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Beyond expected travel time: Unveiling the role of ergodicity breaking in mobility decisions and effective transportation policy

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ABSTRACT

In this paper, we direct the attention of the mobility science community to the concept of ergodicity-breaking, a principle of importance for understanding and addressing the complexities of (personal) mobility. Ergodicity refers to the assumption that a system's evolution over time can be approximated by its ensemble average at one time step: an assumption whose validity has been increasingly put into question. Through a series of thought experiments, we illustrate the non-ergodic properties of travel time. These experiments reveal a new perspective of an old adagio, "People value reliability" more so than transportation speed. We show that this statement does not necessarily stem from heuristics, biases, or idiosyncrasies but rather that it is a consequence of the environment and dynamic in which people make modal choices. Our approach could be a powerful tool for instilling behavioural change. We offer new insights into inducing modal shifts and improving urban mobility systems. Thanks to this shift in perspective, the analytical frameworks used in mobility science could also include non-ergodic dynamics, thereby enriching our understanding and approach to creating more effective mobility interventions and policies.

1. Introduction

In our rapidly advancing, highly mobile world, making optimal transportation decisions is not just an individual concern but a societal imperative. As urban centres grapple with congestion, pollution, and infrastructural challenges, there is a need to achieve modal shifts in transport systems (De Witte et al., 2013; Buehler, 2011; Nurdden et al., 2007). One of the solutions to these urban challenges is to shift citizens' mobility preferences from cars to public transit, from driving to biking, or from taxis to walking Batty et al. (2015).

A common approach to understanding what drives 'modal shifts' is to encapsulate the (dis)utility derived from each travel mode, given an extensive array of factors (De Witte et al., 2013; Ma et al., 2020; Fearnley et al., 2017; Bates et al., 2001; Salas et al., 2022; McFadden, 1972). These factors often reflect either the traveller (social, demographic and culture), the environment (e.g. weather, infrastructure), the travel motive, or the characteristics of the mode of transportation. Changes in these factors engender changes in the utility associated with the related modes of transportation, which could, in turn, lead to a 'modal shift' (Arbués et al., 2016; Small, 2012; Ojeda-Cabral et al., 2016; Carrion and Levinson, 2012). While utility-based models provide a structured way to analyse modal shifts, alternative approaches, such as Agent-Based Models and machine learning, offer different perspectives. In Agent-Based Models, utility functions take a back seat to other transportation considerations such as activity type, feasible routes, and agent characteristics (Cetin et al., 2002; Li et al., 2021). Using these considerations, Agent-Based Models assign realistic travel patterns to different agents (Schneider et al., 2013; Horni et al., 2011), who then use heuristics or their assigned utility function to select travel itineraries, time allocation and travel modes (Mehdizadeh et al., 2022; Habib, 2011; Lopes et al., 2014; Faboya et al., 2020). This approach hard-wires modal preferences into reality by requiring that individual choices yield, to an extent, to the current location and situation of the agent. Another increasingly popular approach to infer modal decisions is through machine learning models (Kashifi et al., 2022; Zhou et al., 2019; Omrani, 2015). These models can reflect highly complex travel preferences but can increase the complexity of linking preferences to a specific individual or modal features (Salas et al., 2022; Zhao et al., 2020; Karlaftis and Vlahogianni, 2011).

One of the determinants at the heart of many of these models is the seemingly straightforward metric: expected travel time (Shen et al.,

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2009; Small, 2012; Yalçınkaya and Bayhan, 2009; Kato et al., 2024). Following the logic of expected travel time, one way to induce a modal shift is by keeping all other determinants the same and reducing the expected travel time of the more desirable mode of transportation. However, as intuitive as it might seem, this metric offers a reductionist perspective of the dynamics underpinning our mobility choices. It requires explanations tied to observed behaviour and psychology to reflect human decision-making better.

We suggest a change in perspective on travel time that not only comes closer to the actual travel experience but also proposes a new baseline from which to judge interventions. In this paper, we employ stylized thought experiments to examine how repeated travel decisions impact individual outcomes over time, that is, the average experience of a single person making many consecutive choices (the time average). Rather than focusing on the expected result for a large group making a single modal choice, we track the experience of a single person making repeated decisions. This perspective makes it possible to capture absorbing boundaries, i.e., real-world thresholds like being fired due to excessive tardiness or losing a driver's license after accumulating too many points. These absorbing boundaries represent permanent, irreversible outcomes that can result from a series of small misfortunes, introducing cumulative risks for individuals. Such risks are not visible when using the expected value, and require additional parameters to account for, whereas they are naturally captured in time averages.

Shifting from expected travel time to time averages and absorbing boundaries can fundamentally alter which modal choices are considered "optimal", i.e., we show that the well-established preference for reliability over speed can arise from environmental constraints, rather than solely from idiosyncrasies. This change in perspective highlights that policies modifying the structure of the decision environment, such as point-based driver's licenses or boundary conditions, may have a greater impact on travel decisions than those targeting personal preferences.

1.1. Travel time and non-ergodicity

The main issue with expected travel time is that it assumes ergodicity to hold (Peters, 2019). This prevalent assumption asserts that a system's ensemble average is equivalent to its time average. Put simply, a dynamic is ergodic when the average outcome of $n \to \infty$ agents performing a task once results in the same outcome as one person performing a task $t \to \infty$ times. Incorrectly incorporating this assumption conceals essential trends in the data and results in models that fail to capture elementary features of the system they model. Additional parameters and idiosyncratic observations can improve the accuracy of an ergodic model, but often at the detriment of generality. Moreover, these additional parameters further obscure the root of the issue, the faulty assumption of ergodicity. Rejecting the ergodic hypothesis has paved the way for fresh perspectives across various disciplines, including the rationality behind human decision-making (Vanhoyweghen et al., 2022; Vanhoyweghen and Ginis, 2023; Meder et al., 2021; Skjold et al., 2023), cooperation (Peters and Adamou, 2022) and insurances (Peters, 2023), GDP limitations (Adamou et al., 2020), psychology (Molenaar, 2004), and reinforcement learning (Verbruggen et al., 2025; Baumann et al., 2023). The type of ergodicity breaking at the root of most of these insights is the one that occurs because of compounding in exponential processes (Peters, 2019). However, this type of ergodicity breaking is only one example of how ergodicity can be broken, and not necessarily the most relevant in the discussion of travel times or mobility decisions. We advocate that the non-ergodicities at the heart of travel time and mobility decisions largely stem from absorbing barriers, restricting the additive travel time increments we experience (Vanhoyweghen and Ginis, 2023).

An absorbing barrier refers to a state from which there is no escape once encountered; for example, getting fired because of too many tardy arrivals. Additive increments reflect how you approach this boundary by increasing or decreasing the observed quantity by a fixed amount. These increments could, for instance, refer to the number of early and late minutes accumulated over all travel days or the number of penalty points you have collected on a driver's license. Drawing from the nuanced insights of Ergodicity Economics, we will illustrate that many of our mobility decisions are made in non-ergodic environments. In these non-ergodic environments, the overreliance on metrics like estimated travel time can misrepresent our transportation preferences, leading to suboptimal modal shifts with broader implications on urban planning, environmental impacts, and societal well-being.

To illustrate how ergodicity and absorbing barriers relate to the question of travel time, consider n commuters deciding between taking the train or the car to work. Consider the case where, on average, the train is faster but is frequently bogged down by significant and unpredictable delays. On the other hand, the car might be slower, because of high but predictable traffic congestion in rush hour. A possible answer is to look at the expected travel time. Which one is the optimal choice? Solely looking at travel time would signal that the train is the optimal choice. Taking the train would entail that many commuters get to their work as efficiently as possible, allowing them to leave home later and spend their time on more enjoyable things than commuting (Small, 2012). However, the remaining train commuters are less fortunate; they arrive late. From the perspective of the average commuter, they spent the least amount of time commuting and lost less of the more enjoyable time. However, for the commuters who arrived late, this could carry lasting consequences; for instance, many tardy appearances could result in an untimely termination of their work contract, i.e. hitting an absorbing barrier.

This example illustrates an instance of the non-ergodicity of travel time by an absorbing barrier (Vanhoyweghen and Ginis, 2023). Here, the termination of a work contract, the absorbing barrier, introduces a lasting consequence which prevents the experienced travel time from returning to the expected travel time. Another absorbing barrier presents itself when choosing which travel mode to use to get to the airport. Either the traveller selects mode one, which is fickle and is equally likely to drop them off at the airport 50 min early or 10 min late, or they choose mode two, which will always drop them off 5 min early. A first-order analysis of the expected travel time tells us that mode one is expected to be 15 min faster than mode two. Therefore, we could conclude that we should pick mode one, 'if all else is the same'. However, if we consider that consistently employing mode one results in the traveller missing half of their flights, taking mode one does not seem like a sensible choice. These examples illustrate that in the setting of personal mobility, it matters that you are on time, rather than the abstract notion that people are on average on time.

A common way to explain this drift away from expected travel time optimization is to look at the first part of that conclusion, 'if all else is the same', and dismiss it for the unlikely hypothesis that it is and introduce different determinants, such as personal preferences (De Witte et al., 2013), culture (Buehler, 2011), aversion to unreliability (Hollander, 2010; Bates et al., 2001; König and Axhausen, 2002; Mishra et al., 2018), and the travel motive (Ma et al., 2020). One could, for example, assume that we value our time at the airport differently than our time at home, so being early at the airport is worth less than the potential time we could have spent at home (Small, 2012; Fosgerau and Engelson, 2011), making mode two more appealing. However, in this paper, we argue that an error occurs even before making the claim, 'if all else is the same'. Accounting for this error sidesteps the need for utility-based approaches, which in return could simplify travel models. Specifically, this pertains to how we employ expected travel time as a criterion for optimal decision-making. Because travel time is non-ergodic, expected travel time poorly reflects the experience of the decision-makers. More specifically, 50 people arriving late at work could be offset by 50 people arriving at work early. In contrast, an individual coming late 50 times will probably be condemned by their employer before the 50 early arrivals can balance their track record.

Table 1
The fictitious travel modes used in the thought experiments. Each mode is defined by two possible normalized travel times (in minutes): a positive value for arriving early and a negative value for arriving late, each occurring with equal probability.

Mode	Standardized travel time
A	+20, −20
B	0
C	+24, −12
D	+6, −2

1.2. An alternative to expected travel time

As argued in the previous section, expected travel time fails to capture a vital aspect of modal selection, namely the need for punctuality, which stems from the negative and lasting consequences of excessive tardiness. This exclusion of the need for punctuality forces model makers to include additional parameters, such as an idiosyncratic aversion to unreliability (Schwanen and Ettema, 2009), to better reflect the individual travel experience. However, asking the ergodic question (i.e., are we allowed to assume ergodicity?) reveals that this desire for punctuality stems from the non-ergodicity of travel time. If we account for this non-ergodicity, a new metric presents itself in the probability of avoiding the absorbing barrier (Vanhoyweghen and Ginis, 2023). This metric captures the trade-off between expected travel time and travel time variance without needing additional assumptions and parameters. The sole assumption made is that individual travellers value punctuality. This value of punctuality can stem from an internal desire to be punctual or external pressure. In the following section, we set up multiple thought experiments that illustrate and model how absorbing barriers affect our model choices.

2. Thought experiments investigating modal decisions in a non-ergodic world

The thought experiments use the two scenarios illustrated in the introduction: the work commute and the airport-bound journey. In both scenarios, we assume that all modes are equivalent except for their expected travel time and travel time variance. Additionally, we start the thought experiments by requiring that each travel mode has the same departure time. These assumptions allow us to normalize travel times into their outcomes rather than the absolute journey length, i.e., we shift the focus from the journey length to the number of minutes we are expected to arrive early or late due to choosing a particular mode of transportation. These strategic choices allow us to zero in on the impact of travel time, a parameter at the heart of most transport models. We will use employment termination throughout the thought experiments to exemplify an absorbing boundary and its effects. This type of 'absorbing' boundary differs from the purely mathematical one in the sense that employment termination does not truly characterize the end of an entire dynamic but rather an important breaking point, where the agent experiences a negative outcome and the dynamic changes. Many such 'absorbing' boundaries exist in mobility choices, each with varying degrees of impact. Nevertheless, as long as this impact is considered important, has a lasting effect, and cannot be undone in a subsequent iteration, it gives rise to ergodicity breaking. In these thought experiments, we will refer to the following four fictitious modes of transportation, given in Table 1.

While we deliberately avoid attaching explicit real-world labels to modes A, B, C, and D in the remainder of this paper, it may be helpful to clarify the kinds of transport options these could most closely resemble. Modes A and C most likely correspond to a bus or train with low frequency, where a cancellation or missing a departure can result in a wide spread of arrival times. Mode D is more akin to a car or subway, which are generally more flexible or operate at higher frequencies. Mode B's real-world counterpart is most closely represented by on-foot travel, which is least susceptible to delays caused by external factors. Nonetheless, these associations are meant to be illustrative rather than definitive. For the purposes of our analysis, we intentionally abstract away from mode-specific features and personal preferences, focusing instead on the dynamics of travel time and reliability as the primary determinants of modal choice.

2.1. The work commute

2.1.1. The impact of the variation of the expected travel time

Within the framework of our study, we introduce an additive dynamic with an absorbing barrier, which introduces a negative consequence when hit. To ease the modelling, we imagine a scenario centred around an agent bound by a unique employment contract, which stipulates a strict punctuality clause or absorbing boundary: the total number of minutes they can be late cannot exceed the total number of minutes they have been early. Hitting the boundary, i.e. failure to adhere to this stipulation, will result in an immediate termination of employment. In our thought experiments, termination will only result from tardiness rather than any factors tied to the individual, economy, or job setting.

Work officially begins at 9 a.m., and the agent sets out from their home every day at 8 o'clock, providing them an hour to commute. The agent is presented with two distinct modes of transportation to choose from. The first mode, mode A, is characterized by its speed but lack of reliability. When opting for this mode, the agent will either arrive at work ahead of time at 8:40 or find themselves 20 min tardy at 9:20. Respectively adding 20 min or subtracting 20 min to the total number of minutes arrived early or a normalized travel time of +20 or −20 min. Mode B offers consistency. Mode B guarantees the agent to reach their workplace at the stipulated starting time, 9:00, every single day. Given the constraints of their contract, the agent must make a calculated decision on which mode of transportation best avoids the absorbing boundary. Looking at the expected travel time indicates that the agent should be indifferent between mode A and mode B. However, these modes are far from interchangeable if the agent desires to avoid hitting the boundary. Considering that mode B can never be late, the agent is guaranteed to never hit the boundary and, as such, does not need to fear breaching the punctuality clause. In contrast, the boundary and all the consequences it brings can be hit within the dynamics represented by mode A.

The probability of a breach of contract when commuting with mode A can be calculated using Fuss-Catalan numbers (Chin-Hung, 2011), as summarized in appendix and described in full detail in Vanhoyweghen and Ginis (2023). For example, if the agent consistently takes mode A for one month (20 working days), the probability of hitting the absorbing boundary is 82.4%. As the number of working days increases, this probability converges to certainty, as shown in Fig. 1.

Consequently, we can conclude that mode B trumps mode A without the need for assumptions regarding the utility derived from each travel mode or a personal aversion to unreliability. By considering the absorbing boundary and the resulting non-ergodic nature of travel time, we deduce that among transportation options with identical expected travel times, the one with more reliability is favoured.

2.1.2. The impact of the expected travel time and the travel time variation

In this thought experiment, we expand our setup to include travel modes with different expected travel times and variances. The same work contract still binds the agent. However, the agent now has the option between mode C and D, see Table 1. Mode C has a shorter expected travel time but more variation, resulting in the agent arriving either 24 min early at 8:36 or at 9:12, 12 min late. Mode D makes the commute potentially longer but has less variance. Mode D allows the agent to arrive either 6 min early or 2 min late, arriving at 8:54 or 9:02, respectively. Because of the severity of the punctuality clause,

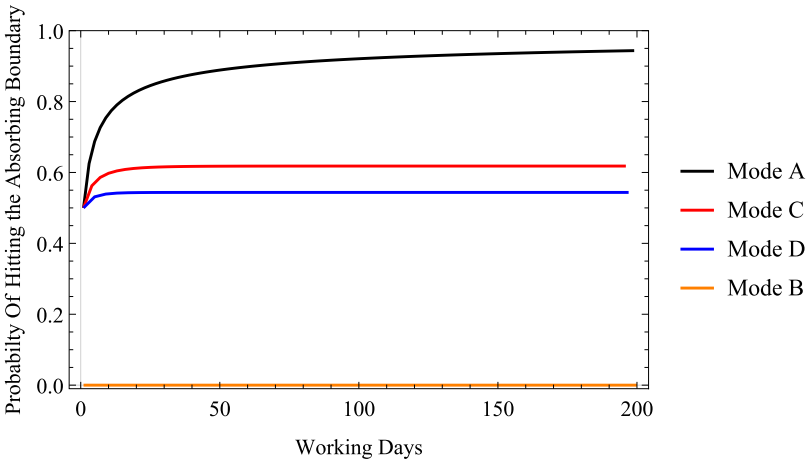

Fig. 1. The evolution of hitting the absorbing boundary over working days for travel modes A, B, C, and D, as outlined in the thought experiment discussed in Section 2.1.1. Mode B never hits the absorbing boundary while A hits the boundary almost surely, i.e. $p_{\text{hitting boundary}} = 1$, when working days$(T) \to \infty$.

neither mode can exclude the possibility of breaching the contract. As stipulated in the setup, when it comes to travel time, mode C is expected to outperform mode D, being, on average, 4 min faster. Unfortunately, this does not translate to higher job retention.

Within 20 working days, the commuter has a chance of 61.1% of hitting the absorbing boundary job when using mode C, compared to 54.3% when using mode D. These odds worsen only slightly when $t \to \infty$, resulting in a probability 61.8% of hitting the boundary for mode C, and 54.4% for mode D. Intuitively, for every early arrival with mode C the agent can be late twice, for mode D the agent can be late three times every time they arrive early. The odds in the limit $t \to \infty$ are obtained using difference equations, which we explain in detail in the appendix. These difference equations allow us to generalize our findings to any additive dynamic with an absorbing barrier that has discrete integer outcomes, e.g. to any mode with integer normalized travel times.

To facilitate a clear discourse on the impact of expected travel time and travel time variance, we limit ourselves to discussing hypothetical modes with only two possible travel times expressed in minutes. The amount of possible travel times or the units used do not change our findings or the arguments in this paper. Limiting the decision to modes with only two travel time outcomes that are equally likely allows us to condense the travel mode down to Fig. 2. This contour plot transparently illustrates the trade-off between the normalized expected travel time and its standard deviation. Furthermore, this plot allows a direct comparison between different travel modes. For example, marked in red, mode C has a normalized expected travel time of six minutes early with a standard deviation of 18 min. Mode D, marked in blue, is expected to arrive 2 min early with a standard deviation of 4. This figure illustrates how expected travel time and travel time variance contribute to the possibility of getting fired.

There are two possible venues to make travel mode C as attractive as mode D, i.e. equal probability of hitting the absorbing boundary. The first is to increase its top speed by 12 min so that taking the new and improved mode C results in the agent arriving either 36 min early or 12 min late. The second is to maintain its top speed but improve its reliability by decreasing its delays by 4 min, resulting in the mode arriving either 24 min early or 8 min late. These interventions equalize the odds of hitting the absorbing barrier, which allows different modal characteristics, such as the travel length, to determine the modal choice. More broadly, the thought experiment shows that travel time alone is an insufficient criterion for judging a travel mode and that relatively small improvements to reliability go a long way in inducing modal shifts.

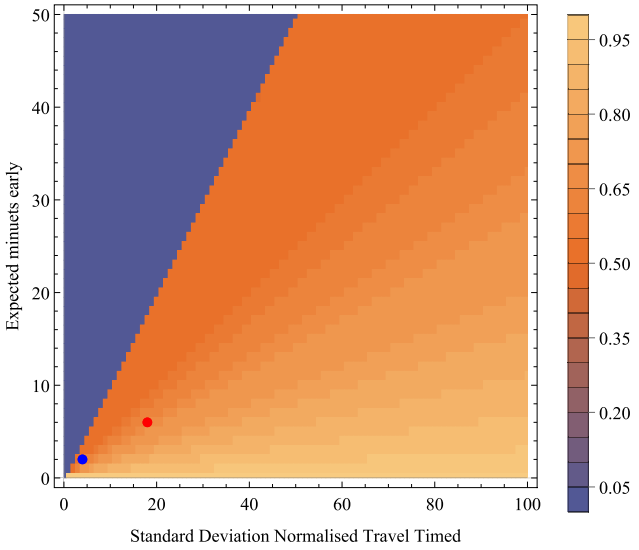

Fig. 2. The contours and their associated colour indicate the probability of hitting the absorbing boundary. Coordinates can be converted to equally likely travel time outcomes by using the following change in parameters: $\text{Outcome}_1 = \mu + \sigma$ and $\text{Outcome}_2 = \mu - \sigma$. The dark blue area on the left relates to travel modes that arrive on time no matter the outcome, i.e. Outcome_1 and $\text{Outcome}_2 \geq 0$. Mode D is marked in blue, and mode C is marked in red, which shows the higher hitting probability tied to using mode C. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.1.3. *A more flexible work contract*

Imagine a work contract with a more relaxed punctuality clause, which allows an agent to exceed the punctuality clause by K additional minutes. This more relaxed punctuality clause reduces the agent's vulnerability to delays. Allowing a small excess of 5 min does not improve the odds of not hitting the boundary for the commuter using mode C, who also exceeds this more relaxed clause 61.8% of the time. However, for the user of mode D, the situation improves significantly from a hitting probability of 54.3% to 16.1%. Fig. 3 shows that the odds of not hitting the boundary improve further as the tolerance increases regardless of the mode. However, no matter the tolerance, using mode D will always result in the lowest probability of getting fired. A large enough tolerance makes hitting the boundary, e.g. getting

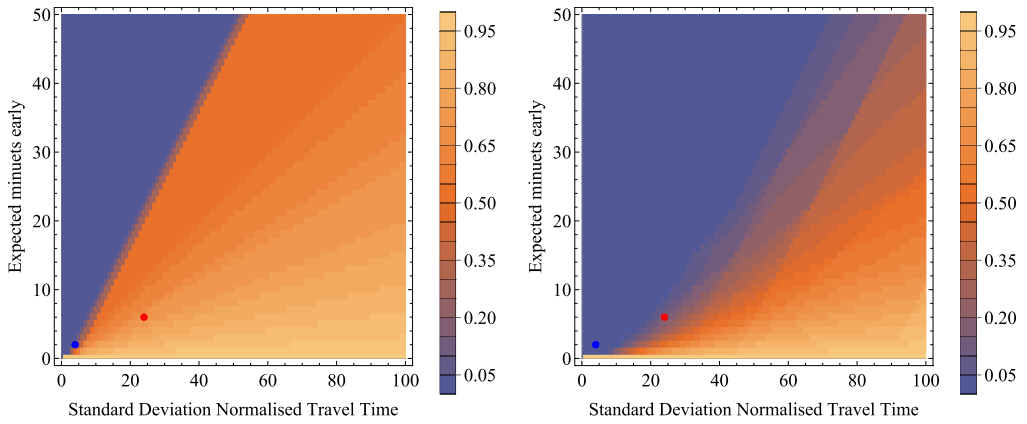

Fig. 3. The left panel contour plots the probability of hitting the boundary when the agent is allowed to accumulate an additional 5 min of delay. The right contour plot illustrates the same but when 90 additional minutes are allowed. The higher the allowance, i.e., the further the absorbing barrier, the greater the blue area where the odds of hitting the boundary get close to zero. The odds of hitting the boundary, e.g. a breach of contract, for mode C is 16.1% in the left panel and $1.23 \times 10^{-10}\%$ in the right panel. The probabilities for mode D are 61.8% and 2.1%, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

fired due to tardiness, incredibly unlikely for both modes, making the ergodic assumption an increasingly appropriate approximation of the experienced dynamic. In that case, the absorbing boundary has minimal bearing on the modal decisions, which enables the user to use different variables to select their preferred travel mode, such as journey length.

This more relaxed punctuality clause bolsters (in particular) the impact of interventions that reduce delays. For instance, an extra allowance of 10 min coupled with a 4-min delay reduction for mode C lowers the agent's odds of losing their job from 61.8% to 29.6% while speeding up mode C's top speed by 12 min, and the same 10-min allowance only reduces it to 54.4%.

2.1.4. Early departures and flexibility preferences

In this thought experiment, the agent can start their commute earlier depending on the travel mode used. However, as a necessary limitation, we assume that an agent has a given earliest desirable departure time. The earliest desired departure time sets a natural boundary for judging travel times and their outcomes. Early departures allow the agent to reduce the odds of hitting the absorbing barrier by making minor adjustments to their routine. Additionally, the earliest desirable departure time excludes travel modes with excessive travel lengths, which would require an insurmountable change in travel schedule. For instance, leaving 4 min early and arriving 4 min earlier reduces the odds of the agent hitting the absorbing boundary to zero for mode D. However, a very slow but reliable mode, which always takes precisely 5 h to get to work, will exceed the agent's departure time tolerance.

In reality, departure times are constrained beyond an agent's intentions. One such limitation is the frequency and flexibility associated with each mode. For instance, mode D could be available only once per hour, requiring the agent to leave one hour earlier to combat the full extent of the punctuality clause. In contrast, if we assume that mode C is highly flexible, the agent will only need to leave 12 min earlier to guarantee timeliness. The high flexibility of mode C allows the agent to regain control by making a minor adjustment to their travel schedule, while mode D requires a significant adjustment. This highlights how frequency and flexibility preferences follow from a desire to be punctual rather than idiosyncratic preferences. Frequency and flexibility enable or disable an agent's control in avoiding the absorbing barrier. For example, when choosing between taking the train or the car, if the train is more reliable but very infrequent, taking the car will not only be preferred, but will also encourage the user to take on additional journeys they would not have taken in its absence (Urry, 2004).

2.2. The airport-bound journey

The final thought experiment looks at the airport-bound journey, which has the harshest absorbing barrier. Before, some flexibility was allowed regarding tardiness; however, when catching a flight, being late cannot be offset by any future or past punctuality. As long as the journey length does not require the agent to breach their earliest departure time, the mode that can guarantee timely arrival will always be preferred. Using the same travel modes and characteristics as for the work commute, we obtain the following modal preferences. Mode B has a 0% chance of arriving late and is preferred over all other modes, which have a 50% probability of missing the plane. If mode B is unavailable, determinants which empower the agent, such as the possibility of early departure or flexibility, will determine the preferences of modes A, C, and D. Only when the agent cannot improve their odds of hitting the boundary will other preferences such as travel length determine the preference relation of the modes of transportation.

2.3. The large n interpretation

In the above thought experiments, we explore the impact of an absorbing boundary on an individual agent. We showed that expected travel time does not accurately describe the realm of a single agent when an absorbing barrier is present. However, in large mobility systems, we care about what happens to the collective rather than to a single agent. For instance, consider a government that wants to shorten the daily commute of its citizens ($n = 500$) and therefore incentivizes or mandates the use of mode C, which has a shorter expected travel time over mode D. Given that mode C has an expected time save of six minutes, the government expects an overall time save of 5 h every working day. Unfortunately, if punctuality clauses bind its citizens, this well-intended intervention has quite an adverse effect, as shown in Fig. 4.

Rather than saving time, the intervention has caused most of its residents to breach the strict punctuality clause of their work contract, here represented by the median in blue. More precisely, after 50 work days, 58% of residents have hit the absorbing boundary and are out of a job because of it. This aligns with the predictions obtained from the Fuss-Catalan numbers (Vanhoyweghen and Ginis, 2023), which tell us that about 62% of commuters will have hit the absorbing barrier after 50 working days regardless of the population size. This results in less time saved, all the while subjecting most of its population to the ill effects of the absorbing boundary. Given the choice between modes C and D, the government should push mode D, which will cause

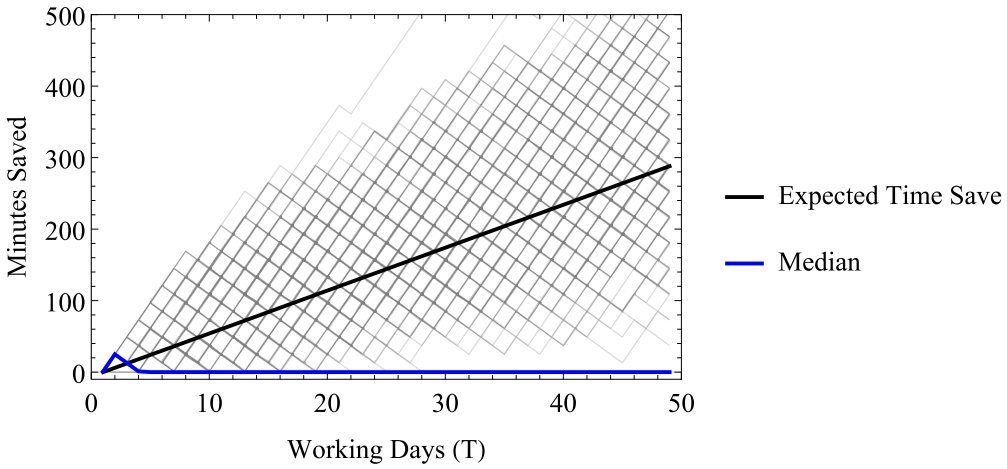

Fig. 4. Evolution of time saved for $n = 500$ simulated Monte Carlo agents using mode C (+24, −12) for their commute. Each grey line shows the trajectory of a single agent's cumulative time saved over consecutive working days. When an agent's cumulative time saved drops below 0 min, they hit the absorbing boundary (i.e., are fired), and their trajectory remains at 0 thereafter. The blue line indicates the median time saved across all agents at each time step (representing the most typical outcome), while the black line shows the expected (mean) time saved. Most agents initially accumulate time saved in line with the expected value, but as more agents cross the absorbing boundary and are absorbed, the median diverges from the mean. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

fewer layoffs and save more time for commuters in the long term. In summary, expected travel times are a poor proxy for individual experiences and a poor metric for large-scale travel optimization when impactful absorbing barriers exist.

3. Discussion

3.1. Thought experiments and reliability

Numerous academic studies have extensively examined the significance of reliability(variance) as a criterion for transportation and modal choice (Chen et al., 2003; Carrion and Levinson, 2012; Hollander, 2010). Our study deviates from this norm by not simply adding reliability as an extra factor but rather by concentrating on simplified real-world scenarios. We emphasize how constraints and boundaries influence decision-making in these real-life scenarios, highlighting the need for timeliness and the increased importance of reliability. Our hypothetical scenarios demonstrate the crucial role of consistent travel time, revealing that a slower, more dependable mode of transport may often be more optimal and preferable (Debbaghi et al., 2025). This finding is crucial for urban development and policy formulation, indicating that enhancing reliability could be more effective in changing transportation preferences than merely reducing travel times. Our study also critiques the focus on optimizing travel time, proposing an alternative model grounded in actual travel experiences. This model accounts for the non-ergodic nature of travel choices.

Our hypothetical scenarios have illustrated that when faced with absolute constraints, there is a mathematical tendency to favour timely and adaptable transportation options. These scenarios assume that such constraints affect everyone equally. Nevertheless, to better mirror reality, we acknowledge the subjective nature of these constraints. Their impact and implications can vary based on individual circumstances. For instance, the flexibility to compensate for tardiness at work by working later hours contrasts with the rigidity of fixed commitments like childcare pickups or scheduled meetings. Our model reflects this by differentiating between various scenarios, such as commuting to work versus travelling to the airport, where the former permits early arrival to compensate for lateness, unlike the latter.

Nevertheless, the hypothetical scenarios provide a very clinical perspective on travel time, travel time uncertainty, and absorbing boundaries. In real-life situations, there are many more reasons someone desires to be punctual without the presence of an as impactful as an absorbing boundary as getting fired. For instance, the absorbing boundary of missing a dentist appointment or a family gathering also has the potential of instilling long-term effects one would rather avoid. Moreover, within our thought experiments, we make no assertion about the source of the uncertainty and variations in travel time. Uncertainty could originate from predictable sources, such as rush hour, or unpredictable sources, such as a technical defect. Additionally, a user's experience with a certain mode could also impact the perceived reliability of a mode (De Witte et al., 2013). In practice, the source of unreliability can mitigate or strengthen its impact, making unreliability easier or harder to adapt to for a user (Carrion and Levinson, 2012).

In summary, while our model accounts for both strict and lenient constraints, it does not fully capture the diversity of personal situations and demographics. Future models must be expanded to include additional confounders and variables, such as age, travel cost, and convenience, within the time-averaging optimization framework for mobility decisions. Moreover, the proposed model must be validated beyond the proposed thought experiments using empirical transport data and current state-of-the-art techniques, such as Agent-Based Models, to be a valid alternative to current transport models. Nevertheless, this null model of modal decisions in a non-ergodic world represents an important shift in perspective, allowing us to think about modal policies from a new vantage point.

3.2. Multi-modality

Multi-modality is often seen as one of the cornerstones of effective urban planning and transport systems, integrating various modes of transportation to create a cohesive, efficient, and accessible network (Alessandretti et al., 2022; Spickermann et al., 2014). This approach recognizes the complexities of modern travel demands and aims to offer seamless transitions between different transportation methods, such as buses, trains, bicycles, and walking paths. By facilitating easier and more efficient transfers, multi-modality strives to enhance the overall travel experience, reduce congestion, and contribute to environmental sustainability.

While we do not explicitly introduce multi-modal transportation in our thought experiments, the travel times studied in this paper could result from a multi-modal displacement, resulting in the same findings. However, these findings are likely an underestimation of the impact of unreliability on multi-modal transportation. A multi-modal trajectory would be more susceptible to the negative impact of unreliability.

Missing the departure of the next mode because of a delay in the previous mode could cause a cascade of additional delays, making multi-modal transportation only as strong as its weakest chain.

3.3. Implications

Accounting for ergodicity could enhance the accuracy of predictions in theoretical transportation models. This consideration might lead to more precise depictions of modal splits in the context of four-step models. Similarly, agent-based models, accounting for non-ergodicities, could bring simulations closer to real-world dynamics by incorporating the relevant absorbing boundaries. Importantly, this time-average perspective is not about supplementing models with additional individual risk factors, but about recognizing that environmental constraints – such as absorbing boundaries – define which modes remain viable or attractive in the long run.

Our findings have implications for urban and transportation planning that extend beyond the theoretical realm and lend themselves to interpreting the variety of absorbing boundaries present within mobility choices. The impact of absorbing barriers and non-ergodicity on individual travel choices underscores the need for policy approaches that are more in tune with genuine travel experiences. Given these insights, several policy recommendations emerge to induce modal shifts. For instance, a policy that has gained increasing prominence after the Covid-19 pandemic is to encourage flexible work hours (Hopkins and Bardoel, 2023), which reduce or weaken the consequences of absorbing barriers related to travel time and promote less reliable modes. This could induce a shift from a reliable, flexible, but polluting mode to a more unreliable, less flexible, but cleaner mode. In a similar vein, enhancing the reliability of a mode of transport is of much greater import than speeding it up. Therefore, to induce a green modal shift, it is paramount to make sustainable modes of transportation as reliable as possible.

Furthermore, we find that this desire for reliability goes beyond personal preferences but is caused by the environment in which decisions are made, i.e. it is the optimal behaviour in the presence of an absorbing boundary. This shows that when a boundary is present, improving the reliability of a transport mode is more efficient than speeding it up. Increasing the importance of reliability over speed in the transportation discussion could lead to new and potentially cheaper ways of inducing modal shifts. Improving reliability does not necessarily require large investments, depending on the source of the unreliability. For example, schedules can be updated relatively easily, but replacing old and unreliable equipment requires considerable investments. These changes target the environment rather than individual preferences.

Lastly, other absorbing barriers present in mobility choices can be used to discourage undesirable travel behaviour, such as driving too fast. For example, a driver's license with points introduces an absorbing barrier with negative consequences. The impact of this absorbing barrier increases as a driver loses more points, i.e., the closer they get to the barrier. For this type of barrier to be effective, it needs to ensure equal skin in the game for everyone, and the impact of hitting it needs to be significant. Another way to ensure equal skin in the game is by employing a fining system that scales with wealth (Kantorowicz-Reznichenko, 2015). This way, a fine has an equally dissuading impact on everyone, as it places everyone equally far from financial ruin, i.e., how many fines they can receive before they have far-reaching consequences. This aligns with other work on non-ergodicity in additive dynamics with ruin Vanhoyweghen and Ginis (2023) and multiplicative dynamics settings (Peters, 2019). Most of these policy recommendations rely solely upon and limit themselves to the non-ergodicity of travel time. Investigating other sources of non-ergodicity could help provide further insights. One interesting area for further investigation beyond the scope of this paper is the non-ergodicity of the health impact related to different travel trajectories. For example, One person commuting daily through a very polluted traffic axis will have a higher probability of health issues than many people travelling through the polluted area once.

While our analysis is based on theoretical models and stylized thought experiments, empirical validation is a crucial next step for fully realizing the practical value of these insights. Future work could examine whether the patterns predicted by our framework are observable in real-world travel data or through choice-based conjoint experiments designed to capture repeated decision-making and the effects of absorbing boundaries. Such empirical investigations would help assess the extent to which absorbing boundaries and non-ergodic effects influence actual modal choices, and would be essential for guiding effective policy and model development.

In conclusion, our research introduces a novel modelling approach that explicitly incorporates absorbing boundaries and non-ergodic dynamics into the analysis of transportation choices. This perspective reveals that the commonly observed preference for reliability over speed can arise directly from environmental constraints rather than individual preferences alone. Our policy recommendations leverage these insights and suggest that modifying the structure of the decision environment, rather than targeting user attitudes, can be a more effective way to promote sustainable, equitable, and user-centric transportation systems.

CRediT authorship contribution statement

Arne Vanhoyweghen: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Vincent Ginis:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization. **Cathy Macharis:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Funding acquisition, Conceptualization.

Availability of computer code and algorithm

The computer code has been made available online at: https://github.com/Arne-Vanhoyweghen/Travel-Time-and-Uncertainty

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT-4o in order to improve the readability of the manuscript. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Computing: absorption probabilities

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Data availability

The computer code has been made available online at: https://github.com/Arne-Vanhoyweghen/Travel-Time-and-Uncertainty.

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