The effect of daily stress in activity patterns: Evidence from a naturalistic experiment

Eleni Papageorgiou[1], Carlos M. Lima Azevedo*[1], and Bastian Henriquez-Jara[2]

[1]Department of Technology, Management and Economics, Technical University of Denmark (DTU), Denmark
[2]Civil Engineering Department, Univeristy of Chile, Chile

Short summary

Stress is a ubiquitous factor in modern life, yet its behavioural consequences in real-world mobility remain poorly understood. Understanding how affective states influence daily activity organisation is central to advancing behavioural modelling in transportation. While laboratory evidence suggests that stress promotes habitual decision-making and reduces behavioural flexibility, empirical validation in real-world mobility contexts remains limited.
This short paper summarises a first effort to develop an interpretable probabilistic modelling framework linking latent physiological stress to daily activity behaviour using multimodal wearable, GPS, mobility diary, and ecological momentary assessment data from 119 participants in a multi-day naturalistic experiment. Daily stress exposures are then tested, together with past behaviour, in explaining activity patterns the following day. Daily activity organisation is analysed along two complementary behavioural margins: (i) activity intensity, measured through the count of distinct activity types undertaken during a day, and (ii) participation in socially oriented activity types. Activity intensity is modelled using Poisson count regression with temporally ordered stress predictors, while participation behaviour is analysed using logistic regression. Results indicate systematic associations between prior stress exposure and subsequent behavioural organisation. Higher lagged stress is linked to measurable proportional changes in activity intensity and altered probabilities of social participation. Robustness analyses confirm that these findings are qualitatively stable across alternative stress constructions and heterogeneous across population subgroups. The study empirically demonstrates the importance of affective dynamics in daily-activity decision making from a naturalistic perspective.

Keywords: daily activity patterns; stress; probabilistic model; wearables; naturalistic panel data; travel demand.

1 Introduction

Transportation behaviour unfolds in complex environments where individuals continuously adapt activity patterns in response to internal states and contextual constraints. Traditional activity-based modelling frameworks often assume stable preferences and rational decision making processes (Ben-Akiva et al., 2002). However, psychological and neuroscientific evidence suggests that stress alters decision processes, increasing reliance on habitual routines and reducing behavioural exploration (Schwabe & Wolf, 2009; Dias-Ferreira et al., 2009).
Recent advances in wearable sensing technologies enable continuous monitoring of physiological activation in everyday life (Smets et al., 2018). When combined with mobility traces and ecological self-reports, these data allow stress to be conceptualised as a dynamic latent variable embedded in activity systems (Onnela & Rauch, 2016). However, empirical evidence on how stress affects activity-mobility breadth remains scarce. Meanwhile, growing literature highlights the benefits of diverse daily activities for psychological well-being and cognitive function (Lee et al., 2018). For transport analysts, quantifying how stress exposure modifies activity participation can inform demand forecasting, behavioural interventions and personalised mobility services. This paper develops a first probabilistic behavioural modelling framework linking latent stress exposure to observable activity organisation using multimodal naturalistic sensing data.

2 Methodology

The Data

This study analyses data collected in the eMOTIONAL Cities project[1], which recruited 116 participants in Copenhagen (Lima Azevedo et al., 2025). For two weeks, participants wore Empatica E4 wristbands that measured heart rate, electrodermal activity, and skin temperature, and carried smartphones with a dedicated application. The latter continuously collected GPS data, detected activity and mobility episodes, allowed user validation and context provision, and prompted short ecological momentary, retrospective, and overall daily assessments (EMA, ERA, and EODA). These ecological assessment prompts included short questionnaires on perceived stress, affective arousal, and valence, each with 2 questions using an ordinal Likert scale ranging from 1 to 5. The data collection period extended over multiple consecutive days for each participant, covering both weekdays and weekends. This design enabled the construction of temporally ordered activity sequences and stress trajectories at the participant–day level. The dataset contained 13,848 observations activity episodes.
First, to infer daily stress for each individual i and activity t, we estimate arousal and valence from a previously estimated Integrated Choice and Latent Variable Model (Lima Azevedo et al., 2026). Arousal and valence are the two fundamental dimensions used to decompose emotions, which can be interpreted as the level of pleasure and the excitement of the emotion (Russell, 1980). Inspired by (Henriquez-Jara et al., 2025), the model maps latent valence (expected value $V_{i,t}$) and latent arousal (expected value $A_{i,t}$) to selected physiological features from the wristband and emotional statements. Both latent constructs are defined at the activity level; they vary across individuals and activities and can be influenced by exogenous variables and random effects. A directional stress index is then defined by projecting the latent affective state onto a stress-oriented axis specified by a direction vector $\mathbf{w}$:

$$\tilde{S}_{i,t} = \mathbf{w}^\top \begin{pmatrix} V_{i,t} \\ A_{i,t} \end{pmatrix}. \tag{1}$$

The direction vector $\mathbf{w}$ is specified as a unit vector encoding the theoretical stress direction associated with increasing arousal and decreasing valence. Specifically, we define

$$\mathbf{w} = \frac{1}{\sqrt{2}} \begin{pmatrix} -1 \\ 1 \end{pmatrix}, \tag{2}$$

such that higher values of $\tilde{S}_{i,t}$ correspond to affective states characterised by higher arousal and more negative valence.

Behavioural outcome and analytical unit

The unit of analysis is the participant–day pair (i, d), where i indexes individuals and d denotes an observed day. The behavioural outcome $Y_{i,d}$ is defined as the number of distinct activity types performed by individual i on day d. The behavioural outcome $Y^p_{i,d}$ indicates whether individual i performed an activity type p on day d. Daily activity categories are counted without regard to frequency or duration. Thus, repeated engagement in the same activity contributes once to the daily total. Our simple formulation of activity diversity still captures the breadth of daily behaviour and serves as a proxy for behavioural flexibility. Aggregating behaviour to the daily scale reflects the theoretical premise that stress operates as a regulatory process shaping the organisation of activities across an entire day rather than isolated episodes (Almeida, 2005). The choice of a count outcome motivates the use of generalised linear models suitable for discrete, non-negative data.

Daily stress predictors

Stress is inferred at the activity-episode level but aggregated to the day to align with the behavioural outcome. For each individual i and day d, let $\tilde{S}_{i,t}$ denote the stress value associated with episode t, derived via projection in valence–arousal space. The primary daily stress measure is the maximum episode-level stress:

$$\text{maxStress}_{i,d} = \max_{t \in T_{i,d}} \tilde{S}_{i,t}, \tag{3}$$

[1] https://emotionalcities-h2020.eu/

where $T_{i,d}$ denotes the set of episodes recorded on day d for individual i. Focusing on peak stress isolates intense stressors that may exert disproportionate influence on subsequent behaviour (Bolger et al., 1989; Schwabe & Wolf, 2009). To mitigate simultaneity between stress and same-day activity, the stress variable enters the model exclusively in lagged form, $\text{maxStress}_{i,d-1}$, representing the maximum stress experienced on the previous observed day. Lagging stress enforces a clear temporal ordering consistent with theories of stress recovery and behavioural carryover, thereby supporting causal interpretation.
To examine whether behavioral adjustment responds instead to cumulative exposure, an alternative specification replaces the primary stress predictor with the proportion of high stress episodes on the previous day. In this specification, cumulative high stress exposure does not exhibit a statistically significant association with next-day activity diversity once baseline controls are included. In contrast, peak stress intensity retains a weaker and less precise association relative to the baseline model. This comparison suggests that short term behavioral adjustment in this dataset is more closely related to salient stress peaks and their temporal positioning than to cumulative exposure across the day.

Baseline behavioural controls

The modelling framework includes baseline controls to account for structural influences on activity diversity:

- **Lagged activity volume** ($\text{numActivities}_{i,d-1}$): the total number of activity episodes performed by individual i on the previous day.
- **Weekend indicator** (isWeekend_d): equals 1 if day d is a weekend and 0 otherwise. Calendar effects capture institutional and scheduling differences that systematically affect activity diversity.

All covariates are aligned temporally such that predictors correspond to information available by the end of day $d-1$.

Statistical modelling framework

Activity intensity model

The relationship between lagged stress and next-day activity diversity is modelled using a Poisson regression with a log link. For each participant–day pair (i, d), the outcome $Y_{i,d}$ conditional on the vector of covariates $X_{i,d}$ follows a Poisson distribution:

$$Y_{i,d} \mid X_{i,d} \sim \text{Poisson}(\lambda_{i,d}), \tag{4}$$

where $\lambda_{i,d}$ denotes the conditional mean. The log link relates the mean to a linear predictor:

$$\lambda_{i,d} = \exp(\eta_{i,d}), \qquad \eta_{i,d} = \beta_0 + \beta_1 \text{numActivities}_{i,d-1} + \beta_2 \text{isWeekend}_d + \beta_3 \text{maxStress}_{i,d-1}. \tag{5}$$

Participant-level clustered standard errors are employed to account for within-individual dependence across days. Overdispersion is assessed using the Pearson dispersion statistic; when substantial overdispersion is detected, a Negative Binomial specification with dispersion parameter α serves as a robustness check. However, in this analysis the dispersion ratio was below one, indicating that the Poisson model is adequate.

Activity participation model

After analyzing the relationship between stress and the number of activities, we next aim to estimate the probability of participating in certain activities conditional on stress experienced the previous day. To narrow the scope, we focus on social activities, as the literature suggests that stress decreases the likelihood of engaging in them (daSilva et al., 2021). The probability of participation in a social activity type p is estimated using logistic regression with the same covariates as the activity intensity model. Estimated coefficients are interpreted as odds ratios representing proportional changes in the likelihood of social engagement.

$$Y_{i,d}^{p} \in \{0, 1\}, \tag{6}$$

$$\log \frac{\pi_{i,d}}{1 - \pi_{i,d}} = \gamma_0 + \gamma_1 \text{numActivities}_{i,d-1} + \gamma_2 \text{Weekend}_d + \gamma_3 \text{maxStress}_{i,d-1}. \tag{7}$$

The activity participation model captures a distinct behavioral margin relative to the activity intensity analysis. Whereas in the latter, the Poisson model examines how stress reshapes the composition and breadth of daily behavior, the logistic specification focuses on the binary decision to participate socially at all. Parameters of both models are estimated via maximum likelihood using `BIOGEME` (Bierlaire, 2003).

3 Results

Affectderived stress vs. selfreported stress

Daily stress trajectories were aggregated to the participant–day level by computing the mean ordinal stress level and cross-tabulated against the self-reported EODA stress scale also collected in the naturalistic experiment. The resulting distribution exhibits a clear monotonic pattern: as self-reported stress increases, probability mass shifts systematically toward higher levels of affect-derived stress (see Table 1). This ordinal redistribution validates that the projection-based stress index preserves the rank ordering of perceived stress intensity, supporting its interpretation as a meaningful operationalisation of daily stress exposure.

Table 1: Row-normalised cross-tabulation of self-reported daily stress and rounded mean affect-derived stress level.

	Mean Affect-derived Stress Level				
Self-reported Stress	1	2	3	4	5
1	0.0659	0.3413	0.2275	0.2455	0.1198
2	0.0162	0.1862	0.3158	0.2955	0.1862
3	0.0529	0.0794	0.3175	0.3280	0.2222
4	0.0606	0.0606	0.2879	0.1970	0.3939
5	0.0000	0.0000	0.2500	0.3333	0.4167

Within-Day Stress Dynamics: Sequence-Based Evidence

For each participant–day, $\tilde{S}_{i,t}$ values form a variablelength sequence (range 1–48 episodes per day; mean of 9.20, σ of 6.68). The set of continuous stress trajectories $\tilde{S}_{i,t}$ was then compared using Dynamic Time Warping (DTW), which preserves magnitude and temporal alignment. Mean DTW distances are 2.239 for between-group pairs, 2.038 for within non-stressful pairs, and 2.210 for within stressful pairs. The difference between between-group and within-group distributions is statistically significant (Mann–Whitney 1.20×10^{-6}; KS 1.03×10^{-5}). This demonstrates that stressful days are not characterized by distinct symbolic patterns, but they do exhibit measurable differences in compositional structure and continuous trajectory similarity.

To examine whether stress exposure is associated with differences in daily behavioral allocation, daily activity counts were compared across stressful and non-stressful days using non-parametric tests. Several activity categories exhibit statistically significant differences. The strongest effect is observed for Work ($p = 9.58 \times 10^{-11}$), followed by Home ($p = 2.78 \times 10^{-5}$). Additional significant differences are detected for Personal Errands/Tasks ($p = 2.77 \times 10^{-3}$), Metro ($p = 2.83 \times 10^{-3}$), Eat Out/Takeout ($p = 1.06 \times 10^{-2}$), and Socialize ($p = 4.06 \times 10^{-2}$). These results indicate that stressful days are associated with systematic shifts in daily activity composition rather than random fluctuations. In particular, both routine domains (e.g., Work, Home) and discretionary activities (e.g., Eat Out/Takeout, Socialize) display measurable differences under stress. Importantly, these comparisons are contemporaneous and descriptive. They do not establish temporal direction or causal ordering. However, the presence of structured activity differences provides empirical motivation for the behavioral modeling framework developed in the following sections.

Activiy intensity model results

The estimation sample comprises 1,389 participant–day observations with complete lagged predictors. Table 2 reports incidence rate ratios (IRRs), 95 % confidence intervals and p-values from the Poisson model from Section 2. An IRR greater than one implies that increases in the covariate are associated with higher expected activity diversity, whereas an IRR less than one indicates a

negative association.

Table 2: Poisson regression results for daily activity diversity. Participant-level clustered standard errors are used.

Covariate	**IRR**	**95 % CI**	p**-value**
Lagged peak stress ($\text{maxStress}_{i,d-1}$)	1.046	[1.001, 1.092]	0.045
Lagged activity volume ($\text{numActivities}_{i,d-1}$)	1.010	[1.007, 1.013]	< 0.001
Weekend indicator (isWeekend_d)	0.89	[0.85, 0.93]	< 0.001

Lagged activity volume exhibits a highly significant positive effect. Each additional activity recorded on day $d-1$ increases expected diversity on day d by approximately 1 % (IRR = 1.010). This result underscores the need to control for prior busyness when studying behavioural reorganisation. The weekend indicator has an IRR of 0.89, implying an 11 % reduction in activity diversity relative to weekdays. This effect reflects more consolidated routines on weekends, consistent with institutional and scheduling constraints. Yet, non-linear effects should be explored in future modeling efforts.

Contrary to the expectation that stress narrows behavioural repertoires, lagged peak stress is positively associated with next-day activity diversity (IRR = 1.046). A one-unit increase in the maximum stress experienced on the previous day corresponds to a 4–5 % increase in the expected number of distinct activities. Note that stress is projected on the stress axis defined by $(\text{Arousal} - \text{Valence})/\sqrt{2}$; thus, a one-unit increment represents a shift toward higher arousal and lower valence. The positive association suggests that participants engage in slightly more varied activities following acute stress episodes. This result could reflect compensatory or coping behaviour: following periods of elevated stress, individuals may engage in a broader range of activities as part of an approach-oriented coping response (Dijkstra et al., 2016). The finding also highlights the temporal scale of stress effects—short-term adaptations may differ from the long-term tendency toward habitual behaviour observed in laboratory studies (Smeets et al., 2023).

To examine whether the association between lagged stress exposure and next day activity intensity varies systematically across individuals, we explored heterogeneity along two theoretically relevant dimensions: stated sleep quality in $d-1$ and age group, also collected in the naturalistic experiment. Across all specifications, there is no statistically robust evidence that the stress–behavior relationship differs by sleep quality or age. Interaction terms between lagged peak stress and poor sleep, as well as interactions with middle and older age groups, are not statistically significant and exhibit wide confidence intervals.

Activiy participation model results

While the main specification models next-day activity diversity as a count outcome, stress-related behavioural adaptation may also operate along a more discrete margin. A social participation outcome, for example, would captures the occurrence of engagement in activities labeled `Socialize`, `Entertainment`, `Eat Out/Takeout`, and `Community/Religious`, irrespective of their frequency or duration.

The results in Table 3 for the model from Section 2 for social activities show that weekend days exhibit a substantially higher likelihood of social participation, consistent with institutional scheduling constraints and greater availability of discretionary time. Lagged peak stress shows a positive association with the probability of social activity participation. This lagged association could be sustained by daily stress process models suggesting that stressors influence behavioural and affective functioning beyond the immediate episode (Bolger et al., 1989). One potential behavioural response is the mobilisation of social interaction as a coping resource (Cohen & Wills, 1985).

Table 3: Logistic regression results for social activity participation.

Covariate	**Odds ratio**	**95 % CI**	p**-value**
Lagged peak stress ($\text{maxStress}_{i,d-1}$)	1.427	[1.105, 1.842]	0.006
Lagged activity volume ($\text{numActivities}_{i,d-1}$)	1.024	[1.007, 1.042]	0.006
Weekend indicator (isWeekend_d)	1.704	[1.328, 2.186]	< 0.001

To further explore these relationships, separate logistic regression models are estimated for next-day participation in each recorded activity category individually, including both social and non-social

activities. Each model uses the same baseline specification as the aggregate analysis. This exercise is descriptive rather than inferential and aims to identify domain-specific patterns in how lagged stress relates to subsequent activity participation.

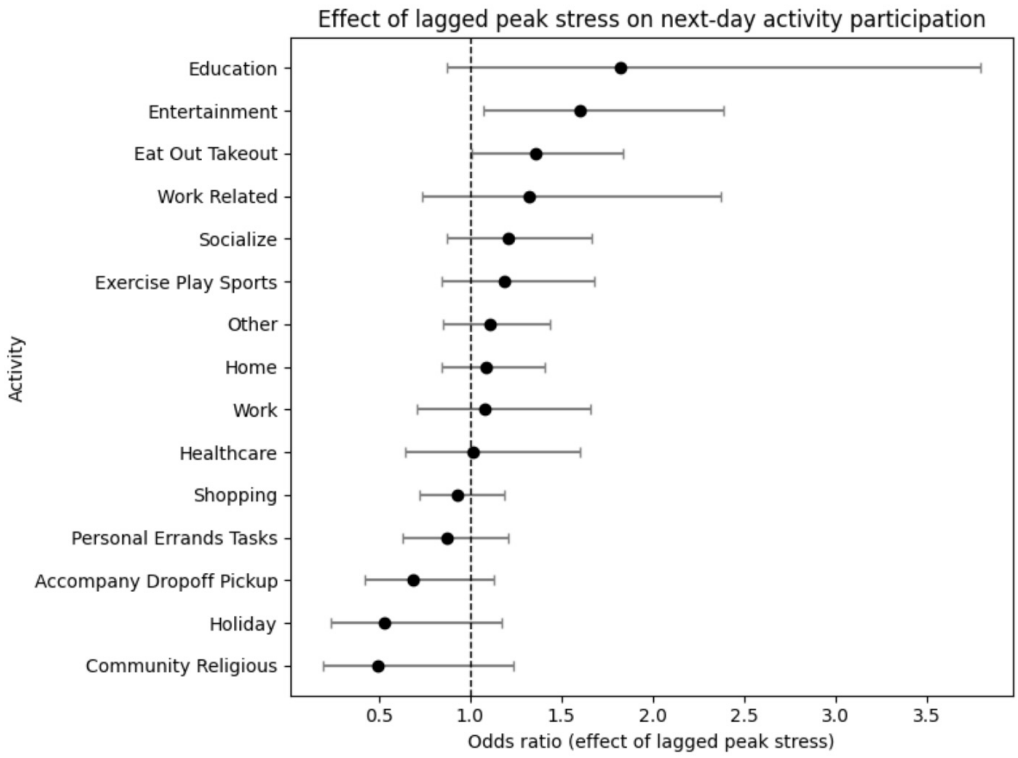


Figure 1: Exploratory activity-specific associations between lagged peak stress and next-day participation in each activity category. Points denote odds ratios from separatelogistic regressions estimated for each activity type; horizontal bars represent 95% confidence intervals. The vertical dashed line indicates no association (OR = 1)

For routine or necessity-driven activities, such as `Home`, `Work` and `Shopping`, estimated odds ratios are close to unity, with confidence intervals that typically span the null. This pattern suggests that participation in these activities is largely insensitive to short-term stress fluctuations once baseline activity volume and calendar effects are accounted for. In contrast, a subset of more discretionary and leisure-oriented activities, most notably `Entertainment` and `Eat Out/Takeout`, exhibits odds ratios consistently above one. Although uncertainty remains at the activity-specific level, the direction and relative magnitude of these estimates suggest that the positive aggregate association between lagged stress and social participation is driven primarily by selective increases in engagement with discretionary activities rather than by a uniform shift across all forms of daily behavior.

Several activity categories, such as `Education` and `Community/Religious`, are characterized by wide confidence intervals. While the first has a low prevalence in the data set, the second can be associated with a more unstructured-schedule and variable-experience natures.

Overall, this exploratory activity-level decomposition clarifies that stress-related behavioral adaptation operates through selective reallocation across activity types. Rather than inducing a generalized increase or decrease in social engagement, elevated stress appears to be followed by changes concentrated in specific discretionary activities. This pattern complements the aggregate social participation results and reinforces the interpretation that stress reshapes the composition of daily behavior rather than uniformly expanding or contracting routines.

4 Conclusion and Discussion

This short paper demonstrates how latent stress estimated from wearable sensors can be linked to daily activity decision making. We explore a theoretically motivated behavioural outcome and analytically align stress predictors and controls. The empirical findings reveal that higher stress on

one day is associated with a modest increase in the diversity of activities on the next day, whereas weekends and lower prior activity volume reduce diversity. These insights suggest that individuals may respond to acute stress by diversifying their activities, potentially as a coping mechanism.
The logistic regression analysis indicates that social activity participation is systematically related to both temporal structure and prior behavioural engagement. Importantly, lagged peak stress shows a positive, statistically significant association with subsequent social participation, indicating that stress exposure influences behaviour along a discrete participation margin in entertainment-related social activities.
Overall, the results suggest that stress affects not only the breadth of activity portfolios but also the likelihood of engaging in socially oriented activities.
The findings of this study should be interpreted in light of several methodological and data-related limitations. First, stress is inferred from latent affect estimates derived from wearable signals, introducing potential measurement error and reliance on modelling assumptions regarding the valence–arousal representation. Second, the modelling framework relies on relatively reduced-form specifications that do not explicitly account for unobserved individual heterogeneity, which may lead to residual confounding if stable preferences or lifestyle traits jointly influence stress exposure and activity behaviour. The use of lagged explanatory variables provides temporal ordering but does not fully resolve potential endogeneity arising from feedback processes between stress dynamics and activity choices. The count and binary outcome models treat daily behaviour as independent realisations, thereby abstracting from richer dynamic dependence and within-day sequencing that could be captured through panel, duration, or state-transition modelling approaches. Finally, activity classification and recording intensity vary across individuals and days, potentially affecting the precision of behavioural indicators. These limitations highlight the need for replication using larger samples, alternative stress operationalisations, and dynamic modelling approaches.
For transport planners and travel behaviour researchers, incorporating dynamic internal states like stress into activity-based models could improve predictions of demand and inform interventions aimed at promoting well-being. Stress-aware mobility services might leverage wearable data to detect stress episodes and recommend varied activities or routes that alleviate stress. From a behavioral perspective, these findings also raise questions about the strategies individuals use to cope with stress, and about how activity and transport systems facilitate (or constrain) the management of daily stress.

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