Agent-Based Modeling of Workplace Accessibility Policies to Mitigate Commute Barriers for Autistic Individuals

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Abstract

This project presents an agent-based social simulation designed to explore the impact of workplace accessibility policies on autistic individuals, focusing on commute-related challenges. Inspired by Aguilera et al.'s work that focuses on mitigating discrimination against poor people by adopting a needs-based framework, we adapt their approach to incorporate spatial reasoning, individual social tolerance, and burnout dynamics to simulate how commuting affects wealth accumulation. Agents navigate a spatial grid, manage needs such as energy and social energy, and experience burnout when these needs are depleted. We evaluate three workplace policy regimes (fixed, flexible, and free) in terms of their effects on burnout rates, and wealth distribution. While the Gini index is used to assess wealth inequality, we show that it can produce misleading results in some scenarios, highlighting the need for complementary metrics. Our findings suggest that less restrictive work policies can mitigate burnout-related wage gaps and offer more equitable outcomes for neurodiverse populations. However, these policies have not produced desirable average income for overall agent populations, suggesting a need for learning-based agent models rather than handcrafted action-needs effects.

Keywords

agent-based modeling, social simulation, policy-making, discrimination

I. Introduction

Workplace accessibility and employment inequality are long-standing challenges faced by autistic individuals. Commute, a seemingly mundane daily activity, can be an overwhelming source of stress for many autistic people due to sensory overload, social interaction, or unpredictability in public transport (see [1]). These challenges contribute to employment disparities and wage gaps between autistic and non-autistic (allistic) populations. In this work, we explore whether workplace policies can mitigate the negative effects of commute-related stress, using agent-based modeling (ABM) to simulate and evaluate possible interventions.

Our project builds on Aguilera et al.'s 2024 work [2], which employed a needs-based agent simulation to study poverty and discrimination. While their agents operated in a grid-like environment with a needs-satisfaction framework, spatial distances between facilities had no effect on action outcomes. In contrast, our study incorporates the spatial component of commute, where travel cost (in terms of energy and social energy) depends on path length and environmental conditions like crowd levels.

To model commute fatigue and social overload, we extend the original needs-based model with path-dependent and randomized satisfaction effects. Agents with varying social tolerance levels experience different rates of burnout, which restricts their ability to work and thus affects wealth accumulation. We define three workplace policies: fixed, flexible, and free. And we simulate how these influence equity and well-being across a population.

Through this framework, we aim to answer whether more inclusive workplace policies can alleviate commute-induced disadvantages for autistic employees and whether simulation tools like ABMs can help explore and guide such interventions. In short, the goal of this project is to adapt Aguilera et al.'s 2024 study [2] to another discrimination field, particularly for autistic people, with a limited scope of work-commute effects on the social energy of these people.

II. Background and Related Work

Social simulations have been adopting agent-based computational models in the literature. Earlier discussions of social laws and simulations are given in as an offline design of a good social law [3] and with a game-theoretic framework [4]. Ghorbani et al. [5] discuss the analysis of policies in agent-based methods as a bottom-up decentralized manner for social policy-making. In addition, Hooten et al. [6] give a statistical implementation for agent-based demographic simulations. Lastly, Chapuis et al. [7] provide a detailed review of the generation of synthetic populations in social simulations.

Agent-based models are also used to analyze inequalities among a synthetic population. Boyd et al. [8] give the review of studies for employment of agent-based models in socioeconomic inequalities in perspective of health. In Montes et al.'s 2023 work [9], an agent-based model is proposed for discrimination policy-making against poverty. As a follow-up work, Aguilera et al. in 2024 [2] address the question of "Can poverty be reduced by acting on discrimination?" again by utilizing agent-based models. They employ discriminative and egalitarian policies and analyze the wealth distribution, whether the rates of poverty are reduced or not. Results show that the adoption of more egalitarian policies reduces wealth distribution inequalities.

This project is inspired by the study in [2] and adopts a similar agent-based model. The essence of this simulation comes from the "needs-based model" (Figure 2) that is used in several social simulation studies including [2] and [10]. Inspired by Maslow's hierarchy of needs (Figure 1), Aguilera et al. employ the needs that are split into different categories including basic needs such as food and sleep, and psychological needs such as friendship and self-esteem. There are several amendments implemented on top of the needs-based model to support the requirements of this study. For example, in Aguilera et al., actions such as "go shopping" or "go grocery" consider no path planning, and the agent's location is rather unimportant. In this work, agents also consider the path length between locations, introducing the effect of spatial information.

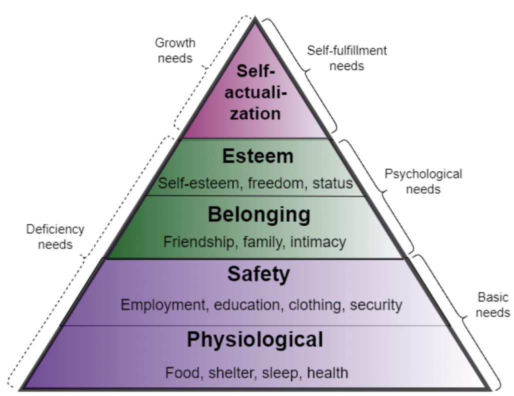

Fig. 1. Maslow's hiearchy of needs (image taken from [2])

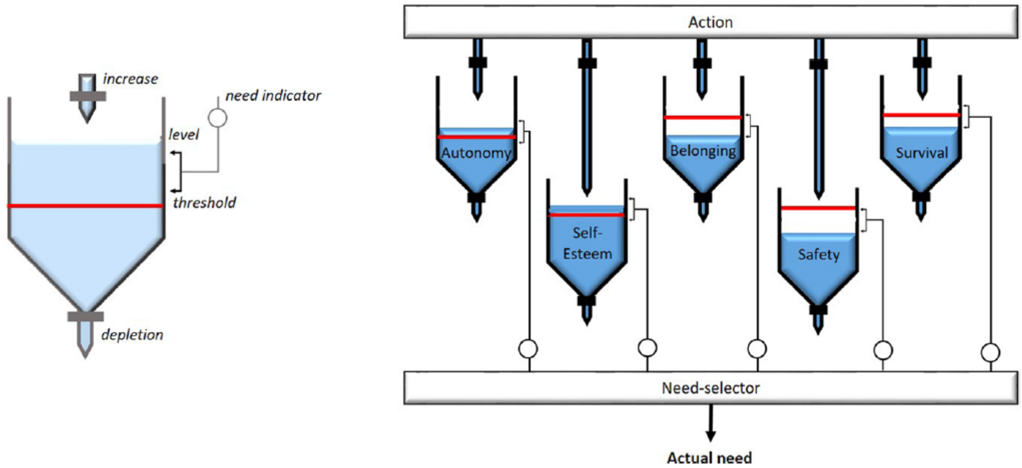

Fig. 2. Needs model (image taken from [10])

The Gini index (or Gini coefficient) is a widely used metric in social simulations (including [2], [11], and [12]) to quantify inequality in the distribution of a resource, most commonly wealth. It ranges from 0 to 1, where a value of 0 indicates perfect equality (everyone has the same wealth), and a value of 1 corresponds to maximum inequality (one agent holds all the wealth while others have none). A lower Gini index thus reflects a more equitable society, while a higher Gini index reveals increasing disparity. In simulations involving social or economic policy analysis, the Gini index is often employed to evaluate the fairness and effectiveness of different interventions. Aguilera et al. also employ the Gini index to measure the effectiveness of different policies in their study. Following this tradition, we also employ the Gini index in our results, accompanied by a discussion of its meaning in our results.

III. Methodology

The core of the agent-based modeling employed in this work and also Aguilera et al. is called *Needs-Based Model* which determines agents' autonomous decision-making. This model as introduced in Dignum et al. [10], is also referred to as *Water Tank Model* as illustrated in Figure 2. In this section, following Aguilera et al.'s formulation, we introduce the necessary concepts together with their corresponding amendments for this study.

In Aguilera et al., each agent has a profile with different attributes such as age, gender, and status. In particular, the status attribute (that is a discrete state, e.g. "homeless") determines the agent's available actions and needs in the context of poverty in Aguilera et al.'s work. In our case, instead of status, we use social tolerance which is discretized as an integer, and burnout state, which is a boolean indicating agent should recover from burnout and hence their actions are restricted accordingly. In the context of autism, these two attributes determine the agent's needs and available actions as also illustrated in Figure 3.

Every agent is associated with a set of needs $\mathcal{N}_c$ and each need $n \in \mathcal{N}_c$ is associated with a need category $c \in \mathcal{C}$. An importance function is defined that maps every category to a scalar value $Imp : C \rightarrow [0, 1]$. For the Water Tank Model, the needs also decay with each time-step based on their decay rate. Let $\gamma_{n,s} \in [0, 1]$ be the decay rate of need n, the need satisfaction level is defined as an iterative function at time t

$$NSL_t(n) = \gamma_{n,s} \cdot NSL_{t-1}(n) \tag{1}$$

where s is the status of the agent. In our implementation, status s is either burnout or the agent's social tolerance level depending on the need; however, we do not use status in needs satisfaction level decay, rather we use it in the action satisfaction matrix that will be explained in upcoming paragraphs. In Aguilera et al. NSL function has two different options, either exponential or iterative. Here we have chosen to employ the iterative version. For the initial values of the needs, we assume the agents start with the same initial conditions (in Aguilera et al. they are sampled from a normal distribution). We also define a capacity for the needs that the agent's action affects the satisfaction levels more than this capacity. This is introduced, as also explained in the following section, we allow the need satisfaction levels to be a real number, rather than limiting them to a range of $[0, 1]$. To be precise, in original formulation the need satisfaction level function $NSL_t : \{\bigcup_{c\in\mathcal{C}} \mathcal{N}_c\} \to [0, 1]$ and in our implementation it is defined as $NSL_t : \{\bigcup_{c\in\mathcal{C}} \mathcal{N}_c\} \to \mathbb{R}$.

Based on the need satisfaction level, the Water Tank Model also requires an urgency function. In Aguilera et al. since the need satisfaction levels are limited to the range $[0, 1]$, this urgency function is defined as $Urg_t(n) = 1 - NSL_t(n)$. In our case, let $max(n) \in \mathbb{R}^+$ denote the maximum achievable satisfaction level for need n, i.e. $NSL_t : \{\bigcup_{c\in\mathcal{C}} \mathcal{N}_c\} \to max(n)$, we define the urgency level at time t as

$$Urg_t(n) = 1 - \frac{NSL_t(n)}{max(n)} \tag{2}$$

which means, the urgency of the need will be zero if the need satisfaction is at its maximum, and it will increase as the satisfaction level decreases, making the action deliberation more inclined towards the urgent needs. At each time step, the available actions for the agent differ depending on the agent's profile (location, burnout state) and workplace policy.

Let $\mathcal{A}$ denote the set of available actions (e.g. action `work` is available if the agent is at a certain location and if the workplace policy allows the agent to work at the current location and time frame), for each action a_t to be taken at time step t, the satisfaction function is originally defined as $Sat_s(n, a_t) : \{\bigcup_{c\in\mathcal{C}} \mathcal{N}_c\} \times \mathcal{A} \to [0, 1]$ that can be also written as a matrix with dimensions $Dim(Sat_s) = n \times a$ for each agent in status s. In our case, with the adjusted ranges, the satisfaction function becomes $Sat_s(n, a_t) : \{\bigcup_{c\in\mathcal{C}} \mathcal{N}_c\} \times \mathcal{A} \to \mathbb{R}$. In the following sections, we will also introduce additional amendments to this satisfaction function to make it more suitable for this study.

In Aguilera et al. [2], the environment is modeled as a 10×10 grid containing facilities such as workplaces, leisure spots, schools, and hospitals. However, the spatial aspect of these facilities does not appear to influence agent behavior. For example, when an agent chooses the action `go_hospital`, the physical distance to the hospital does not affect the outcome or cost of the action. In contrast, since our simulation emphasizes the role of commute, we take into account of agent's home and workplace locations. Facility locations (in our case, homes and workplaces) explicitly influence agent decision-making: whenever an agent takes the action `walk`, its energy cost is scaled according to the actual path length, computed either randomly (for simplification) or precisely using the A* algorithm. This design ensures that location and distance influence how agents plan their actions, aligning the simulation more closely with real-world commuting constraints.

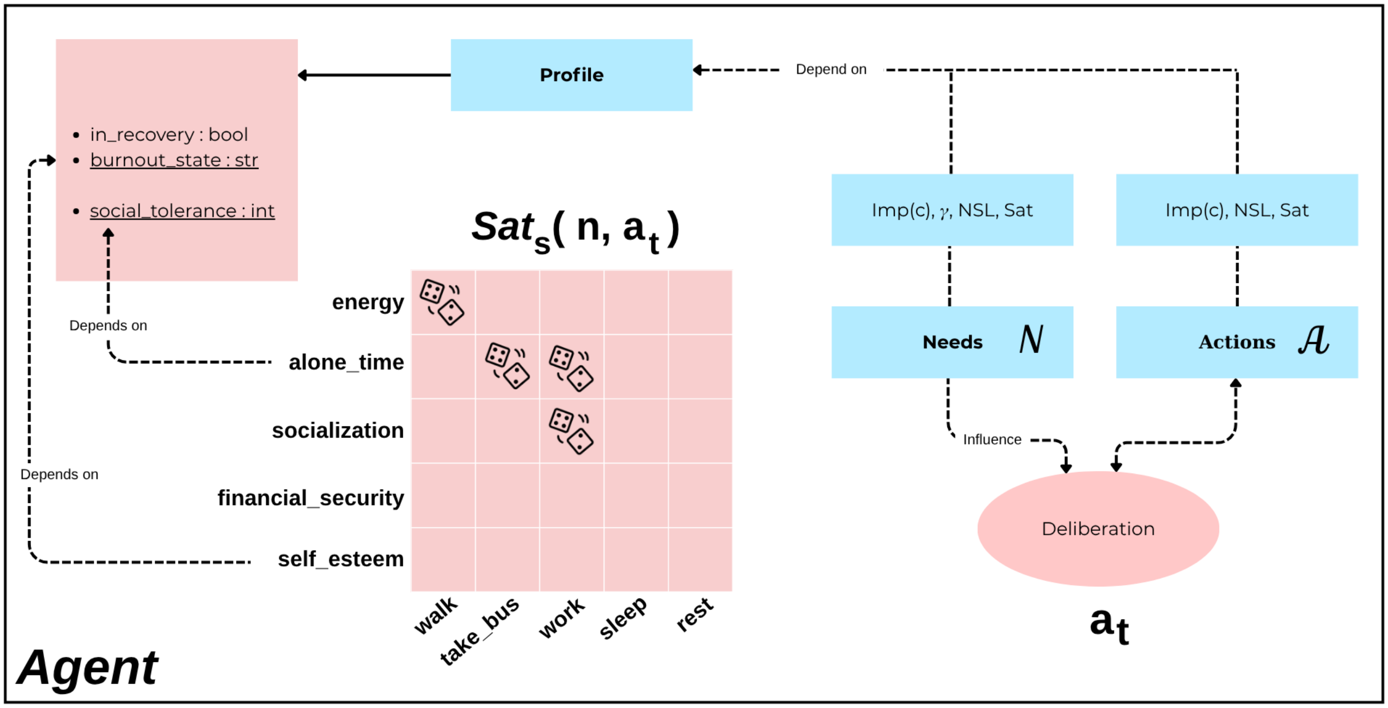

Fig. 3. Diagram of the needs-based model implemented in this project, adapted from Aguilera et al. [2]. The key difference is how satisfaction matrix (Sat_s) is implemented. In Aguilera et al., Sat matrix entries are constants depending on a single agent attribute (e.g., social status such as "homeless"). In contrast, we use randomized needs satisfaction effects for some actions and allow the effect to be a real number, unlike in the original formulation where satisfaction is limited to range $[0, 1]$. Additionally, this implementation introduces richer agent profiles. Here, Sat values can be influenced by multiple factors, such as an agent's social tolerance or burnout state.

In Figure 3, a diagram of the ABM implementation is given. One difference between the original implementation and our implementation is the range of Sat matrix entries. In Aguilera et al., needs-satisfaction matrix always has non-negative entries, which means a chosen action does not negatively impact the agent's need. However, for our implementation, we require some actions to negatively affect the agent's needs. For example, action `work` is expected to lower the energy in contrast to actions like `sleep` and `rest`. This negative impact is specifically introduced to simulate burnout effects, i.e. when the agent's `alone_time` need is depleted, it transitions into a burnout state that limits the available actions of the agent until the recovery is completed. In the original formulation, Sat matrix entries are in the range $Sat_s(n, a_t) \in [0, 1]$ and here, the entries $Sat_s(n, a_t) \in \mathbb{R}$. In the experiments, both a larger range of satisfaction levels and a normalized range $[-1, 1]$ are employed.

Another difference is the randomized $Sat_s(n, a_t)$ entries. In Aguilera et al., Sat matrix entries are taken as constants depending on the agent status. Here, we randomize the action satisfaction for some action-needs pairs. Therefore, our randomized entries are dynamically computed at runtime. For instance, social energy loss from taking a bus depends on observed crowd levels relative to the agent's tolerance, and self-esteem need is updated specifically when the agent is in a social burnout state.

Lastly, unlike Aguilera et al. where the entire Sat matrix depends on a single agent attribute, we allow the satisfaction for different needs to depend on different agent attributes. That is, how much the need for `alone_time` of an agent depends on the agent's social tolerance, and the need `self_esteem` depends on the agent's burnout state. This approach, combined with randomized satisfaction levels, allows us to model the relationship between social tolerance and the agent's wealth as different tolerance levels will affect alone time needs differently, leading to distinct social burnout levels that determine the agent's ability to work at the moment.

Aguilera et al. defines the *deliberation function*, using urgency $Urg(\cdot)$, importance Imp($\cdot$), and satisfaction $Sat_s(\cdot)$ functions

$$a_t = \arg\max_{s \in A} \left[\sum_{c \in C} \left(\sum_{n \in N_c} Sat_s(n, a) \cdot \mathrm{Urg}(n) \right) \cdot \mathrm{Imp}(c) \right] \tag{3}$$

where a_t becomes the agent's chosen action at time t as also illustrated in Figure 3. Once the action is chosen, need satisfaction levels are originally updated as

$$NSL_{t'}(n) = NSL_t(n) + \alpha \cdot Sat_s(n, a_t) \tag{4}$$

for each need n. Here, we also follow this notion with a nuance. Instead of using $Sat_s(n, a_t)$ from Equation 3, we once again compute this satisfaction matrix Sat_s and then use it in Equation 4. We call the satisfaction matrix in Equation 3 as *estimated* satisfaction and the one we use in Equation 4 as an effective satisfaction matrix. Since we randomize some action-need satisfaction pairs, the estimated and effective satisfaction matrices differ. That is, an agent may underestimate the effect of walking to the workplace on their energy, and choose to follow that action, and in return the effective impact on their energy could be more severe, leading to energy burnout (in that case agent has to rest until some energy is recovered).

In Figure 3, both `take_bus` and `work` actions potentially reduce the agent's alone time needs, therefore causing the agent to get in a burnout state when the alone time need is depleted. Similar to action `walk`, these actions also have estimated and effective costs. For taking a bus, the agent estimates a crowd level, that is randomly sampled from a uniform distribution. Similarly, for work, there is a probability of social interaction, causing alone time to decrease, again sampled from a uniform distribution.

There are also many simplifications and assumptions made to limit the scope of the experiments. One assumption is that every workplace pays the same amount per time step for the action `work`. Another assumption is that each need is treated equally in importance, i.e. $\gamma_{n,s} = 1$. We haven't applied any effects for lowered self-esteem; however, in reality, lower self-esteem might potentially also lower work performance, or even one's salary. Here, every agent earns the same fixed income regardless of their self-esteem or performance.

Finally, we define workplace policies that determine the available actions for each agent. In the experiments, we used three simple policies, defined as:

- **Fixed** Agent is only allowed to work at workplace and only at certain hours.
- **Free** Agent is allowed to work at anywhere and anytime.
- **Flexible** Agent is only allowed to work at workplace; however, they can work at anytime.

IV. Results

In this section, we present both the results in the same way as Aguilera et al. (wealth vs. frequency with Gini index) and some additional plots. In our experiments, we expect both the free and flexible policies to lower the Gini index, i.e. equalize wealth distribution, by allowing agents to work in more relaxed conditions; however, we observe that this expectation is not necessarily met for various reasons, including our simplification assumptions.

We also observe that the Gini index is not necessarily a meaningful measurement when it comes to wealth distribution. In Figures 4, 5, and 7, the Gini index of the flexible policy is 0, indicating a *perfect* equality as every agent has the same wealth, that is *zero*. This is a trivial solution to our problem, as we do not want to reduce every agent's wealth to 0, rather we want it to be as high as possible while limiting the standard deviation of the distribution. Therefore, the Gini index might not be the best choice of equality measurements in such social simulations.

In addition to the Gini index, to observe the effects of social tolerance on agent's social burnout rates and wealth, we provide additional plots in Figure 6, 7, and 8. From these plots, we observe our expected relationships for each policy as follows

- **Fixed** The less socially tolerant agents have higher burnout rates, leading to exponential decrease in wealth values.
- **Free** No social burnout occurs, allows the agents to accumulate wealth based on other random environmental conditions.
- **Flexible** No social burnout occurs, but also no wealth is accumulated as agents choose to sleep all the time.

The results we obtain come from two different map environment setups, given in the top left corner of the figures. In one setting, the simulation has a single available house and a single workplace location, in which all the agents with different social tolerance values reside in the same house location and work at the same workplace. In the other setting, there are multiple houses available on the map, as well as multiple workplaces. Note that in each experiment we fix the available workplaces to the selected policy, such that all agents, wherever their workplace is located, are working under the same policy within the same experiment.

Another experimental setup is based on the walking distances, denoted as ”random_walk” and ”shortest_path” in the figures. Random walk refers to the situation where every time agent deliberation function (Eqn. 3) or need satisfaction update (Eqn. 4) queries satisfaction matrix Sat_s for action `walk`, a random path length is returned. In the case of the shortest path setting, the agent deliberation function's $Sat_s(n = \text{energy}, a_t = \text{walk})$ is estimated by the manhattan distance between the agent's location and the goal location. For $NSL_{t'}$ update, Sat_s is taken as the shortest path length, determined by A*, between the current and the goal locations. For the fixed policy, we observe that agents are more inclined to avoid work when the shortest paths are provided instead of a random path length. Note that taking a bus slightly affects the wealth of an agent (determined by a constant bus price) and with actual costs of walking, agents may be more likely to take a bus.

In the figures, the number of agents simulated in the particular experiment is denoted by N which is $N = 100$ in general, or $N = 50$ for smaller additional experiments. Similarly, the number of simulation days is given as $D = 10$ in general, in which every day consists of 240 time steps, making the primary experiments 2400 steps.

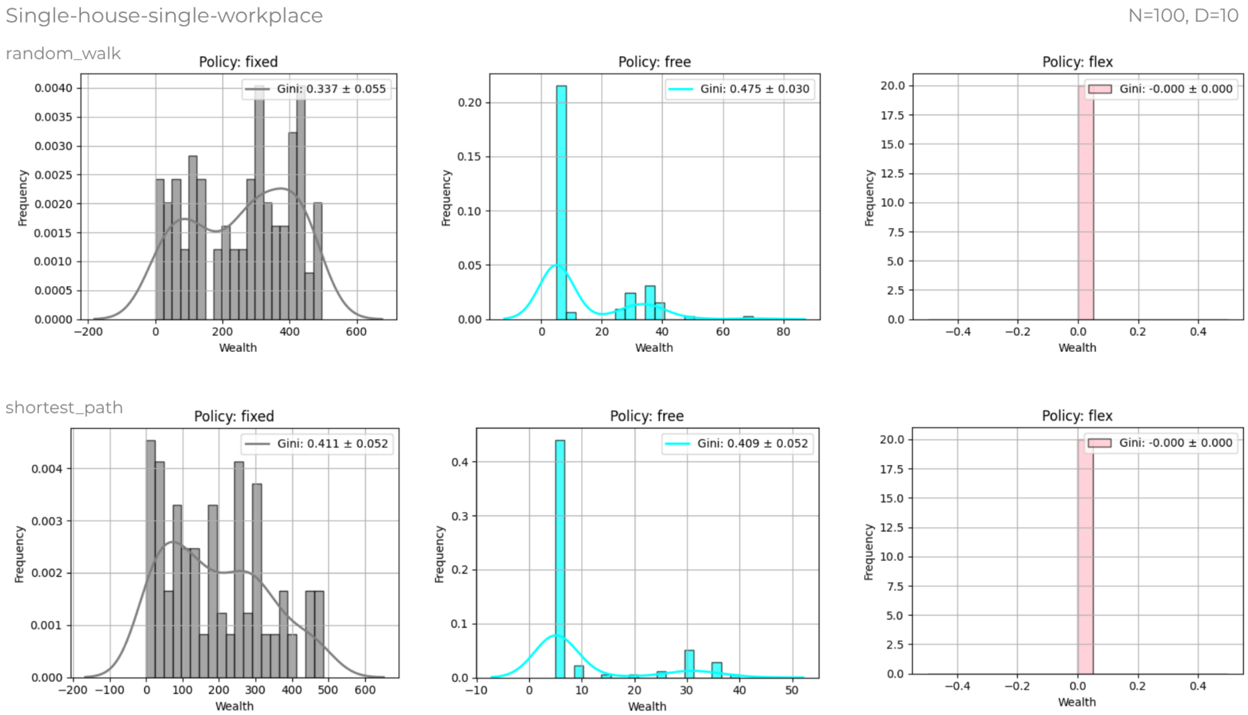

Fig. 4. Experimental results with random walk (top) and shortest path walk (bottom) under single house and single workplace settings. For policies fixed (gray), free (cyan), and flexible (pink). We observe that Gini index of free policy is only lower than fixed policy under shortest path settings.

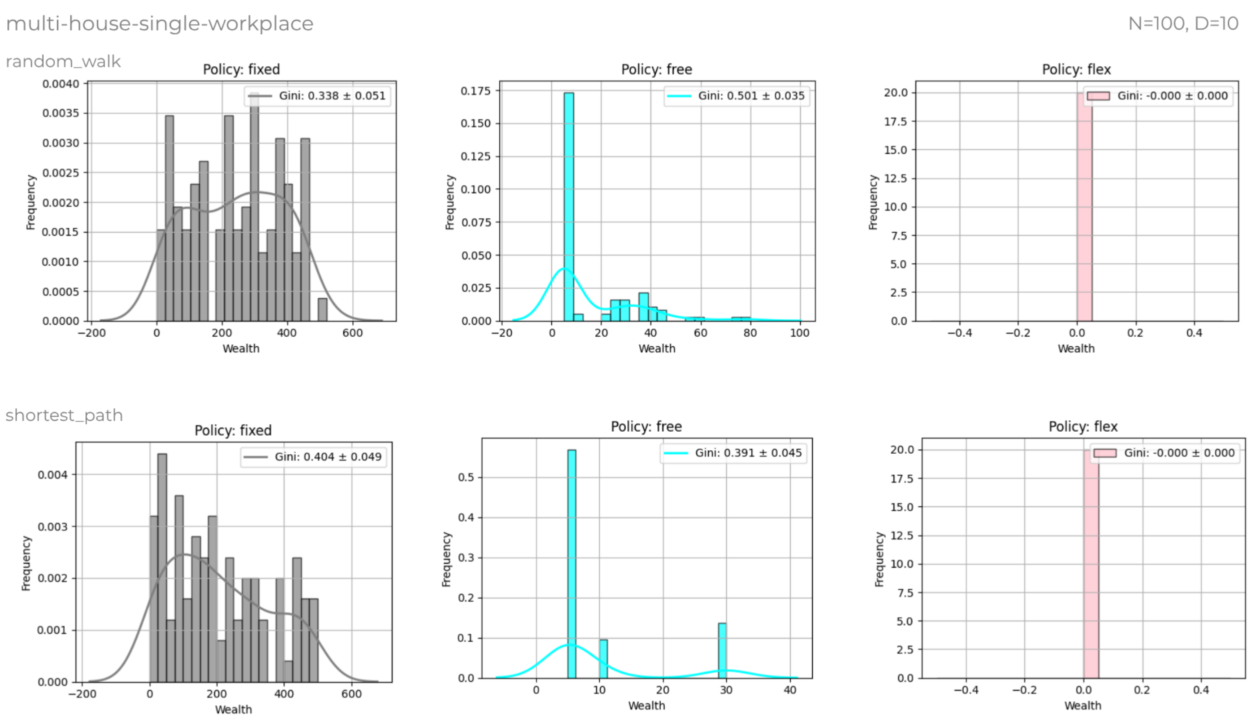

Fig. 5. Experimental results with random walk (top) and shortest path walk (bottom) under multiple house and single workplace settings. For policies fixed (gray), free (cyan), and flexible (pink). This experiment is done in contrast to Figure 4, to observe the effects of home-workplace commute paths.

In Figure 4, despite our aim to lower wealth disparity through lowering the Gini index, it results in a significant drop in average wealth accumulation. In the extreme case under flexible policy, perfect equality of Gini index 0 is achieved when none of the agents are able to earn money. These results demonstrate the ineffectiveness of the Gini index in this particular social simulation.

Comparing single house and multiple workplace setting of Figure 5 with single house and single workplace settings in Figure 4, Gini indices of random walks under different policies negligibly change. This is expected as randomizing walking costs effectively means that agents have different house and workplace locations whenever they decide to change locations. On the other hand, for shortest path walks under fixed policy, the Gini index of multiple house setting is lower, suggesting that the wealth distribution might be more equalized as some agents with lower social tolerances are able to walk to closer workplaces.

In addition to Gini index comparisons, the relationships between social tolerance, burnout rate (total number of social burnouts that occurred), and wealth outcome are highlighted in Figure 6. The satisfaction parameters used in the simulation are first designed to depict the linear relationship between social tolerance levels and wealth outcome (first column, third row) such that the accumulated wealth of an agent increases as their social tolerance increases. When we sum up the number of social burnouts that occur during the simulation, we observe an exponential decay in agents' wealth distribution as the social burnout rate increases. In contrast, introducing a free policy allows agents to work without social burnout.

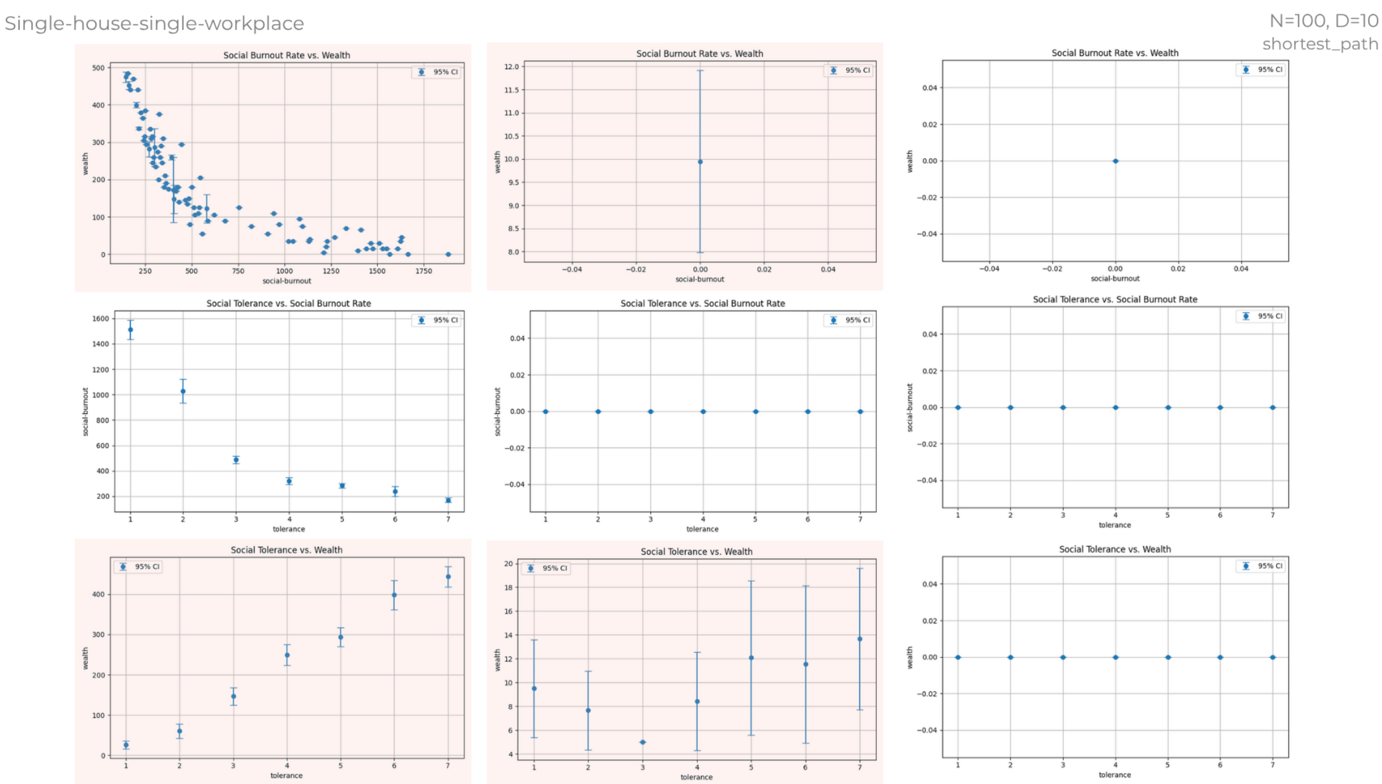

Fig. 6. (First column) Fixed policy. (Second column) Free policy. (Third column) Flexible policy. From the highlighted plots, we observe that higher social burnout rates are correlated with significantly lower wealth under fixed policy (top left), as well as higher social tolerance linearly increases wealth outcome (bottom left). Under free policy, no social burnout is observed (top right) and varying degrees of wealth is achieved for different social tolerance values (bottom right).

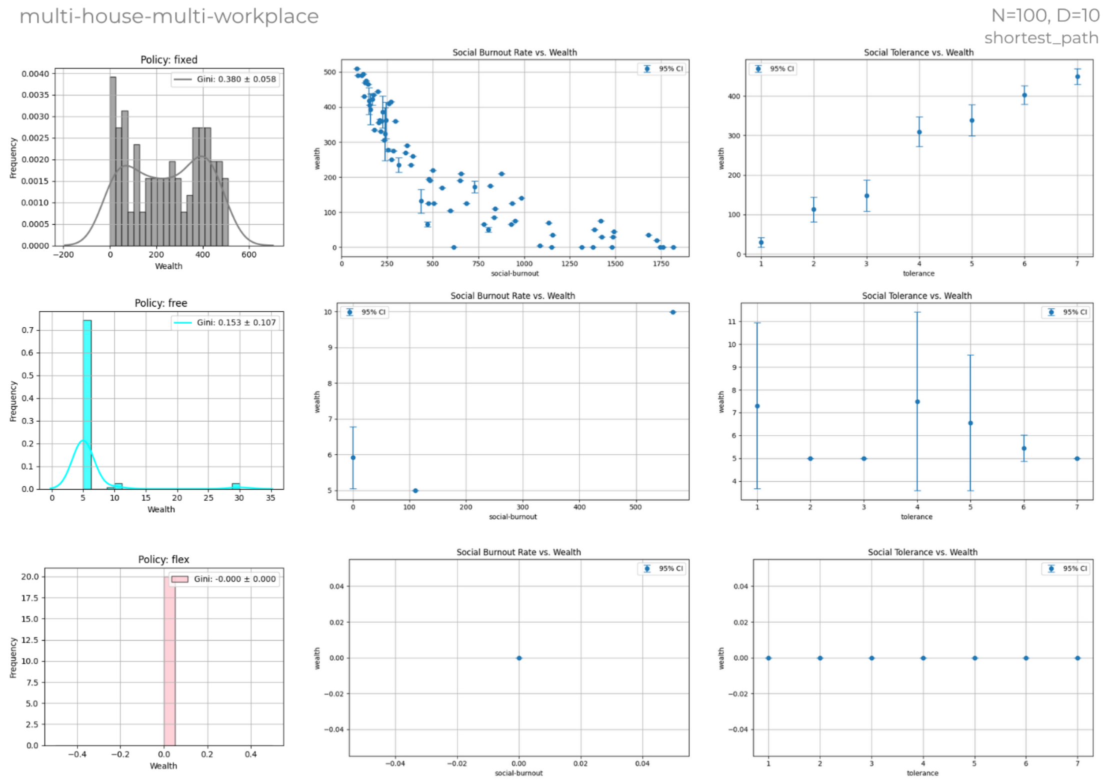

Fig. 7. Additional results aggregating Gini indices, social burnout rate, and social tolerance vs. wealth plots under multiple house and multiple workplace settings.

In addition to Figure 4 and 5, in Figure 7 experimental results of multiple houses and multiple workplaces are given for the shortest path walking option. That is, each agent is assigned to one of the houses and workplaces among various options before the simulation. In this case, the Gini indices of all policies are lower, suggesting that allowing agents to run in different environmental parameters might equalize the wealth distribution as well. However, the average wealth of the free policy under this setting is much lower than the previous ones, making it harder to conclude any improvement by only looking at the Gini index. In such cases, social burnout rates or social tolerance versus wealth comparison plots are more informative. In Figure 7, it is observed that the correlation between social burnout and wealth outcome under the fixed policy is broken once the free policy is adopted. That effectively means, the discriminatory factors causing a wage gap are eliminated and the earnings of the agents now depend more on environmental conditions that are not targeted to the agent's social group (in this case being Autistic).

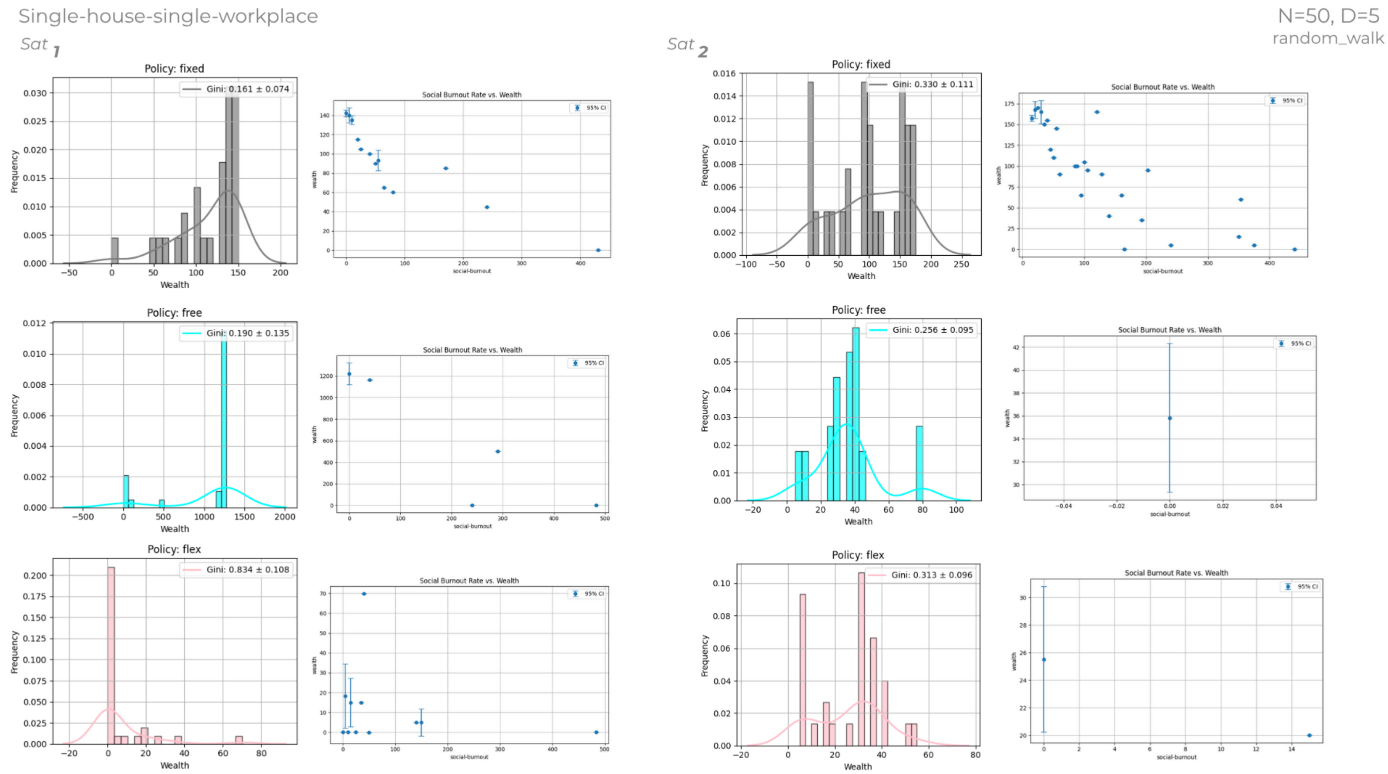

Fig. 8. Additional experiments with different handcrafted satisfaction parameters with range $Sat_s \in [-5, 5]$ (left) and $Sat_s \in [-1, 1]$ (right) allow different distributions even for the flexible policy (pink).

Finally, we observe that the simulations are sensitive to chosen parameters. In all the figures except for 8, the wealth distributions of the agents under the flexible policy were all stuck at zero. With other handcrafted parameter settings for Sat_s in Figure 8, it is possible to achieve non-zero wealth values for agents under the flexible policy.

V. Conclusions and Future Work

In this work, we adapted the study by Aguilera et al. to a new social simulation focused on the commuting challenges faced by Autistic individuals and the resulting impact on their wealth. We defined three workplace policies: a fixed-schedule policy where agents must adhere to strict working hours, and two alternatives (free and flexible) that relax those constraints. To support this expanded modeling, we extended the needs-based framework to incorporate negative, randomized, and path-dependent effects of actions on agent needs. We then simulated agent behavior under each policy scenario.

Our analysis included wealth distributions and explored how attributes like social tolerance and burnout rates influence agent outcomes. One key finding is that the Gini index, while a common metric of social equality, can yield misleading results in such simulations. In particular, we observed that a Gini index of zero can emerge when all agents have zero wealth which is clearly an undesirable outcome. Based on this result, we highlight the limitations of relying on it as the sole measure of equality.

A broader challenge we encountered in agent-based modeling is the need to handcraft numerous simulation parameters, a process that is both labor-intensive and prone to making mistakes. We believe learning-based approaches, such as reinforcement learning, offer a promising direction for future research—especially given the scarcity of agent-based social simulations that explicitly model discrimination and accessibility issues. We also acknowledge the limited scope of this study. Several modeled needs, such as socialization and self-esteem, were not fully integrated into the policy experiments and therefore had no meaningful impact on the results. Future work could investigate the role of these dimensions in more depth.

One should note that this simulation simplifies the experience of being Autistic to a single attribute—lower social tolerance—which does not capture the full complexity of neurodivergence. The purpose of this study is not to make real-world generalizations, but to explore simplified agent relationships and policy interventions in a controlled setting. Within this context, we observe that free workplace policies (where agents are not required to commute in order to earn income) can reduce burnout rates. This, in turn, breaks the link between burnout and diminished wealth, suggesting that simulations like this study might inform more inclusive policy design.

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