairness.

Government AI (GovAI) systems, now at the forefront of public sector decision-making, play a critical role in determining who receives essential benefits, which communities gain new infrastructure, and which individuals are prioritized for services. This report focuses specifically on a subset of GovAI tools—categorical prioritization, predictive, and planning systems—used to distribute community benefits, drive public investment, and advance equitable development. It does not address the use of AI technologies in carceral contexts, such as fraud detection, predictive policing, or criminal sentencing, which pose distinct challenges and ethical concerns.

GovAI tools operate within larger decision-making frameworks, generating outputs like risk scores, maps, and vulnerability predictions that heavily influence the allocation of public goods and services. However, these tools often embed the assumptions, values, and goals of their private developers, which can result in policymakers ceding control over critical decisions. This outsourcing of accountability risks turning these systems into opaque mechanisms that shield decision-makers from scrutiny, enabling them to justify cuts to benefits or services as the impartial outcomes of "data-driven" systems. Furthermore, without careful oversight, these tools can perpetuate inequities by encoding historical funding disparities or biased data, exacerbating issues like the racial wealth gap.

> **This outsourcing of accountability risks turning these systems into opaque mechanisms that shield decision-makers from scrutiny, enabling them to justify cuts to benefits or services as the impartial outcomes of "data-driven" systems.**

However, with legislation in states like California, mandating the creation of a public inventory of consequential GovAI systems, there is now a critical opportunity to examine these tools and ensure they are designed with equity in mind. This report explores nine different GovAI systems, detailing how they function and offering recommendations for embedding fairness into their design and implementation. By identifying these systems early, policymakers and civil society can work together to address potential risks, ensuring that GovAI tools are transparent and equitable. When developed collaboratively with affected communities, these systems have the potential to drive more just, data-informed decisions, ensuring resources reach those who need them most. Understanding how these systems work is the first step in building a more equitable future.

Key GovAI Tools: Categorical, Predictive, and Planning Systems

To assist in understanding these systems, we categorize GovAI tools into three main types: **categorical prioritization systems**, **predictive systems**, and **planning systems**.[1] These categories represent distinct ways of using AI to prioritize who receives access to public resources such as funding, services, or infrastructure. In this report, "prioritization" refers to the process of using the outputs from GovAI systems to influence who gets access to limited public resources—such as affordable housing grants, social services, or transportation infrastructure—based on various criteria set by policymakers and the developers of these systems.

For the purposes of this report, we use the term "AI" and "GovAI" broadly to refer to the systems defined below, including categorical systems that rely on predefined rules and static categories, as well as more complex predictive and planning systems. According to the National Institute of Standards and Technology (NIST), AI refers to "an engineered or machine-based system that varies in its level of autonomy and that can, for explicit or implicit objectives, infer from the input it receives how to generate outputs that can influence physical or virtual environments." The systems assist humans in performing tasks that mimic and influence human decision-making and are included under the broader "GovAI" umbrella for this report.[2]

KEY GOVAI TYPES

Categorical Prioritization Systems

Categorical prioritization systems operate using fixed, predefined rules and static categories to allocate and prioritize public resources. Decisions are made based on criteria established by policymakers, which group individuals or areas into categories (e.g., “disadvantaged” or “vulnerable”). For example, a census tract might be categorized as disadvantaged based on fixed criteria such as income level or pollution exposure, and this designation determines its eligibility for affordable housing grants or transportation infrastructure funding.

Predictive Systems

Predictive systems use machine learning models to predict specifically defined outcomes (e.g., the risk of default or foster care placement) based on historical and real-time data. These systems generate predictions or risk scores, determining which individuals or communities should be prioritized for resources or services. For example, a predictive system may be used to predict a tax debtor’s inability to pay fines. It could analyze data such as income, debt, housing, and criminal justice involvement to flag debtors at higher risk, prioritizing them for targeted interventions like financial counseling, alternative payment plans or public assistance instead of forcing them to pay fines they cannot afford.

Planning Systems

Planning systems use algorithmic techniques such as clustering, forecasting, and optimization to inform long-term decisions about resource allocation. Unlike categorical and algorithmic systems, which focus on determining who gets access to resources, planning systems are designed to determine where and how resources should be allocated to maximize impact. These systems create models based on projected future needs or trends, optimizing resource distribution across various regions or populations. For instance, a planning system may forecast electric vehicle (EV) charging needs and recommend where to build EV charging infrastructure to meet future demand.

Each type of system presents its own set of risks, benefits, and specific use cases. Therefore, advocacy strategies should be tailored to address the unique challenges and opportunities associated with each typology. While a comprehensive assessment of the equity impacts of these systems is beyond the scope of this report, we focus our recommendations on how to make each type of system more equitable in its design and implementation. Additionally, this brief provides more detailed information on the inputs, outputs, and use cases for GovAI systems in the tables located in the Appendix, offering further insights into how they function in practice.

Categorical Prioritization Systems

Categorical prioritization systems have long been used in social programs to determine eligibility or priority for public resources, such as housing assistance. These systems group individuals or communities by characteristics such as income level or health vulnerabilities. Public services and resources are then prioritized for those individuals or communities who meet established criteria. The equitable design of these systems are critical for expanding economic and social opportunities for communities of color and low-income households.

The development of a categorical prioritization system typically involves three steps where decision makers:

1. Select attributes that indicate need and are deserving of higher priority (e.g., income, age, employment status);
2. Simplify these measures of need into categories (e.g., income at 100 or 200% of the Federal Poverty Level, disadvantaged, age 65+), and
3. Select decision rules and thresholds that map categories to priority levels and integrate those prioritization criteria into funding rules or public assistance eligibility requirements.[3]

Categorical systems provide a data-driven way for policymakers to reflect multiple values and policy goals when determining how to allocate and prioritize public resources. This is done, for example, by allowing multiple categories when determining eligibility for public funding or defining a community as disadvantaged based on multiple indicators like poverty levels, environmental risks, and health disparities—when determining which communities receive priority for public resources.

Examples:

- **CalEnviroScreen:** Identifies “disadvantaged” census tracts in California according to exposure to pollution and socioeconomic factors associated with increased vulnerability to the effects of pollution.[4] Projects in census tracts with the top 25% of CalEnviroScreen scores are designated as disadvantaged and eligible for priority investment from California’s Climate Investments program.[5]
- **Climate and Economic Justice Screening Tool (CEJST):** Identifies “disadvantaged” census tracts by determining if census tracts meet specified thresholds for climate risk and socioeconomic indicators.[6] Federal policies direct 40% of hundreds of billions of dollars of public investment from legislation like the Bipartisan Infrastructure Act to fund affordable housing, clean energy infrastructure, and other projects to CEJST-identified disadvantaged communities (DACs).[7]
- **New York City Standardized Housing Assessment Tool:** Assesses the vulnerability of individuals at risk of homelessness by analyzing healthcare usage, psychiatric and psychosocial assessments for impairments, and interactions or contacts with public services to prioritize the distribution of limited housing resources, like supportive and subsidized apartments, to a much larger eligible

population.[8] [9] Local social service agencies use similar tools across the nation as they are required to receive federal funding from the U.S. Department of Housing and Urban Development (HUD).[10] This requirement is part of HUD's larger effort to ensure that homelessness resources are allocated fairly, efficiently, and in a way that prioritizes the most vulnerable individuals and families.

Strengths:

- **Data-Driven Prioritization:** Designed properly, categorical prioritization systems enable policymakers to target resources where they are most needed, ensuring that vulnerable communities and individuals receive increased support. This data-driven approach helps create more equitable outcomes by basing decisions on measurable need rather than subjective judgment.
- **Adaptability and Intersectionality:** Categorical systems are adaptable and can be customized to align with multiple policy objectives simultaneously. By incorporating different indicators as prioritization criteria—such as income, health status, or environmental risk—policymakers can target public assistance in a way that reflects a broad range of social, economic, and environmental priorities.
- **Transparency and Consistency:** Categorical prioritization systems are generally easier to understand and consistent because these systems rely on fixed rules, such as income thresholds or geographic indicators. This relative simplicity allows both policymakers and the public to more easily trace how and why resources are allocated.

Effective Targeting:
CalEnviroScreen has been effective in helping direct $8.1 billion or 76% of the state's $11 billion in California Climate Investments to projects benefiting disadvantaged communities and priority populations.[11] An analysis of 2,007 census tracts found that the effect of receiving a "disadvantaged" designation by CalEnviroScreen was a 104% increase in funding, equivalent to US$2.08 billion in additional funding over four years.[12]

Weaknesses:

- **Oversimplification:** The static, rule-based nature of these systems can oversimplify complex social realities or fail to accommodate unique cases, leading to rigid and potentially inequitable decisions. The categorical systems examined in the appendix have less than 25 indicators of need compared to over 100 for several of the predictive systems discussed below. Furthermore, design choices in these systems can fail to consider and prioritize communities experiencing the cumulative impacts of socioeconomic and environmental challenges.

Cumulative Impacts: Comparing CEJST and CalEnviroScreen

Communities of color are more likely to experience higher cumulative impacts from environmental and socioeconomic challenges or burdens. CalEnviroScreen takes a comprehensive approach to cumulative impacts by giving census tracts experiencing multiple burdens higher CalEnviroScreen scores and increased priority for public investment.

In contrast, CEJST takes a simpler approach, prioritizing a community for infrastructure investment if it meets any one of eight thresholds representing disadvantaged status (e.g., climate change, energy, health, legacy pollution, housing, transportation, waste and wastewater, and workforce development). CEJST does not consider how these factors might interact to produce compounded or cumulative impacts representing greater need for resources and investment.[13]

This difference in methodology between the tools leads CEJST to potentially underrepresent communities of color relative to CalEnviroScreen, impacting eligibility for billions in public investment.[14] It underscores how design decisions in GovAI can have a critical impact on which communities have access to opportunity.

- **Biased and Incomplete Data:** These systems can underrepresent or misprioritize communities when they rely on outdated, biased, or incomplete data. Key factors relevant to certain vulnerable populations, such as housing insecurity or health risks, may be overlooked, perpetuating systemic inequities and excluding underserved groups from receiving necessary support. These risks are compounded for communities that lack representation in the legislative and regulatory bodies that oversee the development of these systems.
- **Circumventing Human Judgment:** While designed to be objective, categorical systems can override human judgment by rigidly adhering to pre-set rules, leaving little room for discretion in addressing complex cases.

Policy Recommendations for Categorical Prioritization Systems:

- **Solicit Community Input in Selecting Categorical Prioritization Criteria:** Agencies should establish working groups that include agency staff, paid community members, policymakers, and independent experts to review and recommend updates to the rules and categories after understanding the trade-offs between alternative methodologies and prioritization criteria. For example, New York City convened focus groups with housing experts, community members, and over 40 organizations representing service providers, government agencies and coalitions to identify factors for their housing assessment tool.[15]
- **Ensure Regular Review and Updates:** Public agencies overseeing categorical prioritization systems should be required to conduct periodic reviews of the rules, data inputs, and thresholds to ensure they remain relevant, equitable, and reflective of current needs and realities.

- Agencies should formalize elements for the public disclosure of decision-making criteria, data inputs, rules and rationale for these systems such as by establishing public portals where community members can access this information and submit feedback or concerns.

- **Collect Data and Track Outcomes:** Agencies and policymakers should implement systems to collect and analyze the outcomes on communities and individuals prioritized by categorical systems to understand their impacts and identify areas for improvement. For example, the Department of Energy is developing metrics to measure and report on the benefits of energy investments in CEJST-identified disadvantaged communities (DACs), and the California Environmental Protection Agency releases regular reports on CalEnviroScreen's impacts on communities of color.[16]

Policy Priority	Example Benefit	Example Metric
Decrease energy burden	Reduction in energy costs due to technology adoption	Annual energy expenditures in DACs before and after program intervention
Decrease environmental exposure and burdens	Reduction in local pollutant emissions	Measurement of local pollutant in DACs before and after program intervention
Increase clean energy access	Increase access to clean energy serving DACs	Percentage of local electricity generation mix from clean energy that serves DACs

Under the Justice40 program the Department of Energy (DoE) is working to establish metrics, measure, and report on the applicable benefits (or disbenefits) that their respective programs can have in a community. Above are examples of benefit metrics developed by the DoE.

Predictive Systems

Predictive systems use machine learning and data analytics to forecast a specific *predicted outcome*, guiding agencies in deciding who should be prioritized for public assistance. These systems analyze historical and real-time data to estimate risks, such as homelessness or inability to pay fines, allowing agencies to allocate resources like caseworkers, rental assistance, or funding for intervention programs more effectively.

A critical aspect of designing these systems is the selection of the predicted outcome, which often acts as a proxy for vulnerability or need. Developers and agencies choose this outcome based on what is measurable and best reflects the risk or challenge the system is meant to address. For example, Los Angeles County's predictive system prioritizes child neglect investigations based on a prediction if a child is at high risk of being separated from their family and entering the foster care system. Those identified as high-risk receive support from more experienced caseworkers and faster response times for child maltreatment investigations.

The choice of predicted outcome is vital in these systems because it shapes who receives priority for resources. For instance, had the system predicted future interactions with the criminal justice system or hospitalizations, it may have prioritized a different set of cases and children for additional support. This decision has significant implications for the communities impacted by these systems in terms of their ability to receive access to the opportunities, support, and resources provided by our social welfare systems.

Examples:

- **Infinite Campus - Early Warning System:** Predicts which students that are "at risk" for failure to graduate in order to identify needs and direct educational resources, such as increased instruction, to students that benefit from them most.[17] In Nevada, this system was used to allocate supplemental aid funding to schools, shifting away from a formula based on income. As a result, the number of students qualifying for increased educational funding dropped from 288,000 to 63,000, leading districts to slash programs and budgets. [18]
- **Los Angeles County Department of Children and Family Services (DCFS) Risk Stratified Supervision Model:** Predicts the risk that children involved in maltreatment cases will be placed in foster care, with high-risk youth receiving more support and faster response times in child welfare investigations.[19]
- **New South Wales (NSW), Australia Revenue Vulnerability Model:** Predicts financial vulnerability among individuals and diverts them from punitive debt collection actions and into debt remediation and forgiveness programs.[20]

Strengths:

- **Efficiency and Data-Driven Insights**: Predictive systems can uncover patterns and correlations that are not visible through manual analysis, offering a more nuanced understanding of complex issues at a faster speed and larger scale than human decision makers can provide.
- **Personalized Decisions**: By analyzing individual risk factors, predictive models can consider more attributes about a person, tailoring interventions to their specific needs or situation—improving the targeting and effectiveness of public assistance programs.
- **Formalization and Specificity**: These systems require policymakers to select a specific predicted outcome, such as homelessness or eviction risk when prioritizing housing assistance, rather than selecting a variety of proxies for need as in categorical systems. The formalization process forces policymakers to clarify their policy goals, such as whether the goal is to keep existing renters in their homes or to house individuals who are already unhoused. Additionally, the formalization process can ensure that interventions are more closely tied to the types of risks that are predicted.

Weaknesses:

- **Bias Amplification and Incomplete Data**: Predictive models can perpetuate and even amplify existing biases if trained on biased or incomplete data, leading to unfair outcomes. If the data used to measure these outcomes is biased or exclusionary, for example if homelessness is only defined by shelter use, entire groups—like those who avoid shelters due to safety concerns—may be overlooked. Additionally, models trained on past data may inadvertently codify existing disparities by flagging individuals who resemble those who have previously benefited from assistance, locking out others whose needs don't align with the assumptions of existing data systems.
- **Opacity and Accountability**: The complexity of predictive algorithms often makes them difficult to understand, raising concerns about transparency and making it harder for impacted individuals and stakeholders to trust how decisions are made. Decisions made by complex models are harder to challenge or review, as the reasoning behind them can be obscured by the algorithm's complexity.
- **Formalization Risks**: Relying on specific predicted outcomes may not always capture the full scope of a program's policy goals, especially if the data used to define those outcomes is incomplete or flawed. A rigid focus on a single outcome can conflict with broader policy goals that aim to balance multiple values, such as helping both existing renters and individuals experiencing chronic homelessness.

Policy Recommendations for Advocates and Policymakers:

- **Community Involvement in Model Design:** Government agencies and policymakers should ensure that the predicted outcomes used in these models are co-designed with the communities most affected by their decisions. This process should be facilitated through participatory design workshops, where agencies collaborate with community members, advocates, and experts to define success, evaluate whether the system should be implemented, and understand the trade-offs between different predicted outcomes.
- **Continuous Monitoring and Feedback Mechanisms:** Public agencies, in collaboration with independent oversight bodies, should implement continuous monitoring systems to gather feedback from community members and caseworkers on the real-world impacts of algorithmic decisions. These agencies should use this feedback to regularly update and refine the models. For example, the Los Angeles County DCFS system uses a racial equity feedback loop to flag when its system mistakenly identifies Black youth as high-risk and studies those cases to help improve the model performance for Black youth and minimize unnecessary intrusions by caseworkers.[21]
- **Algorithmic Accountability and Redress:** Legislators and regulatory bodies should develop frameworks that guarantee individuals the right to challenge and seek redress for decisions made by these algorithms. Independent review boards or ombudsman offices should be established at the state or local level to specifically address grievances related to algorithmic decision-making. For example, the NSW Revenue Vulnerability Model was developed in response to complaints to its ombudsman office that its automated wage garnishment system harmed financially vulnerable individuals.

Categorical vs. Predictive Systems:

Government agencies often choose categorical prioritization systems over predictive ones because they can be implemented more easily, quickly, and transparently. Another key reason is the lack of historical "ground truth" data needed for predictive systems, which rely on accurate, measurable, and labeled outcomes, such as a failure to pay a fine or graduate, to learn how to make predictions. In many cases, agencies don't have the labeled data necessary to train predictive models, especially for complex issues like community resilience or long-term well-being. Categorical systems, by contrast, bypass the need for such labeling by using readily available criteria—like income levels or geographic designations—as proxies for need, ensuring resources are distributed without the need for labeled data.

Planning Systems

Planning systems are designed to forecast future needs, optimize resource distribution, and support long-term decision-making. While categorical prioritization and predictive systems determine **who** should receive priority for public goods and services based on predefined criteria or predicted needs, planning systems allow for further refinement and prioritization, focusing on determining **where and how** public infrastructure should be allocated over time to achieve strategic and equitable outcomes. These systems are essential for infrastructure development, environmental planning, and future-proofing public services, helping governments allocate limited resources efficiently and fairly.

How Planning Systems Work

Planning algorithms use advanced techniques such as clustering, forecasting, and optimization to evaluate scenarios, model future trends, and guide investments in infrastructure and services. By accurately predicting future needs, these systems can ensure that resources are distributed not only efficiently but also equitably, avoiding unintended disparities.

Policy Priority

Optimization Algorithms

Identify the most efficient solution from a set of possible options by maximizing or minimizing an objective function (e.g., cost-effectiveness, coverage) within given constraints like budget, infrastructure availability, environmental impact, equity requirements etc.

Clustering Algorithms

Group similar data points, like census block groups, based on shared characteristics like income, infrastructure needs, or resource usage. By identifying these natural groupings, policymakers can develop targeted policies and allocate resources more effectively, ensuring that different regions or communities receive the most appropriate services and investments based on their specific needs.

Forecasting Algorithms

Use historical data and statistical models to predict future trends, outcomes, or demands such as energy usage, travel patterns, broadband revenue, or housing investment.

Examples

Market Value Analysis Tool: Groups neighborhoods by investment potential based on property values and vacancy rates to inform community redevelopment strategies—including determining which neighborhoods get displacement protections, prioritization for housing development, or blight removal.[22]

Electric Vehicle Infrastructure Analysis Tools (EVI-X): This suite of tools, forecasts future electric vehicle charging needs and optimal locations for charging infrastructure.[23] For example, the EVI-Pro tool models future travel patterns, energy demand, driver preferences to help planners understand infrastructure upgrade needs and how many EV charging stations their locality must build to meet EV deployment goals.[24] The EVI-Equity tool provides suggestions for more equitable EV infrastructure deployment.[25]

CostQuest CA Broadband Priority Areas Investment Model: Uses clustering and optimization techniques to identify locations that should receive priority broadband infrastructure investments in California based on models forecasting financial viability and demand.[26] The recommendations from this tool were rejected in favor of using CalEnviroScreen disadvantaged communities as priority locations.[27]

Abandoning the CostQuest CA Broadband Priority Areas Investment Model:

In 2022, the California Public Utilities Commission (CPUC) planned to use the CostQuest model to guide $2 billion in broadband infrastructure grants, which would have prioritized broadband projects in locations with optimal financial viability and demand. While this approach efficiently maximized return on investment for Internet Service Providers (ISPs) and the number of homes served, it overlooked equity, prioritizing wealthier areas that were more profitable to serve.[28] This left many low-income communities—which are often more expensive to serve—at a significant disadvantage in attracting broadband infrastructure investments.

Community advocates and civil society groups recognized this issue and pushed the CPUC to abandon the CostQuest model, which failed to properly incorporate equity into its objective function and optimization criteria.[29] In response, the CPUC shifted to using CalEnviroScreen, a categorical prioritization system designed to identify disadvantaged communities based on environmental and socioeconomic factors to designate particular census blocks groups as high priority for broadband investment.

Choosing the Right Objective Function for the Job

In planning systems, the objective function drives decision-making. The CostQuest model's objective function was focused on maximizing the benefit of funding according to profit driven criteria which led to inequitable outcomes and community opposition. Instead of discarding the CostQuest model, the CPUC could have updated the objective function to prioritize equity. For example, the model could have been better designed to minimize deployment costs, ensure a reasonable return on investment for ISPs, and maximize investments in the communities with the greatest barriers to broadband adoption (e.g., low income, low digital literacy, low device access, etc.). This would have provided a balanced approach that integrated both financial efficiency and fairness, ensuring that underserved communities were properly prioritized in California's broadband infrastructure program.

Model Misalignment

Model misalignment refers to a situation where the objectives, behavior, or outcomes produced by an AI system do not align with the intended goals or values set by its developers, users, or stakeholders. While CalEnviroScreen is a strong tool for identifying climate-disadvantaged communities it may not be the best measure for broadband needs even if it is an improvement over the CostQuest model in terms of equity. The metrics used in CalEnviroScreen, such as environmental pollution exposure, don't necessarily correlate with areas that have the greatest need for broadband infrastructure. This misalignment shows the limitations of applying a tool designed for one context, such as environmental justice, to an entirely different context—like broadband deployment.

Strengths

- **Strategic Decision-Making and Scenario Analysis**: These systems support long-term resource planning, allowing governments to forecast needs and consider multiple possible futures, helping prepare for uncertainty.
- **Flexibility**: These systems can adapt to evolving data and conditions, allowing them to stay relevant over time. As new information emerges—such as demographic changes or shifting community needs—planning systems can adjust their calculations, offering opportunities to correct imbalances or address inequities.

- **Optimized Resource Allocation**: Planning systems can distribute limited resources to where they are needed most. By using data-driven models, these systems can maximize the impact of public investments and ensure resources are allocated in line with both immediate and long-term needs.

Weaknesses

- **Complexity**: Planning systems are often built on advanced algorithms and statistical models with many assumptions built into them. This complexity makes it difficult for non-experts to understand and scrutinize the outputs of these systems. This lack of transparency can prevent policymakers, communities, and stakeholders from fully grasping how decisions are made.
- **Risk of Misalignment**: Without a clear focus on equity, planning systems may fail to align with broader community needs, leading to the exclusion of marginalized groups. This misalignment can deepen mistrust in government processes, especially if the system prioritizes metrics that the community does not agree with or fully understand.
- **Data Dependency**: The accuracy of planning systems is heavily reliant on the quality and completeness of the data they use. If data is flawed or incomplete, particularly in capturing the needs of underrepresented or underserved communities, the system's recommendations may be skewed, resulting in inequitable resource allocation.

Policy Recommendations for Advocates and Policymakers

- **Integrate Equity into Development and Procurement Contracts**: Policymakers should mandate that contracts or funding for the development of planning systems explicitly require equity considerations and improved outcomes for disadvantaged communities. This ensures that public investment and infrastructure decisions are made with a focus on serving underserved populations.
- **Inclusive Scenario Development**: Agencies should actively engage communities, particularly marginalized groups, in scenario planning through town halls and focus groups. Tools like EVI-Pro, which models EV infrastructure needs based on different uptake scenarios, can help cities plan for equitable and sustainable transportation futures by incorporating diverse input on the number and siting of publicly supported EV charging stations, ensuring that public investment goes towards EV charging stations in apartment complexes and workplaces to support EV adoption by households that are not well-served by existing EV infrastructure.
- **Transparency and Accessibility of Data**: Governments should mandate that data, assumptions, and algorithms used in planning systems be publicly accessible. Modeling tools should have interactive and community-friendly versions, allowing residents to visualize how planning decisions impact local investments and infrastructure. This transparency empowers communities to engage in decision-making processes.

Equitable and Efficient: A Path Forward for GovAI

As GovAI systems take on a larger role in public resource allocation and prioritization, it is critical that they are designed to serve all communities equitably. These systems offer precise, data-driven decisions, but without careful oversight, they risk perpetuating existing disparities and overlooking the needs of underserved populations.

Contrary to the belief that fairness and equity might compromise efficiency, they are mutually reinforcing. By designing GovAI systems to address a range of community needs, governments can target resources more effectively, reduce costly corrective measures, and improve long-term outcomes.

To achieve this balance, several key actions are needed:

1. **Targeted Design and Procurement**: Policymakers should ensure that GovAI systems use comprehensive, data-driven criteria to allocate resources. Procurement contracts must require developers to design models that account for a broad spectrum of needs, ensuring that resources are directed where they will have the greatest impact, as defined in consultation with a diverse group of stakeholders.
2. **Inclusive Community Engagement**: Engaging diverse communities in the design process is crucial for both fairness and effectiveness. By incorporating input from those most affected on issues of decision rules in categorical systems, predicted outcomes in predictive systems or objective functions in planning systems would help ensure that these systems are better aligned with real-world conditions and avoid model misalignment.
3. **Continuous Review and Accountability**: Regular reviews and updates ensure that GovAI systems remain responsive to evolving community needs. Establishing feedback loops with impacted communities and stakeholders will help keep these systems adaptable and accurate over time. Transparency in the data, assumptions, and models used fosters trust and ensures ongoing improvements.

This policy brief offers a starting point for evaluating the strengths and weaknesses of various GovAI systems and their role in resource allocation and prioritization. By embracing principles of **transparency**, **inclusivity**, and **accountability**, advocates and policymakers can work together to make data-driven decisions that are not only efficient but also equitable. Through this approach, we can address gaps where these systems may fail to fully meet the needs of marginalized communities. With a clearer understanding of how these systems operate and how they impact equity, advocates can drive forward more equitable, transparent solutions—whether by addressing biased data, refining decision rules, or ensuring broader community involvement.

Appendix

Categorical Prioritization Systems:

System Details	Methodology & Logic	Inputs	Outputs
Name: CalEnviroScreen (2013) **Purpose**: To identify disadvantaged communities according to exposure to pollution and increased vulnerability to the effects of pollution.[30] **Deployers**: California Environmental Protection Agency; State and Local Government	CalEnviroScreen uses 21 statewide indicators to assess "Pollution Burden" and "Population Characteristics." It assigns relative scores to geographic areas based on percentiles, which are averaged for four components: Exposures, Environmental Effects, Sensitive Populations, and Socioeconomic Factors. The overall CalEnviroScreen score for a location is calculated by multiplying the Pollution Burden score (where Environmental Effects are weighted half as much as Exposures) by the Population Characteristics score, highlighting areas where pollution impacts are compounded by social and health vulnerabilities.[31]	**Pollution Burden** **Exposure Indicators:** Ozone concentrations in air; PM2.5 concentrations in air; Diesel particulate matter emissions; Drinking water contaminants; Children's lead risk from housing; Use of certain high-hazard, high volatility pesticides; Toxic releases from facilities. **Environmental Effects:** Toxic cleanup sites; Groundwater threats from leaking underground storage sites and cleanups; Hazardous waste facilities and generators; Impaired water bodies; Solid waste sites and facilities. **Population Characteristics** **Sensitive Population Indicators:** Asthma emergency department visits; Low birthweight infants; Cardiovascular disease (emergency department visits for heart attacks). **Socioeconomic Factor Indicators:** Educational attainment; Housing-burdened low-income households; Linguistic isolation; Poverty; Unemployment.[32]	**Output**: CalEnviroScreen outputs census tract CalEnviroScreen scores which represent a combined measure of pollution and the potential vulnerability of a population to the effects of pollution. The tool also provides percentile rankings for each census tract for various socioeconomic, environmental and health burdens.[33] **Output Usage:** The census tracts with the top 25% of scores are designated as disadvantaged and eligible for targeted investment from California's Climate Investments program. CalEnviroScreen has been effective in helping direct \$8.1 billion or 76% of the state's \$11 billion in California Climate Investments to projects benefiting disadvantaged communities and priority populations.[34]
Name: Climate and Economic Justice Screening Tool (CEJST) (2022) **Purpose**: To identify whether a community is disadvantaged by considering its environmental, climate or socioeconomic burdens.[35] **Deployers**: White House Council on Environmental Quality; Federal Agencies; State and Local Government	The CEJST methodology involves using a combination of environmental, climate, and socio-economic indicators to identify disadvantaged communities. The tool provides percentile rankings of census tracts based on factors like environmental burdens (e.g., pollution exposure), climate impacts, and socio-economic vulnerabilities (e.g., income, education, health). The methodology applies thresholds for these indicators to determine if a community qualifies as disadvantaged. For example, if a census tract ranks above the 90th percentile for air pollution exposure and has over 20% of its population below the poverty line, it would meet the thresholds for being considered disadvantaged by CEJST.[36]	**Demographics:** Race/Ethnicity, Age (for tracking purposes only); Low Income Status (% households where household income is at or below 200% of the Federal poverty level). **Climate Change:** National Risk Index (Expected losses to agriculture, buildings, population due to natural hazards linked to climate change); Climate Risk Data (Predicted flood and wildfire risk). **Energy:** Average household energy cost; Air Quality (PM 2.5 Exposure). **Health:** Asthma/Diabetes; Heart Disease Prevalence **Housing:** Low Life Expectancy; Historic Underinvestment (formerly redlined areas); Housing Cost Burden; Lack of Green Space; Lack of Indoor Plumbing; Lead Paint Exposure. **Legacy Pollution:** Presence of former Defense Sites, Abandoned mine land; Proximity to Hazardous Waste Facilities, Superfund Sites, Risk Management Plan Facilities. **Transportation:** Transportation Barriers (average relative cost and time spent on transportation); Traffic Proximity and Volume; Diesel Particulate Matter Exposure **Water and Wastewater:** Wastewater Discharge; Underground Storage Tanks and Release **Workforce Development:** Low Median Income; Poverty (share of people living at or below 100% FPL); Unemployment; Linguistic Isolation; High School Education Rate.[37]	**Output:** A score that identifies whether a census block group is disadvantaged. The tool also provides percentile rankings for each census tract for various socioeconomic, environmental and health burdens. **Output Usage:** The Federal Justice40 initiative directs 40% of the overall benefits of certain Federal climate, clean energy, affordable and sustainable housing, and other investments flow to disadvantaged communities identified by CEJST. Over 15 Federal agencies are using the CEJST as their primary tool for identifying disadvantaged communities across 518 different programs, including billions in spending from the Inflation Reduction Act and Bipartisan Infrastructure Law.[38]

Categorical Prioritization Systems:			
System Details	**Methodology & Logic**	**Inputs**	**Outputs**
Name: New York City Standardized Housing Assessment (2018) **Purpose**: The SVA is used to determine the level of vulnerability of individuals and/or families experiencing homelessness or at risk of homelessness.[39] **Deployer**: NYC Department of Social Services	Individuals and families who are homeless or at risk of homelessness will complete a housing application with a healthcare or other public service provider. The SVA pulls applicant data from the application and other databases to assess their functional impairments, utilization of medicaid and other public services and other vulnerability factors to make a vulnerability determination. Applicants classified as "High" vulnerability are at the top 5% of Medicaid utilization or have at least 3 system contacts and 3 functional impairments.[40]	**Medicaid utilization rate** **Functional impairments**: Observed impairments in the following categories: Feeding and Meal Preparation; Housekeeping; Managing Finances; Personal Hygiene; Traveling; Hearing; Sight; Cognitive Functions. **Number of System Contacts from:** Department of Homeless Services (shelter, safe haven, drop-in, street outreach); Department of Housing Preservation and Development (shelter); Veterans Administration (transitional housing and safe haven); HIV/AIDS Services Administration (Emergency Placement Unit); Connection with domestic violence services; HRA contracted domestic violence shelter; Office of Alcohol and Substance Abuse Services licensed inpatient rehabilitation or detoxification program; ACS foster care placement; Open child protective case with ACS; Court mandated to services with ACS; Juvenile Justice involvement (non-secure placement, limited secure placement, Alternative to incarceration, secure detention); Unable to return to adoptive family placement; Department of Correction/Department of Corrections and Community Services (jail, prison, and court-mandated treatment); Medical and behavioral health treatment (inpatient or 3 emergency room visits); Involuntary escort by a street outreach and/or mobile crisis team; Connected to or referred to Adult Protective Services; Runaway Homeless Youth (shelter, drop-in center, or street outreach). **Additional SVA Factors:** Young adults (18 – 25) with a history of commercial sexual activity and/or coerced into sexual or other exploitive situations, i.e. labor or sex trafficking; Individual or family (head of household) that is at serious risk due to intimate partner or gender-based violence; Parents with a child that has significant emotional/behavioral/developmental or health issues; Parent of two or more children under the age of five; Currently unsheltered or recently sheltered individuals that were unsheltered for a year immediately prior to entering shelter.[41]	**Output:** A risk score regarding the client's vulnerability on a Low/Medium/High scale. **Output Usage:** Clients with a "High" vulnerability determination receive priority for HUD funded supportive housing and other forms of housing assistance.[42] For example, the NYC 15/15 program is a New York City-funded rental assistance program that assists eligible families and individuals, who are homeless or at risk of homelessness, by providing an affordable apartment and offering supportive services to help participants achieve long-term stability. The SVA determines who is prioritized for NYC 15/15 housing given that there are fewer vacant units than the number of eligible applicants[43]

Planning Systems:			
System Details	**Methodology & Logic**	**Inputs**	**Outputs**
Name: CostQuest CA Broadband Priority Areas Investment Model (2022) **Purpose**: To identify priority areas in California that should be prioritized for $2 billion in broadband infrastructure investment.[44] **Deployer**: The California Public Utilities Commission	The CostQuest model creates a census block level map of priority areas for broadband infrastructure projects by estimating the financial viability of broadband projects across different California geographies based on current broadband infrastructure data and models of demand/revenues/cost of deployment and operation of that infrastructure. The priority areas process uses clustering techniques to find groups of unserved locations which fall within distance, investment, and location parameters that are used to balance potential funding with potential revenue. The model informs final priority areas where external funding is needed to offset the high costs of construction. The priority areas are optimally designed to mix low cost with high cost and served with unserved locations to maximize the benefit of funding.[45]	**Geography**: Census Block level data; Geographic groupings based on unserved locations. **Network Type**: Fiber to the Premises (FTTP) delivery; Greenfield network (assumes new infrastructure like poles, duct, conduit, and manholes) **Cost and Investment Inputs**: FCC cost models adjusted for current material and labor costs; California Prevailing Wage as the basis for hourly rates; Adjustments for fire hardening; Last mile and middle mile network costs (state-owned and provider-owned portions). **Unserved Areas**: Areas lacking access to at least 100 Mbps downstream and 20 Mbps upstream internet. **Broadband Demand Locations**:Estimated using CostQuest's BroadbandFabric V3 data. **Financial Variables**: Debt/Equity ratio; Discount rate (8.5%, consistent with FCC inputs); Costs associated with poles. **Operating and Capital Expenses**: Network-specific operating expenses (e.g., poles, conduit, cable); Non-network-specific expenses (e.g., general administrative expenses); Marketing expenses; Bad debt expenses; Capital expenses; Replacement CapEx. **Revenue and Subscription Assumptions**:Market price for broadband ($71/month based on service level survey); Low-income and Tribal prices (e.g., $40/month for low-income service); Subscription rates (varies by competition and income levels); Demand growth rate; Churn. **Clustering Parameters**: Initial clustering criteria for census blocks based on locations, radius and investment limits; Breakpoint thresholds for priority area identification (e.g., minimum and maximum per unit investments).[46] **Note**:The list of inputs provided here is a summarized selection of the key factors considered by this tool. This is not a comprehensive list of all inputs used in the model. We have chosen to highlight certain inputs based on the availability of model documentation and to give a clearer, high-level understanding of the model's framework and methodology.	**Output:** A census block level map identifying priority locations for broadband investment based on a balance of funding and revenue considerations. **Output Usage:** The CostQuest model produced a priority area map that was intended to guide the allocation of $2 billion in broadband infrastructure grants to Internet Service Providers (ISPs) to build physical broadband infrastructure in prioritized locations. ISPs proposing to build internet projects to serve areas identified by the CostQuest model would receive higher scores in their broadband infrastructure grant applications. California eventually abandoned the CostQuest model due to community opposition.[47]

Planning Systems:

System Details	Methodology & Logic	Inputs	Outputs
Name: Electric Vehicle Infrastructure Projection Tool: EVI-Pro (2018) **Purpose**: To estimate the charging demand from EVs for intra-and inter-regional travel and to design the supply of residential, workplace, and public charging infrastructure capable of meeting demand.[48] **Deployers:** U.S. Department of Energy (DOE); State and Local Government; Transportation Agencies	The EVI-Pro (Electric Vehicle Infrastructure Projection) analyzes the future needs for EV charging infrastructure by inputting data on vehicle characteristics, driving and charging patterns, as well as adoption, infrastructure and energy data. It uses this data to forecast demand for charging stations, calculates the necessary infrastructure needed and the optimal locations for that infrastructure.[49]	**Vehicle Travel Patterns**: Real-world GPS data that captures daily travel behaviors across various regions. This includes data such as vehicle miles traveled (VMT), trip destinations, and time-of-day trip distributions. **Personal Electric Vehicle (PEV) Driving and Charging Behavior**: Different driving behaviors for both battery electric vehicles (BEVs) and plug-in hybrid electric vehicles (PHEVs), accounting for charging at home, work, and public locations ; Simulated charging behavior based on combinations of driving and charging options. **Infrastructure Parameters**: Charging station characteristics such as the number and types of charging stations required per 1,000 PEVs; Public and shared private chargers (e.g., workplace, multi-unit dwellings) to meet the projected number of PEVs in specific regions; Assumptions on the ratio of chargers to vehicles and geographic distribution, including hot spots and utilization rates. **Projected PEV Stock and Adoption Rates:** Projections of future PEV adoption. **Vehicle and Charger Characteristics**: Vehicle types (BEV, PHEV) with different ranges and charging preferences (e.g., home vs. public charging); Charger types and their availability across various settings (e.g., residential, workplace, public spaces). **Energy and Power Requirements**: Projected electricity demand based on PEV charging load profiles at different times of the day.[50] **Note**:The list of inputs provided here is a summarized selection of the key factors considered by this tool. This is not a comprehensive list of all inputs used in the model. We have chosen to highlight certain inputs based on the availability of model documentation and to give a clearer, high-level understanding of the model's framework and methodology.	**Output**: EVI-Pro outputs, for a given geography, the number, type, and location of chargers required to meet charging demand and the energy load profiles associated with charging demand. Outputs of the model include: anticipating spatial/temporal consumer demand for charging accounting for the impact of residency, weekday/weekend travel behavior, and regional differences in travel behavior and vehicle adoption.[51] **Output Usage:** EVI-Pro results guide city, state, and federal infrastructure planning decisions. City planners will use EVI-Pro results to guide requests for grant funding, determine which locations in a community need charging stations as well as how many, and to determine where energy distribution and generation upgrades are needed.[52 53]
Name: Market Value Analysis (2001) **Purpose**: The MVA is a tool that identifies distinct housing markets in a city and describes their characteristics. it informs community investment and service-delivery strategies in municipalities in ways that leverage private investment and create conditions for investment to occur.[54] **Deployers**: Local Government	Clustering techniques group together similar neighborhoods based on characteristics such as vacancy rates and property values and score them in terms of strength based on an alphabetical scale. These groupings represent the different market value or investment potential of neighborhoods throughout the city. For example, neighborhoods with 'G' and "H' scores may have the highest level of vacant homes and vacant land, substantial levels of financial stress and concentration of subsidized housing.[55]	**Property Value and Investment**: Median home sales prices excluding vacant land (e.g., data from Assessor's Office); Variance in home prices; Housing permits, focusing on the share of homes undergoing renovation or substantial new construction; Sales of Vacant Land (measured by the ratio of sales of vacant lots compared to all residential property transactions). **Blight, Distress, and Vacancy**: Distressed sales such as tax, sheriff, and lien sales; Share of vacant homes and land area categorized as vacant residential lots; Code violations related to health and safety. **Housing Stock and Land Use**: Owner-occupied housing units; Share of parcels used as short-term rentals; Share of households in subsidized housing programs; Housing density (measured by the ratio of residential acres to housing units); Percentage of land dedicated to residential use.[56]	**Output:** Each census block group analyzed receives one of a range MVA market scores ranging from A-Z. These markets are further grouped based on high to low market value with increasing levels of vacancy and blight along with decreasing development, property values and sales. **Output Usage:** Municipalities use the investment grades to target and design housing and urban policies. Neighborhoods with strong or emerging markets may receive investments to further stimulate development and attract private investment, while more distressed areas may be targeted for blight removal and stabilization efforts.[57]

Predictive Systems:			
System Details	**Methodology & Logic**	**Inputs**	**Outputs**
Name: Infinite Campus - Early Warning System (2023) **Purpose**: To identify students that are "at risk" for failure to graduate and allocate supplemental aid funding to schools.[58] **Deployer:** Nevada Department of Education (South Dakota, Montana, Kentucky, Hawaii and Delaware use the related Infinite Campus Student Information System).	This tool is part of the larger Infinite Campus Student Information System. It uses predictive machine learning algorithms to measure how 75 predictors or risk factors related to attendance, behavior, academics, home and school stability interact to predict graduation outcomes. The model was trained on historical student data which was labeled with whether a student needed an "early warning" based on undesirable enrollment outcomes such as dropping out before graduation.[59]	**Academic Performance:** 14 features describing includes the proportion of course grades attributed to each letter grade, overall high school GPA, and the proportion of attempted credits successfully earned. **Attendance:** 6 features describing the proportion of class time a student was actually present, as well as absences grouped by type of excuse. **Behavior:** 7 features describing the number of behavior infractions and resolutions, as well as whether weapons, drugs, or harassment were involved. **Household and Enrollment Stability:** 24 features that describe the presence of past undesirable enrollment outcomes, and how often the student changes home addresses, schools, or districts in the middle of school years, immigration status. **Contextual Data:** 24 features describing information such as gifted status, race/ethnicity, disability, primary language at home, gender, and special education needs.[60] **Note**:The list of inputs provided here is a summarized selection of the key factors considered by this tool. This is not a comprehensive list of all inputs used in the model.	**Output:** A "GRAD" score that ranges from 50 to 150 where 50 indicates high likelihood of undesirable enrollment outcomes in the future and 150 indicates high likelihood of persistence to graduation. **Output Usage:** Schools use GRAD scores to identify students that are at risk and designate them for special attention. Nevada categorizes students into low/medium/high risk categories where high and medium risk students qualify the school for at least 35% more per-pupil funding. In Nevada, the shift to the usage of the Campus Warning System to identify at-risk students resulted in the number of students qualifying for increased funding dropping from 288,000 to 63,000.[61]
Name: Los Angeles County Risk Stratified Supervision Model (2021) **Purpose**: To identify foster youth that present complex risks and designate them for enhanced support from child welfare staff and social workers.[62] **Deployer**: Los Angeles County Department of Children and Family Services (DCFS)	The model uses machine learning techniques trained on child welfare case records which include whether or not the child was removed from the home and placed in foster care within two years of referral to the department. The tool identifies relationships in the training data and uses that to make predictions about the risk a child will be placed in foster care. The score is generated when a child maltreatment referral to DFCS is screened for follow-up investigation.[63]	**Referral characteristics**: 43 features describing the current referral, such as day and time, current allegations, and reporter source. (Office assignment and other geographic information were not included as model inputs.) **Demographics**: 58 Features describing demographic characteristics of alleged child victims and adults on the referral, such as gender and age group. (Race and ethnicity were not included as model inputs.) **Allegations**: 109 Features describing prior allegations for children on the referral and allegations for other children involving adults on this referral. **Cases**: 25 Features describing the nature, timing, and counts of child welfare cases for individuals named on the referral. **Placements**: 33 Features describing the nature, timing, and counts of placement histories for children named on the referral. **Other information**: 24 Features describing other conditions, safety concerns, and history for children and adults on the referral.[64] **Note**:The list of inputs provided here is a summarized selection of the key factors considered by this tool. This is not a comprehensive list of all inputs used in the model. We have chosen to highlight certain inputs to give a clearer, high-level understanding of the model's framework and methodology.	**Output**: A risk score describing the risk of a child's removal and placement in foster care within two years. **Output Usage:** The top 10% of risk identified cases received enhanced support which include faster response times, increased staffing, and other interventions to help prevent abuse, neglect and other harmful outcomes. Conversely, cases identified as high risk resulted in more investigations and scrutiny of black families.[65]

Predictive Systems:

System Details	Methodology & Logic	Inputs	Outputs
Name: NSW Revenue Vulnerability Model (2018) **Purpose**: To identify persons who are likely vulnerable and who may be unable to pay their debts and divert them from enforcement action and towards debt relief plans.[66] **Deployers**: New South Wales, Australia Revenue Department	The model generates a vulnerability score when customers are subject to an automated garnishment of their wages or savings for failure to pay fines, taxes or other debts. The model uses machine learning techniques trained on historical data and records of current customers to predict if the customers are likely to match the profiles of customers previously identified as vulnerable by agency staff.[67]	**Demographic and Socioeconomic Data:** Customer's Current Age; Customer's Age at Last Enforcement Order; Socioeconomic Status Index; State Housing Residence Status; Employment Status; Receipt of Government Benefits **Debt and Financial Obligations:** Total Debt Accumulated by Customer; Weekly Repayment Amount on Last Payment Plan; Number of Defaulted Payment Plans; Time Since Last Payment Plan Payment; Completion Rate of Last Payment Plan; Penalties Paid in Full Without Enforcement; Other Penalties Closed Without Enforcement. **Legal and Enforcement History:** Total Enforcement Orders Issued; Public Transport Offense-Related Orders; Serious Court Offense-Related Orders; Failed Garnishee Order Attempts; Property Seizure Attempts with No Assets Found; Frequency of New Enforcement Orders; Custody/Incarceration History. **Property and Asset Ownership:** Total Number of Properties Owned; Value of Last Land Tax Assessment; Average Value of All Owned Land. **System Contacts:** Customer-Initiated Phone Contacts with Revenue NSW; Advocate-Initiated Contacts on Behalf of Customer.[68] **Note**:The list of inputs provided here is a summarized selection of the key factors considered by this tool. This is not a comprehensive list of all inputs used in the model. We have chosen to highlight certain inputs to give a clearer, high-level understanding of the model's framework and methodology.	**Output:** The model's output is a 'prediction' as to the likelihood, expressed as a percentage, that the person is financially vulnerable. **Output Usage:** The program diverts vulnerable customers away from enforcement action and provides alternative resolution options. This results in fewer vulnerable people being forced to pay fines that they cannot afford. It also increases the overall effectiveness of the garnishee process. This prediction is designed to support or augment, and not replace, human decision making. Revenue NSW staff can review the predictions made by the program and direct the identified customers to more appropriate resolution channels that provide targeted support. This may result in the lifting of sanctions, putting enforcement on hold, establishing repayment arrangements, or implementing a Work and Development Order to enable a customer to reduce their fine by participating in unpaid work, courses, counseling or treatment programs.[69]

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