Statistical Mechanics of Restroom Choice

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ABSTRACT

Human behavior is influenced not only by social interactions but also by the way people interact with their environment. Understanding these different interactions in constrained environments is a central question in behavioral science, but it remains challenging due to the difficulties of data collection. We focus on restrooms with a given number of sites, such as urinals or toilets, as a minimal setting for investigating human behavior. We introduce a web-based platform that enables the collection of large-scale data on sequential occupancy choices in controlled restroom layouts. We analyze transition probabilities between configurations using a statistical physics framework inspired by the Ising model, from which we infer effective interpersonal interactions and site-dependent biases. We further develop a kinetic model describing individual arrivals and departures, which allows us to predict site usage as a function of the utilization factor. Finally, we demonstrate that the model generalizes across restroom of different sizes, enabling prediction of usage and dynamics from limited data. Beyond this specific system, our results demonstrate how simple local rules can generate predictable collective behavior in constrained environments, with implications for a broad class of public spaces such as waiting room or public transportation.

INTRODUCTION

In an episode of the 1990s BBC series *Cracker*, a murder investigation takes an unexpected turn in the most mundane of settings: a public restroom. The victim's body is found in front of a row of urinals, positioned closest to the door. In the episode, this choice is assured to be unusual; most people prefer the more secluded urinal by the wall when available. From this subtle clue, the detectives deduce that someone else must have been present, already occupying the wall urinal at the time of death. This seemingly minor observation illustrates a subtle form of spatial reasoning that many perform unconsciously, governed by unwritten "rules" of urinal selection and spacing. In fact, these rules could be explored, quantified, and modeled statistically.

In restrooms, social interactions can significantly influence individual behavior and well-being. One well-studied manifestation is *paruresis*, or shy bladder syndrome, a condition in which the presence of others inhibits urination. Paruresis has been investigated in terms of its classification as a social phobia, its prevalence in the population, and potential treatment strategies [1–5]. Experimental studies have demonstrated that *personal space invasion* in lavatories directly affects urination behavior and induces individuals to prefer being farther away from each other. For example, Middlemist *et al.* [6] showed that the onset of micturition is delayed when others



FIG. 1. **How a restroom is filled. (a)** We start with an empty array of $N = 5$ urinals, represented by five "0"s. The first user chooses the central position at $x = 3$, denoted by a "1". The next user occupies the position at the back ($x = N$), and so on until the fifth user takes the nearest position to the door ($x = 1$). This sequence corresponds to the most probable filling order observed in our data. **(b)** Same analysis for an array of $N = 5$ toilets.

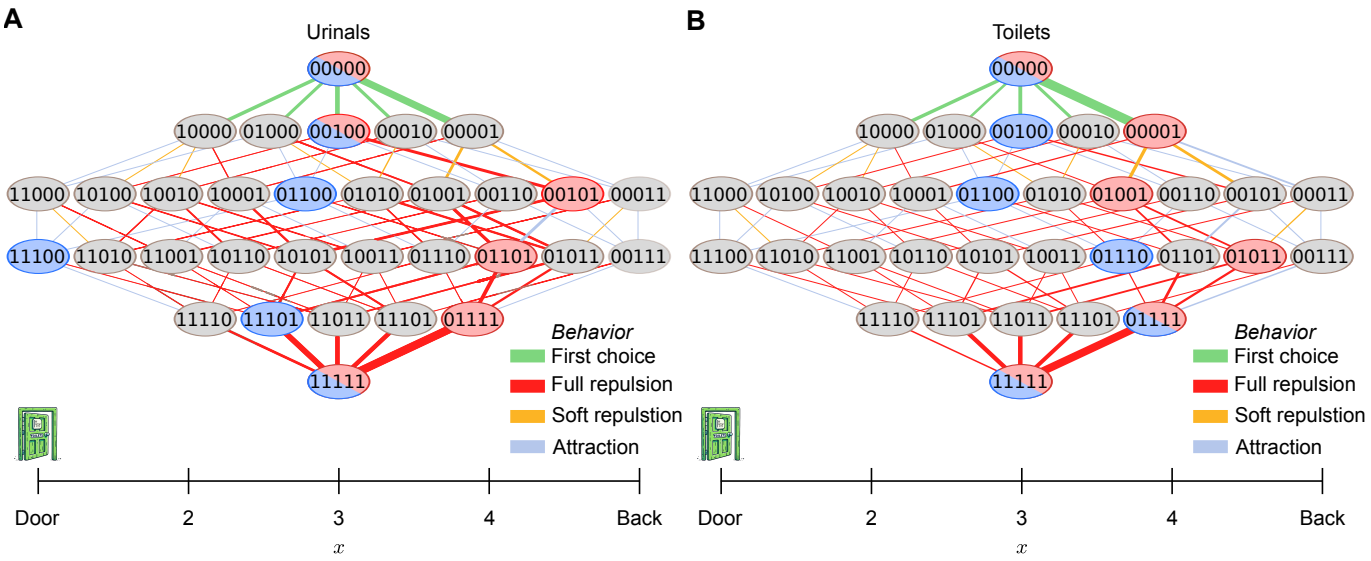

FIG. 2. **Network for Arrival. (a)** Network representing the order of arrivals for $N = 5$ urinals. Starting from an empty state, people enter one by one, with probabilities given by the weights of the links. Probabilities are conserved from empty nodes to full nodes. The width of each link reflects its weight. Red circles correspond to the most probable paths, while blue circles indicate less probable paths. Links are colored according to the behavior of the newly arriving person: green for the first choice, red if the person maximizes the distance from others already present, orange if the distance is not maximized but at least one empty site is left between them and others, and blue if the person chooses a position adjacent to someone else. **(b)** Arrival-order network for $N = 5$ toilets, corresponding to panel (a).

are in close proximity, highlighting the important role of social context, privacy, and social repulsion in restrooms. In addition, Kranakis *et al.* [7] and Trakulthongchai *et al.* [8] have investigated how different strategies, such as *lazy* or *cooperative* behaviors, can affect occupancy patterns and maximize privacy in public restrooms. Beyond behavioral studies, research on restroom and public space design emphasizes both spatial arrangement and the design of individual fixtures to enhance comfort and reduce social discomfort [9–11]. Further improvements in fixture design, such as splash-free urinals or ergonomically optimized toilets and benches, additionally minimize discomfort for adjacent users [12, 13].

Restrooms can also be seen as a minimal example of collective behavior in constrained spaces. Such systems have a small, discrete set of available positions, and individuals choose among them sequentially using only local information. Their collective organization then emerges from the interplay between three ingredients: repulsion or attraction between individuals, interactions with the environment (walls, doors, exits), and the rate at which people enter and leave [14]. This perspective is central to the physics of crowds and pedestrian dynamics, where social-force and cellular-automaton models describe how individuals keep distance from one another and from boundaries [15–17]. It also appears in experiments and models of flow and clogging through bottlenecks, in humans and animals [18, 19]. Related spatial self-organization also appears in how people keep distance in queues and public spaces [20, 21], and in the more general statistical physics of social dynamics [22, 23]. Most of this work addresses dense or moving crowds, or abstract agents. Data on the fine-grained, sequential site choices of individuals in small, discrete, and socially sensitive settings remain scarce, because such behavior is hard to observe directly and is largely unrecorded.

Despite all this knowledge about the individual behavior it is still unclear how people's interactions, site type (urinals versus toilets), site position relative to the entrance door, and restroom utilization (i.e., user arrival rate) impact on restroom usage patterns. To our knowledge, no studies based on real data have yet addressed this question as measuring and modeling social interactions in restroom environments remains challenging. Social interactions and the implicit rules governing them have been shown to underlie the organization of many complex systems, from friendship networks to epidemic spreading [22, 24]. For this study, we developed an online platform [25] to collect data and facilitate the quantitative analysis of occupancy patterns, interaction behaviors, and providing a framework to investigate and model social dynamics.

DATA COLLECTION AND DISTRIBUTION

While the time τ_R required to leave the room can reasonably be assumed to be characteristic of human behavior, about 25 s [26–28], the choice of urinals when individuals enter a restroom with both empty and occupied sites remains largely unknown. To investigate this behavior, we collected data through a large-scale online survey conducted on a dedicated platform [25] that we developed in full compliance with the GDPR (Regulation (EU) 2016/679) [29].

Informed consent was obtained from all participants prior to their participation. Subsequently, each participant was asked, after watching an introductory video shown in Supple-

mentary Movie S1, to sequentially occupy an array of urinals or toilets with 2 to 9 sites, progressing from an empty to a fully occupied configuration according to the choices they would make in real-life scenarios. Each answer on the online platform corresponds to a set of states $\mathbf{s} = (s_1, s_2, \ldots, s_N)$, where $s_x = 1$ indicates that site i is occupied and $s_x = 0$ otherwise, ranging from single occupancy to $N-1$ occupancy, where N is the total number of sites in the restroom. The position x denotes the site location, with $x = 1$ corresponding to the site in front of the door and $x = N$ to the site at the back of the room. An example of responses collected for five urinals and five toilets, with the entrance located in front of the leftmost site, is shown in Figure 1. A total of approximately 3500 responses were collected worldwide, corresponding to roughly 18000 distinct restroom configurations across more than 25 countries on five continents.

There are 2^N possible occupancy states $\mathbf{s}$ for a given number of sites N. Consequently, the number of possible configurations grows exponentially with N, requiring an exponentially increasing number of observations to adequately sample the configuration space. Given the finite number of responses collected, we therefore restrict our analysis to arrays with $N \leq 6$, for which the available data provide sufficient sampling of the possible configurations.

In each trial, a door was randomly positioned either in front of the leftmost or rightmost site. This design enabled us to investigate the effect of spatial asymmetry introduced by the entrance. By comparing the distributions of occupied states for the two door positions, a χ^2 test reveals that the null hypothesis H_0, which assumes equality of the distributions, is rejected ($p < 0.05$) for restroom arrays with 2 to 5 sites. This indicates that door placement systematically influences participants' choices and suggests that individuals adapt their behavior to this random variable, confirming that participants respond rigorously enough to produce reliable data.

TRANSITION PROBABILITIES AND EFFECTIVE INTERACTIONS

The dynamics of a restroom are partially governed by the transition probability $p_{\mathbf{s}\to\mathbf{s}'}$. When an individual enters a restroom in configuration $\mathbf{s}$, they choose an available site, leading the system to a new configuration $\mathbf{s}'$. At this stage, human behavior and interpersonal interactions play a crucial role in shaping the overall dynamics of the restroom system.

Arrivals networks, behavior and strategy

Using the large dataset collected, we compute the probability $p_{\mathbf{s}\to\mathbf{s}'}$ that an individual selects a given empty site upon entry in state $\mathbf{s}$, leading to state $\mathbf{s}'$, as a function of the positions of already occupied sites. This allows us to construct a directed network of arrival dynamics, where nodes represent occupancy states and directed links encode the corresponding transition probabilities between states.

Figure 2a illustrates the directed network of arrivals based on collected data for five urinals. Each node corresponds to a configuration of the restroom, while links represent the transition between configurations when a new individual arrives. Starting from the empty state, individuals enter one by one and select a site according to probabilities measured in the online experiment. The width of each link represents the transition probability between two configurations. The links are normalized to ensure probability conservation at each node.

The color of the links encodes the behavioral strategy adopted by the arriving individual. Green links correspond to first-choice selections when the restroom is empty. Red links indicate choices that maximize the distance from already occupied sites. Orange links correspond to intermediate strategies in which the distance is not maximal, but at least one empty site remains between individuals. Finally, blue links represent choices where the individual selects a site adjacent to another person. The predominance of green and red transitions reveals a strong tendency to maximize interpersonal distance whenever possible, highlighting a robust social-spacing strategy in restroom usage.

The node colors highlight the most and least likely occupancy sequences, shown in red and blue, respectively. Nodes appearing in both sequences are displayed with a combined red-and-blue coloration. Nodes not included in either sequence are shown in gray.

For $N = 5$ urinals, the most likely sequence starts with a first central choice; the next individual moves to the back, while the third prefers positions between the central site and the door. The fourth avoids the position in front of the door, as it has two occupied neighbors at $x = 4$, and the last individual has no choice but to occupy the site in front of the door. The least likely sequence also begins with a central choice; the second individual selects a position between the door and the central site, the third moves in front of the door, and the fourth goes to the back. These patterns provide a first indication of social repulsion and avoidance of the entrance.

Figure 2b is the arrival network for five toilets. The network remains qualitatively similar to that observed for urinals, with individuals generally favoring configurations that preserve interpersonal distance. However, the distribution of transition probabilities is slightly more homogeneous, indicating weaker door avoidance.

The most likely sequence differs from that observed for urinals: the first person goes to the back, the second chooses the site just after the door, the third selects a position just before the back, and the fourth occupies $x = 3$, even when it has two occupied neighbors instead of avoiding the door. The least probable sequence typically starts with a central choice and consists of repeatedly selecting sites with the maximum number of occupied neighbors. Analysis of our data suggests two key mechanisms. First, individuals tend to avoid sites near the entrance. Second, they preferentially maintain at least one empty site between themselves and others whenever possible.

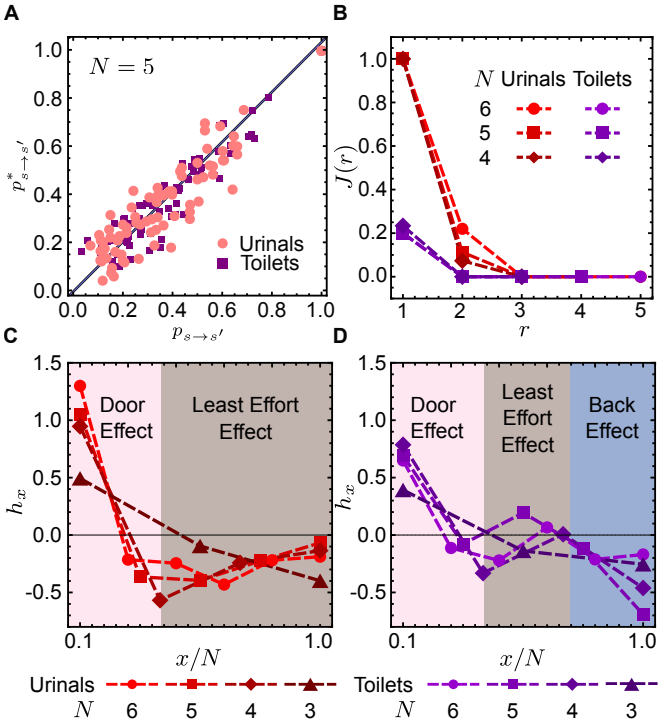

FIG. 3. **Effective interactions.** **(a)** $p^*_{\mathbf{s}\to\mathbf{s}'}$ obtained from the fit over collected data versus the empirical rates $p_{\mathbf{s}\to\mathbf{s}'}$. Red circles correspond to urinals and purple squares to toilets ($N = 5$), and the solid line indicates the identity. **(b)** Interaction coupling $J(r)$ as a function of the interpersonal distance r, with red for urinals and purple for toilets, for $N \in \{4,5,6\}$. Dashed curves are guide for the eye. **(c)** Local field h_x as a function of normalized position x/N for urinals. Circle, square, diamond and triangle respectively correspond to N =6, 5, 4 and 3 Two regimes are identified: a door-effect-dominated regime (light pink) and a least-effort-dominated regime (brown). Dashed curves are guide for the eye. **(d)** Same analysis for toilets, with an additional back-effect-dominated regime (blue).

Effective interaction

To go further with a quantitative analysis of the transition probabilities, we introduce a model to capture effective interactions between individuals and between individuals and the environment, which govern the transition probability $\omega_{\mathbf{s}\to\mathbf{s}'}$ inferred from experimental observations.

The cornerstone of our approach is a cost function $H(s)$, which assigns a cost to each configuration s. The higher the cost, the lower the probability of accessing this state. Formally, we define $H(s)$ as

$$H(s) = \sum_{r=1}^{N-1}\sum_{x=1}^{N-r} J(r)\, s_x s_{x+r} + \sum_{x=1}^{N} h_x s_x, \tag{1}$$

where $s_x = 1$ if site i is occupied and $s_x = 0$ otherwise. The first term represents pairwise interactions between sites separated by a distance r, with coupling $J(r)$: it describes how the presence of another individual at a given distance influences the cost of occupying a site. The second term corresponds to the local field h_x, which encodes site-specific preferences, such as avoidance of sites near the entrance.

For example, when an individual considers occupying an empty site x, the change in the cost function can be understood as a local contribution from h_x together with interaction contributions from the already occupied sites. Thus, h_x captures the intrinsic preference associated with the location itself, independently of who is already present, whereas $J(r)$ captures the interpersonal effect of the distance to other occupants. This decomposition provides a direct separation between spatial preferences associated with the environment and interactions arising from the presence of other individuals. The model is inspired by the Ising model and its generalizations [30–35].

The assumption that the coupling $J(r)$ is independent of the position x is a convenient modeling choice, as it reduces the number of interaction parameters from $N(N-1)$ for a fully position-dependent coupling $J(r,x)$ to $N-1$. This reduction is motivated by the limited amount of data available for small N, as introducing additional parameters could lead to overparameterization. This assumption is nevertheless a strong one. The entrance and the back of the restroom introduce significant spatial asymmetries, so it is not obvious that the effective interaction between two individuals should be independent of their absolute positions. We additionally assume that the coupling is independent of the occupancy of other sites and depends only on the pairwise distance.

We assume that the probability of transitioning from a state s to a state s' is proportional to $e^{-\Delta H(s,s')}$ with $\Delta H(s',s) = H(\mathbf{s}') - H(\mathbf{s})$. More formally, the probability $p^*_{\mathbf{s}\to\mathbf{s}'}$ of selecting an empty site in configuration s leading to s' is given by

$$p^*_{\mathbf{s}\to\mathbf{s}'} = \frac{e^{-\Delta H(\mathbf{s}',\mathbf{s})}}{\sum_{j\in\mathscr{E}(\mathbf{s})} e^{-\Delta H(\mathbf{s}^{(j)},\mathbf{s})}}, \tag{2}$$

where $\mathscr{E}(\mathbf{s})$ denotes the set of empty sites in configuration $\mathbf{s}$, and $\mathbf{s}^{(j)}$ is the configuration obtained by filling site j in state $\mathbf{s}$. The normalization in the denominator ensures that the probabilities over all available empty sites sum to one.

Using the previous equation, we determine the parameters $J(r)$ and h_x by minimizing the mean squared difference

$$\mathscr{L} = \frac{1}{N_{\rm tr}} \sum_{\mathbf{s}\to\mathbf{s}'} |p_{\mathbf{s}\to\mathbf{s}'} - p^*_{\mathbf{s}\to\mathbf{s}'}|^2, \tag{3}$$

where the sum runs over all experimentally accessible transitions. Here, $p^*_{\mathbf{s}\to\mathbf{s}'}$ denotes the transition probability predicted by the model, a $p_{\mathbf{s}\to\mathbf{s}'}$ the corresponding empirical probability and $N_{\rm tr}$ the total number of transitions considered. Therefore, $J(r)$ represents an effective behavioral interaction inferred from the observed conditional probabilities, rather than a directly measured interpersonal interaction. Similarly, h_x is an inferred quantity and is not directly measured.

Figure 3a shows the empirical probabilities $p^*_{\mathbf{s}\to\mathbf{s}'}$ as a function of the predicted probabilities $p_{\mathbf{s}\to\mathbf{s}'}$ for a five-site restroom, obtained after fitting the parameters $J(r)$ and h_x. Red circles correspond to urinals, while purple squares correspond

to toilets. The coefficient of determination R^2 is 0.87 for urinals and 0.91 for toilets, indicating good agreement between $p_{\mathbf{s}\to\mathbf{s}'}$ and $p^*_{\mathbf{s}\to\mathbf{s}'}$.

By applying the same procedure to restrooms of size 3, 4, and 6, we obtain coefficients of determination R^2 equal to 1.00, 0.93, and 0.72 for urinals, and 1.00, 0.96, and 0.59 for toilets, respectively. These results indicate a strong agreement between the predicted transition probabilities and the empirical measurements for smaller system sizes, with a gradual degradation as the system size increases. Despite this decrease in performance for larger systems, the coefficient of determination remains significantly large compared to what is typically expected in the behavioral sciences [36].

Figure 3b shows the fitted values of $J(r)$ as a function of r, in red for urinals and in purple for toilets, with dashed lines as guides for the eye. The value of $J(1)$ for urinals is set to 1 to define the scale. For toilets, $J(1) = 0.21 \pm 0.01$, which is approximately five times smaller than for urinals; this provides the first quantitative measure of differences in human interaction between urinals and toilets. We observe that the fitted interaction decreases rapidly with interpersonal distance r, so quickly that for toilets all terms vanish for $r > 1$. Thus, it is reasonable to neglect interactions beyond nearest neighbors. For urinals, interactions vanish for $r > 2$, with $J(2) = 0.14 \pm 0.04$, which is about six to seven times smaller than $J(1)$. Therefore, $J(r)$ is relatively independent of the restroom size N.

The values of the local field h_x for urinals are shown in Figure 3c, where circles, squares, diamonds, and triangles correspond to $N = 6, 5, 4$, and 3, respectively, plotted as a function of the normalized site position x/N. Two distinct regions can be identified. First, in the light pink region, h_x takes positive values of the same order as $J(1)$, indicating that occupying sites close to the door is associated with a higher effective cost. A natural interpretation is to regard the entrance as an effective repulsive boundary, reflecting the observed tendency to avoid urinals located near the entrance. We refer to this inferred spatial preference as the *door effect*. Secondly, in the brown region, h_x is negative but increases toward the back of the restroom, indicating an increasing effective cost of occupying more distant urinals. We interpret this inferred spatial dependence as a competing *least-effort effect*: while individuals tend to avoid urinals near the entrance, they also appear reluctant to walk all the way to the back of the restroom. The interplay between these two tendencies produces a minimum of h_x near the center of the row. For small restrooms, such as $N = 3$, the door effect dominates, leading to a monotonic decrease of h_x with x.

Figure 3d shows a similar analysis for toilets. As for urinals, a door effect is observed, although its amplitude is smaller. Moving away from the entrance, h_x decreases and reaches a local minimum. After, the field increases and reaches a local maximum this is the *least-effort effect* region. Finally, h_x decreases again from the second region toward the last sites. Thus, sufficiently close to the back of the restroom, the effective cost no longer increases and instead decreases. We interpret this additional decrease as a *back effect*, suggesting that the sites located at the back may be comparatively more attractive. As for the *door effect* and *least-effort effect*, this interpretation describes a possible behavioral mechanism underlying the inferred spatial dependence of h_x, rather than a directly measured effect.

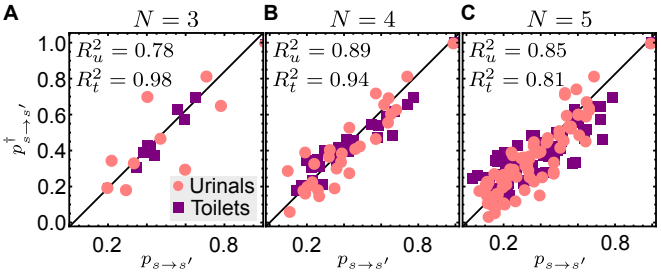

FIG. 4. **Model prediction. (a–c)** $p^\dagger_{\mathbf{s}\to\mathbf{s}'}$ as a function of $p_{\mathbf{s}\to\mathbf{s}'}$ for $N \in \{3,4,5\}$. Urinals are shown as red circles and toilets as purple squares. The solid curve represents the identity line. R_u^2 and R_t^2 denote the coefficients of determination for urinals and toilets, respectively.

We have quantitativelyinferred a measure of interpersonal effective interaction $J(r)$ and the local field h_x, and made the assumption that we can decouple the influence of social interactions from architectural effects in restrooms. The interaction $J(r)$ decreases with distance r, and is five times smaller for toilets than for urinals. Supplementary Movie S2 illustrates the *door effect* and $J(r)$ behaviors.

We also identify an effective cost associated with sites near the door, which is slightly weaker for toilets than for urinals. Together, the effective interaction $J(r)$ and the effective position-dependent field h_x provide a coherent inferred characterization of human behavior in restrooms. h_x can be naturally interpreted in terms of a repulsive door effect combined with a least-effort tendency and, for toilets, an additional back attraction. Plus, $J(r)$ can be interpreted as an effective social repulsion.

Predictability capability

To further assess the predictive capability of the model, we compute $p^\dagger_{\mathbf{s}\to\mathbf{s}'}$ derived from Eq. 2, without additional fitting, using the parameters $J(r)$ and h_x previously estimated from the data for $N = 6$, and apply them directly to smaller values of N. The field h_x for $N \neq 6$ is interpolated using a cubic spline based on the data for $N = 6$.

Figure 4 shows $p^\dagger_{\mathbf{s}\to\mathbf{s}'}$ as a function of $p_{\mathbf{s}\to\mathbf{s}'}$ for $N = 3, 4$, and 5. Urinals are represented by red circles and toilets by purple squares. The solid curve is the identity line.

Our model reproduces remarkably well the transition probability $p_{\mathbf{s}\to\mathbf{s}'}$ without any fit on the corresponding data. The coefficients of determination for urinals, R_u^2, are 0.78, 0.89, and 0.85 for $N = 3, 4$, and 5, respectively. For toilets, R_t^2 is 0.98, 0.94, and 0.81 for the same values of N.

These coefficients of determination are significant for behavioral science [36], as they open the door to the predictability of human behavior in constrained environments such as re-

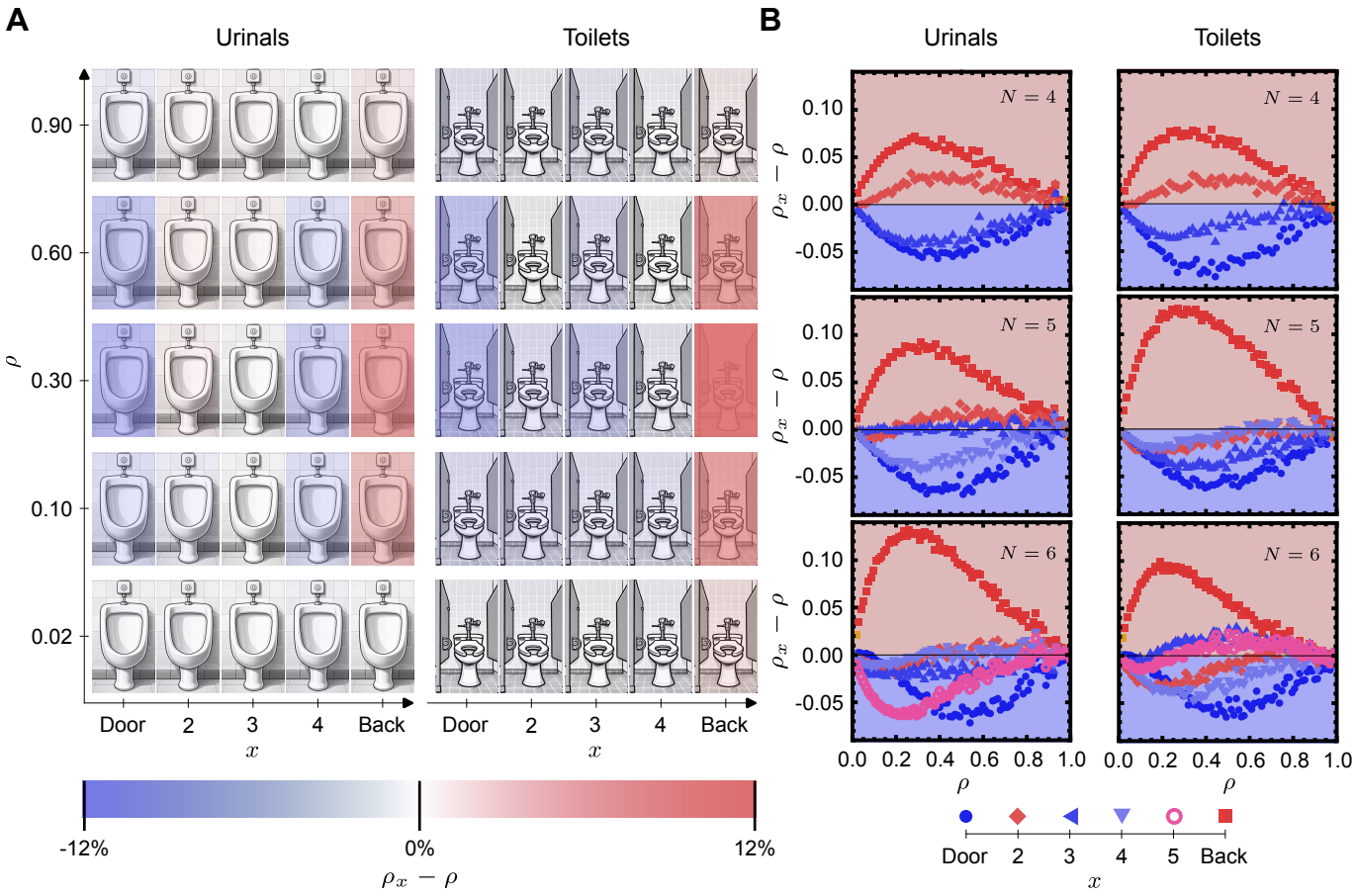

FIG. 5. **Occupancy imbalance as a function of ρ. (a)** Occupancy imbalance of each site in an array of five urinals and toilets as a function of the utilization factor ρ. The color scale indicates the occupancy imbalance. **(b)** Occupancy imbalance as a function of the utilization factor ρ for urinals and toilets with $N \in \{4,5,6\}$ sites. Different markers correspond to different site positions in the array: the first site is shown as a blue circle, site 2 as a red diamond, site 3 as a blue triangle, site 4 as an light blue triangle, site 5 as a pink circle, and the last site as a red square. The shaded regions highlight the sign of the imbalance: the red region corresponds to a positive imbalance, whereas the blue region corresponds to a negative imbalance.

strooms or waiting rooms. The transferability of the model to larger systems was not investigated due to the limited amount of data collected for arrays with $N > 6$. Increasing the system size does not introduce new architectural elements but rather extends the same underlying geometry. We therefore expect the main qualitative features of h_x and $J(r)$ to remain broadly similar as the system size increases, although a quantitative validation for larger systems would require additional data.

TRANSITION RATES AND KINETIC MODELS

Restrooms are environments in which time plays a central role. Two fundamental time scales characterize their dynamics: the average residence time of individuals, denoted by τ_R, and the average time between successive arrivals, denoted by τ_A. These characteristic times govern the utilization, occupancy, and overall dynamics of the restroom.

To assess the influence of the ratio τ_R/τ_A, we introduce a kinetic model that accounts for the stochastic dynamics of arrivals and departures. This framework enables the computation of site occupancy, providing a dynamical observable that captures the temporal evolution of usage patterns.

Discrete-Event Restroom Model

Indeed, to simulate the arrival and departure dynamics of a restroom with N urinals or toilets, we assume that both processes are stochastic and characterized by two time scales: τ_A, the mean inter-arrival time between two consecutive users, and τ_R, the mean residence time that individuals spend in the restroom.

Both arrivals and departures are modeled as stochastic processes with constant rates, implying that events occur randomly in time without memory of past events. Arrivals occur as a Poisson process with rate $1/\tau_A$.

Upon each arrival, an independent residence time is assigned from an exponential distribution with mean τ_R, corresponding to a Poisson process at the individual level with rate

$1/\tau_R$. Each occupied site therefore carries its own stochastic departure clock.

At the population level, the departure process is state dependent, with an instantaneous rate given by $n(t)/\tau_R$, where $n(t)$ is the number of occupied sites at time t.

At each event, the state of the restroom is updated: if all sites are occupied, arriving individuals join a queue, and when a departure occurs, the first individual in the queue, if any, occupies the newly available site.

In this framework, the system evolves as a continuous-time Markov process. For a given arrival time scale τ_A and service time scale τ_R, the expected occupancy per site in a perfectly symmetric system is

$$\rho = \left\langle \frac{1}{N}\sum_x s_x \right\rangle_{\text{time}} = \frac{\tau_A}{\tau_R N}. \tag{4}$$

The quantity ρ can be interpreted as an occupation factor.

Therefore, the sites are not symmetric, and the transition rates depend on both the initial and final states when an individual enters the restroom. When an individual arrives in the restroom, their choice probability is directed by $p_{\mathbf{s}\to\mathbf{s}'}$ so we can define a rate $k_{\mathbf{s}\to\mathbf{s}'} = p_{\mathbf{s}\to\mathbf{s}'}/\tau_A$

Occupancy Imbalance

The asymmetry introduced in the model through the transition rates leads to an occupancy imbalance at site x in a restroom, defined as

$$\rho_x - \rho, \tag{5}$$

which quantifies the deviation of the local occupancy from the symmetric case.

To estimate the occupancy imbalance for different configurations, we perform simulations of restroom arrays consisting of N urinals or toilets. Each simulation is run for 10^5 events to ensure convergence to the steady-state regime and to obtain robust statistical sampling of the system dynamics.

Figure 5a shows the occupancy imbalance for each site in an array of five urinals or toilets as a function of the utilization factor ρ. The imbalance is highlighted by a color scale. For both urinals and toilets, the most frequently used site is located at the back of the room, whereas the least used site is the one closest to the entrance. The magnitude of the imbalance reaches a maximum of roughly 12% around $\rho \approx 0.3$. For urinals, the $N-1$ site is also underused, while the $N=2$ and $N=3$ sites display a roughly zero imbalance. For toilets, the central site is likewise underused, whereas the $N=2$ and $N=4$ sites exhibit an approximately zero imbalance.

In Figure 5b we display the occupancy imbalance as a function of the utilization factor ρ for urinals and toilets with $N \in \{4,5,6\}$ sites.

For all situations, the back site consistently exhibits the largest positive imbalance, with a maximum occurring around $\rho \approx 0.3$. Conversely, the site closest to the entrance is generally the least used. An exception appears for $N=6$ and $\rho \lesssim 0.3$, where the $(N-1)$ site becomes the least occupied. For urinals with $N=4$, the back site and site 2 show positive imbalance, while the remaining sites exhibit negative imbalance. As the number of sites increases, the imbalance at the extremities becomes more pronounced, whereas the central sites approach the average occupancy, i.e. an imbalance of 0.

For toilets, a similar behavior is observed: for $N=4$ the pattern resembles that of urinals, while for larger N the imbalance alternates with increasing and decreasing amplitude across the array. Notably, the preferred sites tend to be separated by a distance of one site, suggesting a spatial structure in human site-selection behavior.

Our kinetic model shows evidence of an occupancy imbalance of up to 12% for intermediate utilization factors ρ. Individuals tend to favor certain sites over others, with a strong preference for the ends of the restroom and an avoidance of entrance-adjacent locations.

The imbalance strongly depends on the utilization factor, revealing the temporal dimension underlying the effects encoded in $J(r)$ and h_x. This demonstrates that the observed spatial preferences are not solely determined by static interactions or architectural biases, but also emerge from the interplay between arrivals, departures, and occupancy dynamics.

CONCLUSION

In this work, we introduced a quantitative framework to investigate human behavior in restrooms, combining large-scale data collection with tools from statistical physics and stochastic dynamics. Using an online platform, we gathered thousands of occupancy sequences for urinals and toilets across a wide range of restroom configurations, allowing us to identify spatial patterns in human site selection and quantify human repulsion.

Our analysis reveals that restroom usage is governed by a combination of social repulsion and environmental effects. Individuals strongly avoid immediate proximity to others whenever possible, particularly in the case of urinals, and strongly avoid sites located near the entrance. In contrast, sites at the back of the restroom are generally preferred. These behaviors were quantified using an effective interaction framework inspired by the Ising model, in which we assume that pairwise effective interactions $J(r)$, capturing interpersonal spacing effects, can be decoupled from local fields h_x, which encode architectural influences. $J(r)$ is s dominated by nearest neighbor repulsion, with a much weaker next-nearest-neighbor contribution for urinals. The inferred effective position-dependent field h_x can be naturally interpreted in terms of a *door effect*, a *least-effort effect*, and a *back effect*. The fitted parameters can be generalized to smaller restroom sizes with good accuracy, opening the door to applications in restroom design and management, but also to other constrained situations such as waiting rooms. For larger systems, we do not expect substantial qualitative changes, as increasing the system size does not introduce new architectural features. However, this expectation remains to be validated with additional data.

Extending beyond transition probability description, we de-

veloped a kinetic model that incorporates stochastic arrivals and departures. This approach reveals that occupancy imbalance emerges dynamically from the interplay between transition rate and utilization factor. In particular, the strongest asymmetries occur at intermediate utilization factor, where preferred and avoided locations become most pronounced. It will be applicable to a wide range of situations, from low-utilization regimes to high-utilization events.

Beyond restrooms themselves, our results provide insight into how humans organize in constrained public environments. Similar mechanisms of spacing, boundary avoidance, and occupancy imbalance are likely to arise in settings such as public transportation, waiting rooms, theaters, parking areas, or shared workspaces. More broadly, this study illustrates how simple local behavioral rules can generate complex collective spatial organization in everyday social systems.

ACKNOWLEDGMENTS

This work was financially supported by the GRASP Lab. A.F. is a Research Fellow of the Fonds de la Recherche Scientifique-FNRS. We thank all users of the website for providing the data. A.L. research is supported by the ARC (Concerted Research Action) project EsPOIR (Eco-friendly high Performance cOncrete for sustainable InfrastructuRes), funded by the Fédération Wallonie-Bruxelles. A special thanks to Mehran Kardar for indicating the Cracker episode, mentioned in the introduction. We gratefully acknowledge Lyse Gathoye for her guidance and expertise in statistics and cognitive neuroscience. We also acknowledge financial support from the Portuguese Foundation for Science and Technology (FCT) under Contracts no. UIDB/00618/2020 (https://doi.org/10.54499/UIDB/00618/2020), UIDP/00618/2020 (https://doi.org/10.54499/UIDP/00618/2020), and UID/00618/2023.

AUTHOR CONTRIBUTIONS

A.L., N.V., A.F., and M.D. developed the website used to collect the data. All authors contributed to promoting the website, with N.A.M.A. playing a key role in outreach efforts in Portugal and South America. A.F., A.L., M.D., N.A.M.A., and N.V. carried out data processing and analysis, while A.F. and N.A.M.A. developed the model. A.F. wrote the original draft. A.F., A.L., M.D., N.V., and N.A.M.A. contributed to writing and revising the manuscript. N.V. and E.O. supervised the research.

COMPETING INTERESTS

The authors declare no competing interests.

ETHICS STATEMENT

This study was anonymous, voluntary, and non-interventional and did not involve clinical procedures, sensitive personal data, or vulnerable populations. In accordance with the ethical framework of the University of Liège, formal ethical approval was not required for this type of research in the human and social sciences. The study was conducted in accordance with applicable ethical guidelines and the GDPR (Regulation (EU) 2016/679). No IP addresses or precise geographic locations were collected or retained; only the country associated with each IP address was recorded. Participation was voluntary, and all participants were informed about the study before providing their responses. Informed consent was obtained from all participants prior to their participation.

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I. SUPPLEMENTARY MATERIAL

ONLINE PLATFORM

To investigate restroom occupancy behavior, we developed an online platform [25] where participants could anonymously indicate how they would occupy a restroom. Upon accessing the platform, users were first presented with an explanatory video, available as Supplementary Movie S1. The website consists of a single-page interface featuring with

1. A title *2 pee or not 2 pee* and subtitle *The Ultimate Peeing Strategy Challenge!* .
2. The number of records since website april 2025.
3. An introduction text.

   > Welcome, brave strategist!
   >
   > Ever found yourself in a public restroom, carefully choosing the perfect urinal?
   >
   > You're not alone! Scientists (that's us, the GRASP from ULiège !) are studying how people navigate this delicate decision.
   >
   > Now, it's your turn to test your instincts and help us decode the hidden rules of urinal selection.

4. How to answer.

   > How to Play
   >
   > Select one toilet/urinal at a time until all are occupied.
   >
   > The green door is the restroom entrance.

5. A non-constraining incitation to answer at least 10 sequences

   > Ready to prove your strategy? Complete 10 rounds and show us your genius!

6. A case to choose the size of the restroom.
7. A representation of the restroom with N sites and an entrance randomly placed either at the rightmost or leftmost site.

Users are required to select a first site corresponding to their real-life choice. After each selection, the empty icon is replaced by an occupied one. The user must continue selecting sites sequentially until full completion of the restroom. Once a configuration is completed, a new array is automatically generated with randomly placed urinals or toilets, and an entrance located at either the leftmost or rightmost site. To obtain sufficient sampling across all restroom sizes and to cover the $N!$ possible occupancy sequences, the probability of presenting a restroom with N sites was weighted linearly with N. Users may optionally choose the restroom size manually, although this is not mandatory.

DATA COLLECTION

In total, approximately 3,500 responses were collected worldwide, corresponding to roughly 18,000 distinct restroom configurations. All responses were collected in compliance with GDPR regulations [29], ensuring participant anonymity.

Country	Count	Country	Count
Belgium	1531	Colombia	25
Portugal	599	Finland	18
Brazil	231	Luxembourg	18
Italy	196	Croatia	15
Czechia	178	India	8
United Kingdom	130	Morocco	8
France	130	Japan	3
Germany	127	Hong Kong	3
Netherlands	123	Switzerland	2
Austria	60	Slovenia	2
Spain	57	Australia	2
United States	37	Ecuador	1
Canada	31	Total	3535

TABLE I. Distribution of responses by country and continent. Each row corresponds to a country and the number of responses received. The background color of each cell indicates the continent of the country: blue for Europe, orange for Americas, green for Asia, purple for Africa, and brown for Oceania.

Participants from diverse locations were invited to play the game [25]. The link to the platform was disseminated through QR codes distributed during summer schools and scientific conferences, including STATPHYS29 and FPSPXVI, as well as via LinkedIn and University of Liège student associations.

Table I reports the geographical distribution of responses inferred from IP addresses. The dataset is strongly skewed toward Europe, which accounts for the majority of participants, with Belgium being by far the main contributor, followed by Portugal and several other Western and Central European countries. Outside Europe, participation is more limited but spans multiple regions, including the Americas (notably Brazil and the United States), a few answers in Asia (India, Japan, Hong Kong), Africa (Morocco), and Oceania (Australia).

N	Urinals			Toilets		
	p_{value}	n_{left}	n_{right}	p_{value}	n_{left}	n_{right}
2	6.8e-08	85	54	5.0e-10	68	66
3	1.9e-06	84	84	1.4e-06	83	91
4	1.7e-07	97	91	3.5e-04	90	87
5	1.4e-04	112	102	6.6e-03	112	103
6	0.052	129	114	0.091	129	118
7	0.104	125	121	0.108	132	129
8	0.256	137	130	0.188	144	133
9	0.206	148	129	0.115	159	147

TABLE II. Number of responses and χ^2 test for the influence of the door. For each number of toilets/urinals N, p-values comparing left vs right door distributions are shown, along with the number of observations. Green cells indicate $p < 0.05$.

DATA MIRRORING

To improve statistical convergence, we apply a data mirroring procedure. Because the entrance door can appear on either side of the restroom layout, we exploit the left–right symmetry of the problem by mirroring configurations in which the door is located on the right, mapping them onto equivalent configurations with the door on the left. This transformation preserves the relative spatial structure of the choices while standardizing all configurations to a common reference frame. As a result, the effective size of the dataset is doubled, improving statistical accuracy without introducing additional bias.

DATA RELIABILITY AND DOOR EFFECT

Can we trust the collected responses? Were participants answering randomly, or is there a systematic bias, for example toward the left side? Do we have a sufficient number of responses to draw conclusions? These are crucial questions. To address them, we study the potential effect of the door on participants' choices. In each game, there is a door and a number of toilets or urinals. The door is randomly placed either in front of the leftmost or the rightmost site. If the door placement influences participant choices, the distribution of occupied states in the left-door condition will differ from that in the right-door condition. Conversely, if the door has no effect, if participants did not notice the door, if most responses were not serious, or if the sample size is too small, the two distributions should be statistically indistinguishable.

To evaluate this, we perform a χ^2 test on the observed state distributions for a given number of toilets or urinals. The null hypothesis H_0 is that the two distributions are equal, while the alternative hypothesis H_1 is that the distributions differ. This approach allows us to quantify whether door placement introduces a measurable bias in participant choices. By convention, H_0 is rejected if the p-value of the test is below 0.05, which can be interpreted as the probability of observing the distribution under the assumption that there is no door effect. In Table II, the p-values are reported for all considered cases, together with the number of responses for the left-door condition (n_{left}) and the right-door condition (n_{right}). Green cells indicate cases where p-value < 0.05. For these cases, we can conclude that the two distributions differ, suggesting that a door effect exists and that participants mostly noticed the door and responded seriously. For the other cases, naturally a larger number of responses would be required to detect a difference. This is also consistent with the idea that the door effect is limited in space and tends to decrease as the number of toilets or urinals N increases.

SPIN MODEL FITTING

The minimization of Eq. 3 is performed as follows. In practice, the parameters are determined using an alternating optimization procedure. Starting from $J(r) = 0$ and $h_x = 0$, we first optimize the local fields h_x while keeping $J(r)$ fixed, and

then optimize the interactions $J(r)$ while keeping h_x fixed. These two steps are repeated iteratively until convergence. The local fields are optimized using the L-BFGS-B algorithm, while the interactions are optimized using SLSQP, with the natural constraint $J(r) \geq J(r+1)$ and bounds imposed on the accessible interaction distances. The optimization is performed independently for each restroom type and system size. The quality of the resulting fit is quantified by the coefficient of determination R^2 between the empirical and model transition probabilities. The alternating optimization is considered converged when the change in all fitted parameters between two successive iterations is smaller than 10^{-8}.

MOVIES

Supplementary movie SM1 is available on the online platform before playback, illustrating how the sequence is encoded, with annotations highlighting the encoding process.

Supplementary movie SM2 highlight the effect of the door and social interactions in the choice dynamics, including explanatory annotations.

DATATSET

The file *data_collected.csv* contains the complete set of experimental observations used in this study. Each row corresponds to a single sequential filling event in a restroom configuration. The dataset is structured as follows. The first column is a unique identifier for each trial. The second column encodes the filling sequence as an array of size equal to the number of sites; entries indicate the order in which sites are occupied, from 0 to $N-1$. The third column gives the total number of sites N in the restroom. The fourth and fifth columns encode site type (1 for toilet, 0 for urinal) and door placement (-1 for entrance at the leftmost site, 1 for entrance at the rightmost site), respectively. The sixth column provides the timestamp of the measurement. The final column indicates the country associated with the originating IP address.