Agent-Based Modelling for Public Social Service Distribution

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Abstract. The paper introduces an agent-based modelling approach for assessing beneficiaries in public social service distribution. The {Anon} project combines empirical research, gamification, and agent-based models (ABM) to assess the fairness of AI-based distribution in different countries and propose improvements. The paper presents a participatory research strategy, where ABM and serious games are used to identify more desirable social assessment routines within heterogeneous cultural contexts. By following this approach, the paper suggests that context-specific ABM can be used for co-designing AI systems with stakeholders, to assist ex-ante evaluation for testing and prototyping AI systems before implementation thus reducing risks and costs, and for scenario analysis and asking what-if questions to reduce uncertainty. Besides offering a useful tool to help social workers in reflecting on and improving their assessments in their immediate workplace, the proposed ABM-centred approach is also relevant more generally for public, social and technology policy. Prototyping helps to avoid risk of failure, unintended consequences, and systems that turn out to be ineffective following expensive development. The option to address what-if questions, to test interventions before implementing them, and to evaluate the advantages and disadvantages of different scenarios, is of great relevance in many policy domains.

Keywords: Social Assessment, Public Service Provision, Context-Specific ABM

1 Introduction

Public administrations are increasingly using Artificial Intelligence (AI) algorithms to decide on the provision of public social services such as unemployment benefits, pension entitlements, kindergarten places and social assistance to their citizens, hoping to achieve greater efficiency and objectivity [1, 2]. Criteria vary widely around the world. There is no approach to social assessment that would be perceived as fair everywhere. The {Anon} project is investigating AI-based public service provision of national welfare systems within a range of country case studies, aiming to show how to co-design context-dependent, value-sensitive, responsive and dynamic AI systems starting from existing systems that are perceived as problematic. It combines empirical case study research on AI-based social service delivery with community-based multi-stakeholder workshops and a series of case-specific agent-based models (ABM) for assessing the status quo of AI-based distribution fairness in different countries, for simulating desired policy scenarios, and for generating an approach to 'Better AI'. The paper is structured as follows: In Section 2 we give a short overview of the overall {Anon} modelling approach. In Section 3, we introduce the ABMs developed in {Anon} to illustrate the potential of this approach in practice. Our conclusions are outlined in Section 4.

2 The {Anon} Modelling Approach

A participatory modelling strategy (see Figure 1) was designed [3] to support the transition from existing to desired social assessment systems, with the following elements for each case study:

1. A workshop is held to map out the overall existing case study system.
2. An ABM that models the current social assessment system, including an initial ruleset[1] (ruleset 1) and exemplar agent attributes, is written.
3. Ruleset 1 is checked and iteratively refined by running the ABM.
4. Rules for an ABM-based game to be played with stakeholders, are written.
5. At a gamification workshop with stakeholders, rules are gradually adapted.
6. A 'better ruleset', ruleset 2, is extracted using the records from the game play.
7. A synthetic population is created to match the real population on relevant attributes.
8. Ruleset 2 and the synthetic population are used to generate a training dataset.
9. A machine learning system to be used to assess applicants is trained using the training data.

[1] By 'ruleset' we mean a collection of rules that when followed (by a clerk or by agents in the ABM) can be used to classify an applicant as deserving of full, partial or no social services allocation.

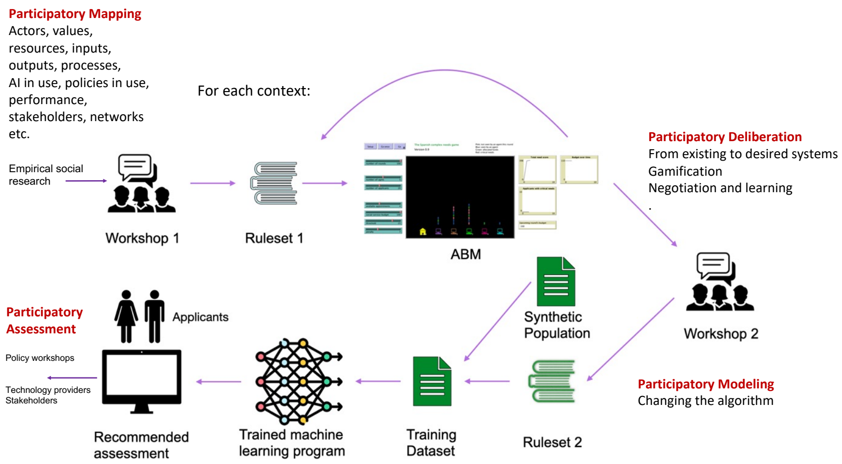

Fig. 1. The modelling strategy

Mapping the existing actor network requires research, both quantitative and qualitative, complemented by Participatory Systems Mapping [4] to reconstruct the existing system from the perspective of stakeholders. This work provides information on the actors involved, the societal norms and values, the organizational practices and routines in place, the current use of AI in the system, and the system's performance. This data is used to create an ABM representation of the existing social assessment routines, examples of which are presented in the next section.

3 The Case Study ABMs for Improving Social Assessment Practices

3.1 The Spanish Complex-Needs ABM

[5] examine the perceptions, attitudes and acceptance of AI-based social assessment technologies by policy makers and administrative agencies locally in Catalonia, a front-runner Spanish region in the adoption of digital technologies for the public sector. The Spanish ABM is set in a social service agency in a municipality in Spain, where social service clerks are faced with the challenge of seeking to allocate (limited) social service resources to deserving applicants, many of whom have multiple, complex needs.

Agents. The clerks' aim is to allocate social service resources to applicants to maximise the sum of applicants' wellbeing. The model is based on an existing system of social assessment used by local authorities in Catalunya, the SSM-CAT[2], a relatively easy-to-use tool designed to assist core social service professionals in identifying individuals with complex social care needs across 13 dimensions. For simplicity, our model focuses

[2] See https://suport-hestia.aoc.cat/hc/en-gb/articles/4415411394321-Self-Sufficient-Matrix-Screening-Tool-SSM-CAT

on the following 6 applicant attributes: household income, accommodation, work and training, mental health, physical health and number of dependents. Each applicant receives a score of between 1 and 5 according to their level of self-sufficiency in each of these dimensions. The sum of an applicant's scores is used to calculate their overall need score of between 6 and 30.

Environment and Global Attributes. During the simulation, applicants can either be at home or in a queue at a social service clerk's desk. The number of desks in the environment is defined by the number of clerks chosen at setup. The following global attributes are used in this ABM to define the environment and corresponding applicant-clerk interactions: number of the round, number of applicants, number of clerks, social services budget, available appointments, threshold.

Actions and Interactions over Time. At the start of each round, applicants who are self-sufficient (≤ 2 across each of the 6 wellbeing dimensions) stay at home. All other applicants are randomly assigned to clerks. Clerks evaluate applicants using an algorithm based on a ruleset and applicants' attributes.

The initial algorithm is described below, but new rules can be introduced to adjust the system, such as modifying the order in which applicants are seen, changing the scoring algorithm, or altering how the budget is allocated at the end of each round. Each round corresponds to a day of the agents' lives (home, desk, office meeting, home) and a round is completed when every agent is home again.

Scoring Algorithm. For *household income* and *number of dependents*, applicants are ranked against each other and given between 1 and 5 need points based on their rank relative to others in that round. Need points are allocated.

At the end of each round the social service budget is distributed to successful applicants in order of severity: the highest-scoring applicant is allocated an amount equal to their overall need score, then the next highest, and so on until the budget for that round is used up. Applicants' need scores are then updated:

- If the applicant received support: one need category improves (score decreases by 1)
- If the applicant did not receive support: one need category worsens (score increases by 1), as well as all categories with a score ≥ 4.
- Additionally, there is a 10% chance that one attribute worsens by 1 and a 10% chance that one improves by 1.
- If there are any critically needy applicants (overall need score ≥ threshold) at the end of the round, this impacts the upcoming round's available budget but does not improve applicants' need scores. The run ends if there is no budget left at the beginning of a round to allocate to applicants.

By playing the game, agents are supposed to develop an "interpretation culture" on fairness issues as agents converge in judging applicants' profiles according to the self-sufficiency matrix. This is in line with the central objective of the tool SSM-CAT, which is to identify complex social care needs after having completed specific training.

3.2 An ABM of the German Asylum Application Process

This ABM illustrates the asylum application procedure in Germany, following refugees (here: applicants) as they progress through the various stages at which they are "assessed". The ABM is based on insights gained from desktop research and five exploratory and seven in-depth interviews, as well as several focus groups and participatory modelling sessions. The link to state-of-the-art AI used for assessment is the language-/dialect recognition software, used to identify the country/region of origin of asylum seekers [6]. The interviews indicated the relevance of legitimacy [7-10], and agency of refugees [11,12], mirroring particular challenges in the asylum procedure posed by (a) the lack of (assured) knowledge due to, for example, missing documents or high workload when administrative workers try to assess the applicant's credibility [13], and (b) the lack of transparency partly due to opaqueness of decision-making, language barriers and refugees' personal experiences (e.g. having little trust in institutions; being traumatized). The ABM aims to display the tension between asylum bureaucratic legitimacy and refugees' agency and represents a tool to reflect upon potentials and risks – inhibiting "value trade-offs" (e.g. efficiency vs. fairness) - of using AI in the different assessment processes.

Agents. The central agents are applicants applying for asylum status in Germany. Their aim is to get full asylum status and the right to stay and work in Germany. Applicants are initialised with the following attributes: Country of origin (applicants from certain countries have a higher chance of receiving asylum status than others); proof of identity and education; number of years the applicant has lived in Germany; whether the interpreter is 'good', which is the case when there is a positive match between the applicant and interpreter's genders, ethnicities and spoken languages; German language proficiency; which of the 16 federal states in Germany the applicant is applying from and being processed in; whether the applicant has personal support from a lawyer, voluntary worker or migration councillor from a welfare organisation (having a supporter improves an applicant's chances of a positive decision outcome); whether the applicant has done voluntary work; health status.

Environment and Global Attributes. During the simulation, applicants move between six different 'stations': registration, hearing, decision, post-decision, (court) appeals and Hardship Commission ('HC'). The first three stations (registration, hearing and decision) represent key stages in the application process. After receiving a decision on their asylum application, applicants move to the post-decision station which represents everyday life in Germany. The appeals and Hardship Commission stations are where asylum seekers can go to challenge their asylum decision and right-to-remain status. The following global attributes are used in this ABM to define the environment and corresponding applicant interactions: Number of the round, initial number of applicants, number of new applicants, administrative workload, workload threshold, and appeals quota.

Actions and Interactions over Time.

Registration: On setup and at the start of each new round, new applicants begin at the registration station.

Hearing: Applicants must wait for a hearing before they can proceed. Those assigned a "good" interpreter (indicating a positive match between the applicant and interpreter's genders, ethnicities and spoken languages) have a higher chance of advancing in a given round.
Decision: Applicants wait for their cases to be assessed by an administrator, who assigns one of three statuses: rejection (least desirable), tolerance, or full asylum (most desirable). Some may wait multiple rounds.
Post-decision: After receiving a decision, applicants move to the post-decision station, where they have the chance to get a job if they have the right to work. From here, some applicants may choose to appeal their decision through the courts, the Hardship Commission, or both.
Court appeals: Applicants may appeal to the courts if their case may have been treated unfairly or poorly (e.g. due to discrimination or administrative errors). Applicants who have received full refugee status do not appeal their status. Appeals are more likely in federal states with heavy workloads or organizational bias. Each round, a limited number of appeals are heard. Successful applicants improve their status by one tier (rejection → tolerance; tolerance → full asylum).
Hardship Commission: Applicants appealing to the Hardship Commission are at risk of being repatriated. Unlike court appeals which assess procedural fairness, the Hardship Commission focuses on the applicant's degree of integration in Germany. To get a positive recommendation from the Hardship Commission, applicants must have a job, a good command of German and be engaged in additional activities (e.g. voluntary work). Approximately 75% of those with positive recommendations go on to win the right to stay in Germany.

The run ends when the maximum number of rounds defined at setup have elapsed.

3.3 The Estonian Career Counselling ABM

The Estonian ABM is based on the career counselling support for job-seekers available through the Estonian Unemployment Insurance Fund (EUIF) which has been extensively investigated by [14].
Agents. The agents in the simulation are jobseekers ('clients') who are applying for career counselling support and the consultants who are assessing them and providing support. The consultants' aim is to allocate career counselling resources to maximise the number of clients in employment. The attributes by which applicants are initialised are as follows: Work experience, fluency in Estonian, fluency in other languages, driving license, education, dependents, health, time unemployed. Consultants can then draw on these applicant attributes to calculate an assessment result which grants the client access to counselling sessions and/or additional training. Consultants can then draw on these applicant attributes to calculate an assessment result which grants the client access to counselling sessions and/or additional training.
Environment and Global Attributes. During the simulation, applicants can either be at home, in work, or in a queue at a consultant's desk. The number of desks in the environment is defined by the number of consultants chosen at setup. The following global attributes are used in this ABM to define the environment and corresponding

consultant-client interactions: number of the round, number of clients, number of consultants, new clients, and the score that applicants need to achieve to be offered a job.
Actions and Interactions over Time. At the beginning of the simulation and each subsequent round, new applicants are initialised at home and then randomly allocated to a consultant. They have their first meeting with the consultant and are assessed to determine what degree of support they are likely to need. Consultants assess clients using an algorithm based on a ruleset and applicants' attributes. The initial algorithm is described below, but new rules can be introduced to adjust the system, such as changing the scoring algorithm and the attributes it uses as inputs, or changing the point thresholds required for each assessment result.
Scoring Algorithm. Based on their number of points, the algorithm gives a red, yellow or green result. Clients who receive a red result (< 10 points) are considered to need the greatest amount of support. They attend weekly career counselling meetings and get priority access to training courses. Clients with a yellow result (≥ 10 and < 20 points) attend fortnightly meetings and those with green (≥ 20 points) are invited to attend monthly meetings. At the end of each round, clients have the opportunity to get a job. A client's chances of getting a job are positively influenced by the following factors: Number of years of work experience; attended a training course; number of career counselling meetings attended; driving licence; higher education levels; fewer dependents; less time spent unemployed. Applicants stay with the same consultant until they find a job. The run ends when the maximum number of rounds defined at setup has elapsed.

3.4 An ABM of the Targeted Subsidies Plan in Iran

An agent-based model was developed to simulate and evaluate the socio-economic impacts of the Targeted Subsidies Plan (TSP) in Iran. Details of the TSP can be found in [15]. The model allows policymakers and decision-makers to evaluate the effects of decisions regarding the amount of subsidies paid to different deciles of society and changes in income deciles.
Agents. The agents in this model represent households, with the default configuration simulating 230 households as a scaled representation of 23 million households in Iran. The number of agents in the model can be adjusted within the user interface, ranging from 100 to 23,000 households. Each household has the following characteristics:
Income: The income characteristic is randomly assigned to agents based on a power distribution pattern derived from the Iranian Welfare Database (IWDB).
Wealth (Assets): In IWDB, another influential parameter for household decile classification is household assets, which is used to reflect economic inequalities in modelling.
Household (family) size: This characteristic is also quantified using data from IWDB using a normal distribution.
Monthly expenses: estimated to indicate the standard cost of living.
Household decile: indicates the household's membership in one of the income deciles, which is determined by the model based on the Test Means.
Subsidy amount: This is the amount of subsidy the household receives. The amount of subsidy is a function of income decile and the size of households.

The key point is that the households are regrouped every year depending on variations in income and wealth. To increase the degree of realism of this model, two extra parameters have been considered: the first parameter is the enrichment rate that, because of causes such as inheritance or successful investment, may alter the percentage, adjustable from 0 up to 10 percent of the totality of the households simulated, and the second is the household bankruptcy rate, which causes a sudden shift in the status of households from high-income deciles to low-income deciles due to reasons such as business failure and loss of capital.

Environment. The environment reflects the socio-economic landscape affected by the TSP, including:

The budget of TSP: the funds that the government must pay to households as subsidies each month.

Household grouping: Households are divided into ten deciles based on income and wealth, with subsidies allocated only to the bottom four deciles. In the model, subsidy amounts vary by decile, reflecting real-world practices, with the first decile (lowest-income households) receiving the highest subsidy.

Economic dynamics: The model assumes random shocks to income, such as a 2% increase or decrease in household wealth each year, as representative of natural fluctuations in the wealth-income levels in the model.

This environment is designed to reflect the unequal patterns of wealth and income distribution prevalent in Iranian society, as documented in the IWDB.

Actions and Interactions over Time. The main operations of the model revolve around the mechanisms of subsidy targeting, such as decile allocation, subsidy allocation, and re-decile allocation. The main operations include the following:

Initialization: At the beginning of the simulation, each household is assigned income, wealth, and size. The values of these three parameters are randomly assigned but follow patterns extracted from IWDB data, using normal and power distributions.

Subsidy distribution: Monthly distribution of subsidies to households in the lower four deciles, proportional to decile and household size.

Re-assignment to deciles: Households, after receiving updated income and wealth values reflecting changes in their economic status, are re-grouped at the end of each year.

Upward and downward economic mobility: Some households will experience upward or downward mobility due to policy interventions or natural variation.

Emerging effects: The interactions between agents and the TSP will reflect the overall socio-economic trends such as changes in income and mobility across deciles.

The model runs for 60 years on monthly cycles. Each cycle includes subsidy allocation, economic adjustments, and annual re-assignment. It demonstrates upward income shifts for low-income deciles, highlighting the potential of the TSP to improve the economic conditions of vulnerable households. Despite the increasing income of the low-income classes, the range of income from the bottom to the top deciles remains very broad.

The annual re-grouping points out the impact of policy on economic stability and mobility. The dynamic in the model helps us understand the impact of policies and decisions on reducing the gap between different social deciles and reducing inequality and poverty. Since the grouping is repeated continuously and annually, the impact of policies can also be visualized and understood in the long term [16].

3.5 An ABM of the Indian Public Distribution System (PDS)

Hunger alleviation and poverty eradication are the twin objectives of the Public Distribution System (PDS) in India. The PDS is intended to provide essential goods and services at so-called "ration shops", mainly food items such as rice, wheat, sugar, kerosene etc. to beneficiaries, especially "the poorest of the poor", at reasonable cost contributing to general social welfare. The effectiveness of the PDS largely depends on adequate policy decisions regarding operational and organisational aspects of the system [17].

The ABM of the PDS in India focuses on three key objectives: fairness in ration allocation, transparency in operations, and accountability to reduce corruption. By modelling the interactions between beneficiaries, ration shops, suppliers, and officials, the simulation provides insights into system performance under various scenarios.

Agents. There are four types of agent in the model:
Beneficiaries: Represent the population depending on PDS for rations.
Ration Shops: Serve as distribution points for commodities.
Suppliers: Provide stock for ration shops.
Officials: Inspect ration shops to maintain transparency / detect irregularities.

Environment. A number of key characteristics of the model are tracked, including:
Corruption Risk Levels: Each shop is assigned a corruption risk.
Total Beneficiaries Served: N. of individuals successfully receiving rations
Stock Levels: Track available stock across the system.
Corruption Incidents: Record instances of corruption identified.
Metrics: Include fairness, transparency, and accountability scores.

Actions and Interaction over Time. Each of the agents react at each time step, according to the states of other agents:
Beneficiaries: Move to the nearest ration shop to collect their eligible rations.
Ration Shops: Manage stock levels and distribute rations or request resupply.
Suppliers: Transport stock to ration shops using trucks.
Officials: Randomly inspect ration shops to detect corruption and ensure compliance.
Metrics Updates: At each tick, system performance metrics are updated to reflect changes in fairness, transparency, and accountability.

Enhancing transparency, improving accountability, and ensuring fairness are critical to optimizing PDS performance. Regular inspections play a pivotal role in significantly reducing corruption and enhancing system transparency. When corruption risks are minimized through rigorous monitoring, accountability scores improve, reflecting a more responsible system. Furthermore, the fair distribution of rations relies on efficient stock management and the reduction of corruption, ensuring equitable access for all beneficiaries. Insights derived from the simulation can guide policymakers in addressing systemic inefficiencies and formulating strategies to optimize PDS performance.

4 Conclusions and Outlook

Case studies offer a chance to bring data from empirical research to models and simulations for better futures. The ABM of the Spanish case study acts as a kind of theorem checking device for the assessment algorithm in place in the empirical system under investigation, in this case social assessment in Catalunya. The ABM not only ensures that the ruleset is coherent and complete but also acts as a starting point for stakeholders to devise a better algorithm. The case study ABM for Estonia uses modelling to shift the focus more explicitly to citizens and their requirements concerning AI systems in the context of (un)employment services; particular attention is directed towards potentially vulnerable groups to gain a deeper understanding of their interactions with and requirements for AI systems. The German case study ABM focuses on the agency of refugees (for more and quicker integration into society and the job market) and the legitimacy of administrative decisions (for accountability and correctness of bureaucratic procedures in granting asylum), and the trade-offs between these two policy objectives. Thereby, the ABM helps to identify tensions (and entanglements) arising in the different assessment processes, which is crucial to be able to reconsider where AI might be truly helpful, contributing to more efficiency and fairness for both sides. Iran's case study ABM uses insights gained from the analysis of TSP in Iran to explore future scenarios involving the implementation of various policy options. The case study ABM in India will help to explore the pivotal role of deep learning in the development of community-specific vulnerability prediction models in the Indian scenario, which will be an innovation in community-based interventions.

For Spain, Germany and Estonia, using an interacting cycle of agent-based modelling and serious games pointed to an approach by which AI technology can be specified in a stakeholder-driven way, so that it is more transparent and discursive about bias and discrimination, includes the social justice values of the society in which it will be used, and is responsive to the needs of vulnerable groups. Interactive and participatory formats at multi-stakeholder workshops exposed the culturally shaped and heterogeneous value perspectives of the local social groups. As a central component, participants 'played the ABM'. Stakeholders suggested, discussed, co-developed and tested interventions in all parts of the game situation, including the social assessment criteria ('changing the algorithm') to propose a 'better' ruleset for that assessment system. The advantage of iterating between games and ABM is that stakeholders can deliberate in the game context with options to 'change the rules of the game' as result of their discussions, the ABM then codifies and formalizes the rules showing the results of their application in the game environment, which, in the next iteration, informs stakeholder discussions.

Following the modelling strategy introduced in Section 1, this approach also offers the possibility of producing relevant training data that can be used to prototype algorithms fitting desired futures. In welfare systems, decision-makers often face complex cases that require a nuanced understanding of policies, individual circumstances, and broader social contexts. The use of methods that facilitate a collaborative environment in this way allows for the exchange of knowledge and experiences, leading to more informed and effective decision-making. To test the reasonable suggestions of social workers familiar with the system, however, was not previously an option – especially not with a view to determining whether and how an AI system could take up these suggestions and make things better than they are. Once the existing and 'better' ruleset have been determined through the iterative process of building ABMs and running gamification workshops for each case study country, these rulesets can be used for the next step in the modelling process.

Although the outcomes of the rulesets have been already demonstrated by the ABM, this is only in a small game environment. It does not show what the rulesets would do for the whole population of case study countries, especially not given population dynamics. Rather than using micro-data for the population itself, to comply with research ethics and data protection issues, a synthetic population database is generated that resembles the real-world data for a case study country. First, the ruleset of the *existing* system is run on the synthetic population. It produces an output database with some individuals getting service and others not. To validate this, we could check against real-world data on the socio-demographics of social service recipients; however, in most cases such data is not available. Instead, we can check whether the synthetic population database reproduces the number of service recipients in the real world (if available), whether it reproduces the stylized facts on bias and discrimination in the literature, and whether it reproduces the case study's empirical research results. Second, the ruleset of the *desired* system is run on the synthetic population. It produces an output database with different distributions from the first. Stakeholders (and decision makers) can now compare these two "data worlds" and check the effects of different assessment algorithms on the overall population and the expected population dynamics. Once the assessment algorithm is confirmed, the corresponding database can be used as training data for a neural network that recommends social assessment decisions for distributing services in the real-world context. This step of the modelling strategy has only been implemented for the Spanish case study so far [18]. Rather than focussing on the assessment situation in a social service agency and following the approach with games and synthetic data (Spain, Germany, Estonia), the ABM of Iran and India depicted the whole social welfare systems of TSP and PDS using empirical data for calibration. Both case studies intend to use their ABM to directly create training data.

Summarising, although the ABMs might differ in purpose, utility or scope, they can all be used for co-designing AI systems with stakeholders, to assist ex-ante evaluation for testing and prototyping AI systems before implementation thus reducing risks and costs, and for scenario analysis and asking what-if questions to reduce uncertainty. Besides offering a useful tool to help social workers in reflecting on and improving their assessments in their immediate workplace, the proposed ABM-centred approach is also relevant more generally for public, social and technology policy. Prototyping helps to avoid risk of failure, unintended consequences, and systems that turn out to be ineffective following expensive development. The option to address what-if questions, to test interventions before implementing them, and to evaluate the advantages and disadvantages of different scenarios, is of great relevance in many policy domains. Results will be discussed in the near future with representatives of the policy community responsible for AI use in public social service provision.

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