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Exposure to built and social environments and momentary well-being: A geographic ecological momentary assessment study in Montreal

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ABSTRACT

Understanding how built and social environments shape momentary well-being is essential for advancing urban health research and planning. This study investigated temporal, social, and environmental predictors of daily well-being using a geographic ecological momentary assessment (GEMA) approach. Seven-day GEMA measures were collected between 2018 and 2021 among 889 residents of Greater Montreal, recruited through the INTERACT and REM studies. Participants (mean age = 41.7 years; age range = 18–80 years; 55.7% women) completed the Short Mood Scale three times daily via the EthicaData smartphone app, yielding over 10,600 prompts linked with GPS data. Multilevel mixed-effects models were used to assess the associations between well-being and temporal, social, and environmental exposures. Well-being varied significantly across time and contexts (conditional $R^2 \approx 0.6$). Higher well-being was reported in the afternoon (β = 0.23, 95% CI: 0.03–0.43) and on weekends, particularly Sundays (β = 1.11, 95% CI: 0.74–1.49), whereas evenings were associated with lower well-being (β = –0.31, 95% CI: –0.52 to –0.10). Social interactions, especially with friends (β = 1.97, 95% CI: 1.26–2.67) and family (β = 0.83, 95% CI: 0.42–1.25), were strongly associated with higher well-being. Built environment features, including greenness, proximity to parks, and road density, showed limited associations. Older adults (60–80 years) reported substantially higher well-being than younger (18–40) adults (β = 4.31, 95% CI: 3.44–5.18). An interaction indicated that women reported lower well-being than men when surrounded by others without direct interaction (β = –0.66, 95% CI: –1.17 to –0.09). Temporal rhythms, age, and social interactions were central determinants of momentary well-being, while built environment factors played a lesser role. Integrating GEMA approaches provides robust evidence to inform urban planning and public health strategies that promote supportive social and temporal environments.

1. Introduction

Well-being is increasingly recognized as a cornerstone of population health, shaping both life expectancy and quality of life (Diener et al., 2018; Huppert, 2017). It encompasses two complementary dimensions: hedonic well-being, reflecting momentary affective states such as happiness, calmness, or fatigue, and eudaimonic well-being, referring to longer-term experiences of meaning, purpose, and life satisfaction (Deci and Ryan, 2008; Ryan and Deci, 2001). While both are vital, hedonic well-being is especially sensitive to immediate physical and social contexts, making it a powerful indicator of how daily exposures shape mental health. Ecological momentary assessment (EMA) offers a unique opportunity to capture these short-term fluctuations in real time, reducing recall bias and linking subjective experiences to specific environmental and social exposures (Dunton, 2017; Shiffman et al., 2008; Stone and Shiffman, 1994). Despite rapid advances in environmental psychology, urban studies and public health, the way daily exposures to built and social environments contribute to our mental well-

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being needs to be better understood (Helbich, 2018). To that end, researchers are increasingly interested in observing real-life exposures to understand the interdependent and complex influences of city living on mental health and well-being (Jiang et al., 2024; Reichert et al., 2016; Wedyan and Saeidi-Rizi, 2024).

Until recently, a significant portion of the evidence was derived from epidemiological studies demonstrating a mere association between access to or availability of resources in residential areas and human health and well-being (Reyes-Riveros et al., 2021; van den Berg et al., 2015). With developing technology facilitating momentary data collection and location tracking, more studies have considered environmental exposure across an individual's activity space (Fancello et al., 2023; Kwan, 2018; Mennis et al., 2018). Today's growing ubiquity of smartphones and wearables makes it possible to collect and analyze intensive longitudinal data, often combining passive data collection, including location, with self-reports about psychological states, behaviour or physical health (Kestens and Kingsbury, 2024; Trull and Ebner-Priemer, 2014). Momentary reports provided by participants as they go through their daily activities can limit recall bias, often associated with retrospective assessments (Dunton, 2017; Ebner-Priemer and Trull, 2009; Wilhelm and Schoebi, 2007). Contextual parameters can also be used to trigger e-diaries or prompts, for example allowing the assessment of momentary well-being in areas with varying degrees of urban green space, such as inner-city parks (Kanning et al., 2022; Törnros et al., 2016).

Building on these methodological advances, an expanding body of research has provided empirical evidence linking daily exposures to natural and built environments with momentary and long-term aspects of mental well-being. Various studies have shown the positive effects of exposure to greenness or natural environments on mood, attention restoration, and stress reduction (Berto, 2014; Fancello et al., 2023). For instance, the frequency and duration of outdoor green space visits and time spent in one's garden were correlated with lower rates of depression and greater social cohesion (Cox et al., 2018; Shanahan et al., 2016). On the other hand, studies indicate that individuals with lower socioeconomic status (SES) derive more significant health benefits from exposure to certain features of the built environment than those with higher SES (Mitchell et al., 2015; van den Berg et al., 2016). Additionally, (Li et al., 2018) observed that daily exposure to greenery was linked to a better mood at the end of the day. In addition, exposure to disordered spaces (broken windows, litter, and cracked sidewalks) was linked to momentary spikes in pain and fatigue among older adults, indicating real-time physical and mental impacts of environmental features (York Cornwell and Goldman, 2020). Exposure to urban greenspaces, such as accessible parks, has been linked to anxiety and mood disorders (Nutsford et al., 2013), while green and blue environments have been linked to physical activity and social interaction (Grellier et al., 2017; Lachowycz and Jones, 2013; Sugiyama et al., 2008). These findings emphasize the need for comprehensive urban planning that leverages natural environments to enhance mental well-being.

This paper focuses on momentary well-being, particularly exploring how both social and built environmental contexts influence it. In doing so, we consider a range of contextual dimensions—from social interactions, social exclusion, and deprivation, to features of the physical environment such as neighborhood structure and exposure to green spaces—that together shape individuals' momentary emotional states in daily life. Up to now, research using cross-sectional survey data has highlighted several important patterns. Using cross-sectional survey data (SHARE, Wave 5), (Terraneo, 2021) finds that material and social deprivation correlate with higher stress and lower quality of life among older adults. Bellani and D'Ambrosio (2011), using European panel data, show that both material deprivation and social exclusion significantly reduce life satisfaction, with social exclusion exerting an independent and particularly strong negative effect. Steinmetz-Wood et al. (2017) and Freeman (2012) reveal that gentrification can improve collective efficacy but also increase psychological distress, especially among vulnerable groups (Tran et al., 2020). These studies underscore the psychosocial effects of gentrification and provide insights into factors affecting momentary well-being.

It is important to note that the studies cited above are not based on EMA designs and primarily rely on cross-sectional or longitudinal survey data. While this body of work demonstrates that neighbourhood social conditions such as deprivation, social exclusion, and gentrification are associated with broader indicators of mental and emotional health, EMA research has to date paid comparatively little attention to these types of neighbourhood-level social contexts. Nevertheless, it is plausible that such conditions also influence momentary affective states as individuals move through their daily environments. This consideration motivated our inclusion of neighbourhood gentrification as a contextual predictor within a GEMA framework.

Previous studies have also demonstrated the importance of momentary social interactions for emotional well-being. Higher satisfaction with social contacts boosts positive affect and reduces negative affect but is influenced by prior emotions (Liu and Lou, 2020). Positive interactions with strangers enhance well-being (Gunaydin et al., 2021). Momentary social interactions have also been linked to increased positive affect, greater happiness, and reduced tiredness in daily life (Bernstein et al., 2018; Monninger et al., 2022). Even brief, minor social interactions, such as greeting someone during a commute can promote positive affect (Gunaydin et al., 2021; Roshanaei et al., 2024; Sandstrom and Dunn, 2014). Improving social interactions has been found to contribute to improved overall well-being (Helliwell, 2012; Helliwell and Putnam, 2004; Schwanen and Wang, 2014). Social interactions significantly influence momentary well-being, with frequent social engagement linked to higher well-being (Hegewald et al., 2020) and meaningful interactions boosting emotional health (Gong et al., 2021). Face-to-face interactions are particularly beneficial for older adults, reducing loneliness and enhancing positive affect (Roshanaei et al., 2024; Terraneo, 2021). However, virtual interactions show no such correlation (Bellani and D'Ambrosio, 2011), and in certain contexts, higher levels of social interaction have been linked to negative impacts on mental health (Steinmetz-Wood et al., 2017). Other contextual factors also play a role. Weather, for instance, has been shown to influence emotions and mood, even if not directly modifiable. Kööts et al. (2011) found that cold and darkness are associated with fatigue, while sunlight enhances positive emotions, varying depending on age and personality. Additionally, Ettema et al. (2017) observed that weather influences travel mood, where higher temperatures improve the mood of public transport users, and a complex relationship exists between sunlight and mood for cyclists and pedestrians.

This study seeks to enhance our understanding of how built and social environmental factors impact momentary well-being during daily routines. Addressing existing research gaps, we specifically examine the relationship between built environment, social environments, momentary social interactions, and momentary well-being, controlling for temporal and weather-related conditions. Additionally, we test whether the relationship between social interactions and well-being is moderated by individual characteristics such as educational attainment and gender. By exploring these moderating effects, we aim to better understand how environmental and individual-level factors interact to shape momentary well-being.

Although prior EMA studies have investigated environmental or social determinants of well-being, few have simultaneously integrated GPS-linked built environment indicators, social interactions, and temporal rhythms within momentary assessments.

Our study addresses this gap and tests how these domains jointly predict real-time affective states.

Beyond examining these associations individually, the present study makes three key contributions to the existing literature. First, it simultaneously integrates momentary social interaction, temporal rhythms, and GPS-linked environmental exposure within a single GEMA framework, whereas most prior EMA studies have focused on only one or two of these dimensions in isolation. Second, it extends EMA research by incorporating neighbourhood-level social conditions—such as deprivation and gentrification—that have largely been examined using cross-sectional or home-based exposure designs, but rarely within momentary, mobility-based assessments. Third, by directly comparing the relative strength of social, temporal, and environmental correlates of momentary well-being in a dense North American urban context, this study provides empirical insight into which dimensions appear most salient under current exposure measurement constraints.

Drawing on affective science and ecological models of well-being, momentary affective states are understood to arise from the interaction of situational social context, temporal rhythms, and environmental conditions. Social interactions can exert immediate emotional effects through mechanisms of social support, stress buffering, and interpersonal engagement. Temporal rhythms, including time of day and weekday–weekend patterns, structure affective experiences through circadian processes and daily role demands. Built environment context, captured through GPS-linked proximity-based indicators, represents background conditions that may shape affect indirectly by influencing stress exposure, activity opportunities, and social encounters. Together, these pathways suggest that momentary well-being reflects the combined influence of dynamic situational factors and slower-changing contextual conditions.

Based on these theoretical pathways, we propose the following hypotheses:

H1. Positive social interactions are associated with higher momentary well-being.
H2. Higher exposure to greenness and park proximity is associated with higher momentary well-being.
H3. Higher exposure to large road density is associated with lower momentary well-being.
H4. Neighborhood deprivation and gentrification capture slow-changing contextual conditions and are hypothesized to relate more weaklyto momentary well-being than time-varying social and temporal factors.
H5. Temporal factors (time of day, weekday/weekend, weather) are associated with systematic variation in momentary well-being.

2. Methods

2.1. Study design and procedures

This is a geographical ecological momentary study (GEMA) in which participants were asked to answer short questionnaires on well-being and social interactions on their smartphones thrice a day for seven consecutive days. Location data was captured through the embedded GPS receiver when participants answered the prompts. We adhered to the GEMA-STROBE extension guidelines to report our study (Kingsbury et al., 2024).

2.1.1. Participants

This study combines participants from the Montreal arm of the longitudinal INTERACT study (Fuller et al., 2021; Kestens et al., 2019) and the Montreal Mobility Survey aimed at studying the impact of the new Reseau Express Metropolitan (REM), a new light-rail train that was launched in Montreal in the summer of 2023 (Elgeneidy et al., 2020). Both studies used the same protocol for EMA and drew participants from the same geographic area. From INTERACT, we utilized data from participants involved in the EMA protocol during the first wave (July 2018–March 2019) and the second wave (September 2020–February 2021). Eligibility requirements were to be at least 18 years old, live on Montreal Island, the south-shore cities of Longueuil, St-Lambert, Brossard, or the north-shore town of Laval and not have a plan to relocate out of the area within the following two years. Recruitment was conducted using various methods, including social media, news media, partner communication, snowball recruitment, and in-person activities. Full details of the INTERACT study protocol and recruitment, as well as a description of the wave one cohort, can be found in Fuller et al. (2021), Kestens et al. (2019), and Wasfi et al. (2021). Recruitment of wave 1 of the REM study took place between October and December 2019, using multiple methods and incentives. Most recruitment efforts targeted people in areas directly affected by the REM and its construction, including people living within two kilometres of existing commuter train lines that were shut down because of REM's construction. Participants living in areas not affected by the construction were also recruited as controls. Further details on the REM study can be found in (Dent et al., 2021). Ethical approval for INTERACT was received from the Université de Montreal Hospital Research Center ethics board (#CER CHUM 16.397), for the REM study from the McGill ethics board (#99-0719), and for this research protocol from Université de Montréal (#2021-1225).

2.1.2. Procedure

In both studies, participants were invited to download the Ethica-Data app (now renamed Avicena Research (Avicenna Research, n.d), compatible with iOS and Android smartphones. Participants were provided instructions about the GEMA protocol to optimize understanding and compliance. The monitoring period spanned seven consecutive days, including weekdays and weekends. Prompts were signal-contingent, i.e., sent three times per day, at random times within the following time windows: morning (8:00–9:00 a.m.), afternoon (12:00 a.m.–1:00p.m.), and evening (6:00–7:00 p.m.).

Participants could respond within a two-hour window after each prompt. GPS location data were captured at the time participants completed the prompt, ensuring that contextual exposure measures correspond to the moment of survey completion rather than prompt delivery. As a result, environmental context reflects the location at response time, which may introduce temporal displacement if responses were delayed.

2.2. Variables and measurement

Momentary well-being was measured using the Short Mood Scale (Wilhelm and Schoebi, 2007). It consists of six items measuring affect (unwell-well / content-discontent / agitated-calm / relaxed-tense / tired-awake / full of energy-without energy). Responses are given on a 6-step Likert scale from one to six. Three of the items were presented in a positive term (one: negative to six: positive), and three negatively (one: positive to six: negative). Thus, the negative items were reverse-coded so that high scores for each item indicated a positive mood. The Cronbach's alpha for the total score was 0.85, which was sufficient to justify summing the item scores for analysis. The sum score was calculated across all items for an overall momentary well-being measure ranging between 6 and 36. Structural validity, sensitivity to change and reliability have been reported before (Wilhelm and Schoebi, 2007).

An additional question with multiple-choice response options asked about momentary social interaction ('At this moment, I am interacting with'). Response choices were 'No one, I am alone' / 'No one, but there are people around me' / 'Friend(s)' / 'Family member(s), spouse, partner' / 'Colleague(s)'.

We did not impute missing EMA data as such imputations may introduce assumptions about mood trajectories. Instead, we conducted complete-case analyses acknowledging possible bias due to non-random missingness.

Area-level environmental factors: Using the GPS location obtained when participants answered the questionnaire, we computed built environment exposure to greenness (canopy), major road density, and distance to the closest park. We used the Canopy Index provided by the Communauté Métropolitaine de Montréal (Indice Canopée Métropolitain, 2019). It combines an NDVI measure with height information obtained from LIDAR data, distinguishing vegetation that is higher than 3 m in height (canopy) from vegetation that is lower (not canopy). This data are limited to the Montreal metropolitan region and matched with EMA responses that fell in that area only. GPS points outside of this area have missing canopy data. Major Road Density was computed as the ratio of the length of roads classified as 'major roads' to land area within a 0.1 km buffer. Data came from the 2018 DMTI CanMap dataset (DMTI Spatial Inc., 2018). Distance to the closest park was computed using the CMM land use layer from 2020 using a road-network distance (Communauté métropolitaine de Montréal, 2020).

It is important to note that GPS-derived environmental measures represent potential rather than experienced exposure. Proximity to greenness or parks does not necessarily indicate visual, auditory, or physical interaction with the environment. Without information on activity type or indoor/outdoor status, exposure misclassification is possible.

Area-level social indicators included neighbourhood gentrification, using the Ding metric (Ding et al., 2016; Firth et al., 2021). A dichotomous variable indicated whether the EMA response was provided within a Census tract that had gentrified between 2011 and 2016. We also assigned the local dissemination area (DA) social and material deprivation indices as provided by the Institut national de santé publique du Québec (2016). These indices provide standardized factor scores, where 0 represents the average deprivation level. Positive scores indicate higher than average deprivation (e.g., +1 = one standard deviation above the mean), and negative scores indicate lower than average deprivation.

Temporal variables included a day of the week, weekend indicator, and the time window during the day (categorical variable: morning, noon, evening) (see Table 1).

Using the closest airport weather station, we added meteorological data at the day level obtained from Environment Canada. We estimated the daily mean temperature in degrees Celsius (°C) by averaging the minimum and maximum temperatures recorded during the day and calculated the total daily precipitation as the sum of rainfall and the water equivalent of snowfall, measured in millimetres (mm).

Individual-level data were obtained from an online self-reported questionnaire that participants completed before engaging in the EMA protocol. We used the following variables: age group (18–39; 40–60; above 60), gender (man, woman, other: transgender, genderqueer, gender non-conforming, different identity), educational level (primary/secondary school, trade/technical school or college diploma, university degree and more), and ethnic group (white vs. other). We did not use income categories because they differed in the INTERACT and REM studies.

2.3. Missing data

Environmental data were missing for some prompts (Table 1), and the sources of missingness varied by variable. For Canada-wide variables, such as major road density and Pampalon deprivation indices, some values were unavailable because EMA responses occurred in locations without data coverage, including certain parks and First Nations reserves. Missingness in temperature and precipitation arose from days when some weather stations did not report data. Gentrification status was only available at the Census tract level, limiting coverage to Census Metropolitan Areas. For Montreal-specific variables, including parks and tree canopy, data were obtained from the Communauté métropolitaine de Montréal, and observations outside this boundary did not have measures.

To maintain data completeness and analytical accuracy, all analyses that incorporated Montreal-specific environmental variables were restricted to participants whose EMA responses were located within the Montreal metropolitan area, ensuring that each observation was matched with corresponding ecological measures.

Table 1
Descriptive statistics of 889 participant characteristics and 10,600 EMA surveys in the INTERACT and REM studies for built and social environmental variables and momentary well-being in Montreal.

Variables	n	%	Variables	n	%
	N (person) = 889			N (EMA) = 10600	
Participant source	**n = 889**	**%**	**Completed questionnaires**	**n = 10600**	**%**
INTERACT. W1	467	52.5	INTERACT. W1	5411	51.1
INTERACT. w2	160	18	INTERACT. W2	2294	21.6
REM	262	29.5	REM	2895	27.3
Age category	**n = 887**	**%**	**In gentrified area**	**n = 9700**	**%**
[18,40)	453	51.1	FALSE	5792	59.7
[40,60)	319	36	TRUE	3908	40.3
[60,80]	115	12.9	**Canopy**	**n = 9625**	**%**
Mean (Median)	41.71(39.0)		Mineral	6947	72.2
Gender	**n = 886**	**%**			
Man	375	42.3	Lower Green Cover	1071	11.1
Woman	494	55.7	Upper Green Cover	1607	16.7
Other	17	2	**Major Road Density (100m Buffer)**	**n = 10157 (km/km^2)**	
Racial group	**n = 887**	**%**	Min.	0.00	
White	772	87	Mean (Median)	1.00 (0.00)	
Other	115	13	Max.	36.00	
Education	**n = 887**	**%**	**Material Deprivation**	**n = 9395**	
			Min.	−0.16	
Primary/ Secondary School	28	3.2	Mean (Median)	−0.02 (−0.02)	
			Max.	0.17	
			Social Deprivation	**n = 9395**	
			Min.	−0.11	
			Mean (Median)	0.04 (0.04)	
			Max.	0.1	
Trade/ College Diploma	130	14.7	**Distance to Closest Park**	**n = 9635 (meters)**	
University Degree and higher	728	82.1	Min.	0.00	
			Mean (Median)	213.2 (170.7)	
Other	1	0.1	Max.	7295.6	
Latency (Response delay)	**(minutes)**		**Temperature**	**n = 8871 (Degree Celsius)**	
Min.	0.00		Min.	−20.1	
Mean (Median)	22.25 (6.7)		Mean (Median)	9.2 (9.6)	
Max.	120.00		Max.	30.0	
Day of week	**(Completed prompts/ proportion)**		**Precipitation**	**n = 9165 (mm)**	
Monday	1596 (60%)		Min.	0.0	
Tuesday	1591 (60%)		Mean (Median)	2.98 (0.2)	
Wednesday	1556 (58%)		Max.	58.0	
Thursday	1497 (56%)		**Time of Day**	**(Completed prompts/ proportion)**	
Friday	1501 (56%)		Morning	3536 (57%)	
Saturday	1427 (54%)		Afternoon	3587 (58%)	
Sunday	1432 (54%)		Evening	3477 (56%)	

2.4. Modeling approach

This study employed a three-level linear mixed-effects regression model with maximum likelihood estimation to examine the relationship between momentary well-being and potential predictors, taking into consideration the longitudinal and hierarchical structure of the data (Fig. 1).

The three-level mixed-effects model with random intercepts at levels two and three can be written as:

$$Y_{ijk} = \beta_0 + \beta_n X_{ijk} + v_k + u_{jk} + e_{ijk} \qquad v_k \ \mathrm{N}\left(0, \sigma_v^2\right)$$
$$u_{jk} \ \mathrm{N}\left(0, \sigma_u^2\right)$$
$$e_{ijk} \ \mathrm{N}\left(0, \sigma_e^2\right)$$

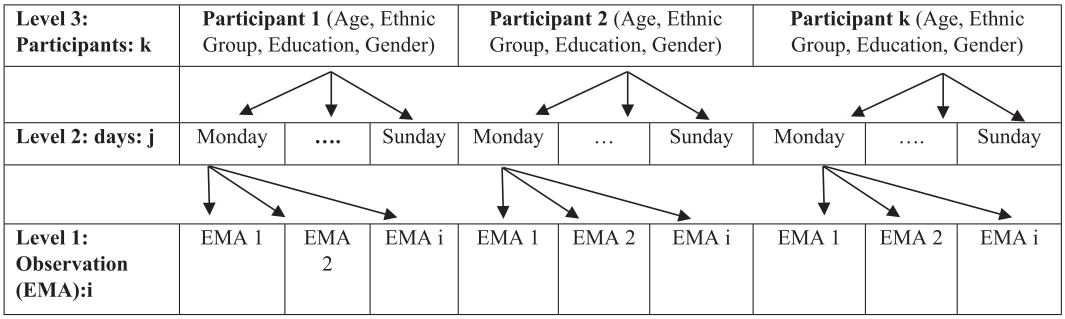

Fig. 1. Three-level model structure with observations nested within days within participants.

The outcome $\mathbf{Y_{ijk}}$ is the well-being measure of participant **k** at day **j** and for observation **i**. The covariate vector $\mathbf{X_{ijk}}$ comprises explanatory variables at levels **1**, **2**, and **3**, and **β** represents the corresponding vector of regression coefficients. The random participant effect ***vk*** reflects the impact of participant **k** on well-being, while the random time effect ***ujk*** represents the influence of participant **k** at day **j** on well-being (Fig. 1).

Predictors were organized according to the three-level model structure:

- **Level 1 (Observation / EMA level, (i))**: Variables that vary across EMA prompts and are linked to participants' GPS locations at the time of response, including built environment exposures (e.g., canopy cover, road density, distance to parks), neighbourhood-level contextual indicators (including gentrification and deprivation), and reported social interactions at the moment of answering.
- **Level 2 (Day level, (j))**: Variables that are constant within a given day but vary across days, including meteorological conditions (daily mean temperature, total precipitation), temporal indicators (day of the week, weekend/weekday), and time window of the EMA prompt (morning, noon, evening).
- **Level 3 (Participant level, (k))**: Time-invariant participant characteristics, including age, gender, education, and ethnic group.

All environmental predictors, including neighborhood deprivation and gentrification, were linked to participants' GPS locations at each EMA prompt and therefore assigned at the momentary level. However, these indicators reflect relatively stable contextual characteristics that change slowly over time, in contrast to more rapidly varying situational predictors such as social interaction or time of day.

Continuous predictors were standardized (Z-score) to improve scale comparability. Categorical variables (gender, education, ethnicity) were included as factor variables using treatment coding, as these variables served mainly as covariates rather than contrast targets. While alternative coding approaches such as effect or contrast coding may enhance interpretability in certain contexts (Yaremych et al., 2023), treatment coding was considered appropriate for the current research focus.

Confidence intervals were set at 95%. Initially, we fitted a null model to assess baseline variations in the outcome variable. Subsequently, we fitted the expanded null model, which incorporated random intercepts at the participant and day levels. We evaluated the model fit using a likelihood ratio test by comparing the expanded and null models. We then added individual-level variables, including age, gender, education level, and ethnicity, in Model 1, as well as environmental, social, and day-level variables in Model 2. A combined model incorporated both sets of variables simultaneously (Model 3).

In the last model, we added interaction terms to test if the social interaction-well-being relation was modified by educational attainment and gender (Model 4). We assessed model fit using information criteria, including AIC and BIC. To estimate the proportion of variance explained, we calculated the marginal R-squared (R2m) and conditional R-squared (R2c). Additionally, we computed intraclass correlation coefficients (ICC) to assess the proportion of variance at different levels, specifically ICC at the participant (ICC-Participant) and the day level (ICC-Participant-Day). Model diagnostics involved analyzing residuals, conducting heteroscedasticity checks, and examining histograms of residuals. All analyses were performed using R version 3.5.3 (packages lmer and lme4) (The Comprehensive R Archive Network, 2023).

3. Results

3.1. Participants' characteristics

Table 1 provides summary statistics for the 889 participants and the 10,600 completed EMA prompts. Some 627 participants (70.5%) were recruited in the INTERACT study and 262 (29.5%) in the REM study. Most participants identified as white (87%), and more than half identified as female (55.7%). Half (51.1%) were in the 18–40-year age range. Some 75.8% of participants reported French as their primary language, and 82.1% had a university degree or higher.

On average, participants responded to 57% of prompts or 12 out of a maximum possible of 21. The proportion of answered prompts was relatively similar across days of the week, although a slight decreasing trend can be observed from Mondays (60%, highest completion rate) to weekend days (54%). Negligible differences in completion rates were observed for the time of day, with 57%, 58%, and 56% of prompts answered in the morning, afternoon, and evening, respectively. The average (median) delay between prompt and response was 22.3 (6.6) minutes. Table 1 also shows the proportion of responses in gentrified and non-gentrified areas and environmental data on Canopy, Major Road Density, Material and Social Deprivation, Distance to Closest Park, Temperature, Precipitation, and Time of Day.

The average (median) momentary well-being measured through the Short Mood scale was 27.0 (27.0), with a standard deviation of 5.5. Thus, the observed median score of 27.0 suggests that, on average, participants reported moderate to high levels of momentary well-being during the study period. The interquartile range spans from 23.0 (Q1) to 31.0 (Q3).

3.2. Modelling results

Modelling results are presented in Table 2 and Table 3. Model fit improved as explanatory variables were added, as reflected in decreases in AIC and BIC values. More importantly, the conditional R-squared values were around 0.6, indicating that the models explained a substantial proportion of the variance in momentary well-being. The log-likelihood and deviance statistics were also consistent with improved fit across successive models. Half of the variance (48.9%) was attributable to between-participant differences, indicating substantial heterogeneity among individuals. Between-day variability explained 18.9% of the total variance, while 32.2% was at the observation level.

Age was the only individual-level variable significantly linked to momentary well-being (Table 3). Relative to their young peers aged 18

Table 2
Multilevel linear mixed-effects modeling analysis of individual and environmental factors: random effect and fit statistics.

Random Effect		M1	M2	M3	M4
Within-person residual variance (level-1)	σ_e^2	12.41 (3.52)	12.53 (3.54)	12.56 (3.54)	12.51 (3.53)
Between-day variance (level-2)	$\tau_{00,Subj\_Day}$	3.53 (1.88)	2.92 (1.70)	2.93 (1.71)	2.92 (1.71)
Between-person variance (level-3)	$\tau_{00,Subj}$	11.93 (3.45)	13.99 (3.74)	11.99 (3.46)	12.00 (3.46)
Information of models					
	N_{Subj}	886	827	824	824
	N_{Subj_Day}	4958	4055	4041	4041
Number of level 1 observations	Observations	10,564	8112	8081	8081
Akaike Information Criterion	*AIC*	60,649	46,722	46,482	46,473
Bayesian Information Criterion	*BIC*	60,736	46,911	46845.8	46,704
	Deviance	60,625	46,668	46,407	46,378
Variance attributable to between-day variation*	ICC_{Subj_Day}	0.22	0.19	0.19	0.19
Variance attributable to between-person variation**	ICC_{Subj}	0.49	0.53	0.49	0.49
Marginal R-squared (Fixed effect)	R^2m	0.07	0.03	0.09	0.09
Conditional R-squared (Fixed and Random effects)	R^2c	0.58	0.58	0.58	0.58

M1: model with individual variables only, **M2:** model with momentary environmental variables only, **M3:** Model with both individual and environmental variables, **M4:** model M3 + Interaction terms (momentary social interaction × gender and education levels).
* ICC_{Subj_Day} null = 0.1178.
** ICC_{Subj} null = 0.4726.

to 39, participants between 40 and 59 and between 60 and 80 had higher well-being scores (1.2 and 4.3 increases, respectively). Neither gender, educational attainment, nor ethnic origin was associated with well-being.

Neither daily mean temperature nor daily precipitation was associated with well-being. The estimated coefficient for temperature was positive (β = 0.21, 95% CI: –0.01 to 0.43), but the confidence interval included zero. Well-being also varied across the day. Scores were higher in the afternoon (β = 0.23, 95% CI: 0.04 to 0.42) and lower in the evening (β = –0.31, 95% CI: –0.52 to –0.10), compared to mornings. Variation was also observed across the week: well-being was higher on Saturdays (β = 0.82, 95% CI: 0.42 to 1.22) and Sundays (β = 1.11, 95% CI: 0.71 to 1.51) compared to Mondays, while other weekdays did not differ. Other weekdays did not differ, although a non-significant positive premium was observed for Fridays (β = 0.32, 95% CI: −0.05 to 0.68).

At the observation-level, no association was found between well-being and exposure to environmental variables, whether to canopy, park proximity, major road presence, or social indicators of gentrification or deprivation. Yet, momentary social interaction was linked to momentary well-being: interacting with friends (β = 1.96, 95% CI: 1.26 to 2.67) or family members (β = 0.83, 95% CI: 0.42 to 1.25) was

Table 3
Parameter estimates from multilevel linear mixed-effects regression models of momentary well-being, individual and environmental factors: fixed effects.

Fixed Effect				
Outcome: Momentary well-being	M1: Coef. (CI)	M2: Coef. (CI)	M3: Coef. (CI)	M4: Coef. (CI)
(Intercept)	**26.02** (25.53 to 26.53) ***	**26.41** (25.84 to 26.98) ***	**25.36** (24.71 to 26.01) ***	**25.31** (24.64 to 25.98) ***
Age: 18–40	**Reference: age 18–40**			
40–60	**1.30** (0.76 to 1.85) ***		**1.22** (0.64 to 1.79) ***	**1.22** (0.64–1.80) ***
60–80	**4.39** (3.61 to 5.18) ***		**4.33** (3.46 to 5.2) ***	**4.31** (3.44–5.18) ***
Gender: Man	**Reference: Man**			
Woman	−0.45 (−0.96 to 0.06)		−0.40 (−0.94 to 0.15)	−0.33 (−0.93 to 0.28)
Other	−0.75 (−2.58 to 1.08)		−0.62 (−2.5 to 1.27)	−0.70 (−2.71 to 1.32)
Highest Education Level: University Degree and higher	**Reference: University Degree and Higher**			
Trade/Technical	0.45 (−0.25 to 1.17)		0.20 (−0.56 to 0.96)	0.34 (−0.5 to 1.18)
Primary/Secondary School	−0.48 (−1.94 to 0.97)		−0.83 (−2.41 to 0.74)	−0.88 (−2.66 to 0.9)
Other	−1.48 (−9.03 to 6.06)		−1.04 (−8.57 to 6.49)	−4.65 (−14.88 to 5.58)
Ethnic Group: White	**Reference: White**			
Other	−0.17 (−0.92 to 0.58)		−0.19 (−0.99 to 0.6)	−0.19 (−0.98 to 0.61)
Social Interaction: Alone	**Reference: Alone**			
Alone, but people around	–	−0.15 (−0.42 to 0.11)	−0.12 (−0.38 to 0.15)	0.21 (−0.22 to 0.64)
With Friend(s)	–	**1.96** (1.51 to 2.4) ***	**1.99** (1.55 to 2.43) ***	**1.97** (1.26 to 2.67) ***
With Family	–	**0.78** (0.52 to 1.04) ***	**0.80** (0.54 to 1.06) ***	**0.83** (0.42 to 1.25) ***
With Colleagues	–	**0.36** (01 to 0.71) *	**0.40** (0.04 to 0.76) *	0.13 (−0.44 to 0.69)
Time of Day: Morning	**Reference: Morning**			
Afternoon	–	**0.25** (0.05 to 0.45) *	**0.24** (0.04 to 0.44) *	**0.23** (0.03 to 0.43) *
Evening	–	**−0.29** (−0.5 to −0.08) **	**−0.30** (−0.51 to −0.09) **	**−0.31** (−0.52 to −0.1) **
Days of Week: Monday	**Reference: Monday**			
Tuesday		0.04 (−0.32 to 0.4)	0.05 (−0.31 to 0.41)	0.05 (−0.31 to 0.41)
Wednesday		0.02 (−0.34 to 0.39)	0.05 (−0.31 to 0.42)	0.05 (−0.31 to 0.41)
Thursday		0.05 (−0.32 to 0.42)	0.07 (−0.3 to 0.44)	0.07 (−0.3 to 0.44)
Friday		0.30 (−0.06 to 0.67)	0.32 (−0.05 to 0.68)	0.32 (−0.05 to 0.68)
Saturday		**0.83** (0.46 to 1.21) ***	**0.83** (0.46 to 1.21) ***	**0.82** (0.45 to 1.2) ***

(*continued on next page*)

Table 3 (*continued*)

Fixed Effect				
Outcome: Momentary well-being	M1: Coef. (CI)	M2: Coef. (CI)	M3: Coef. (CI)	M4: Coef. (CI)
Sunday		**1.11** (0.73 to 1.48) ***	**1.13** (0.76 to 1.5) ***	**1.12** (0.74 to 1.49) ***
Gentrified: False	**Reference: False**			
True		−0.04 (−0.32 to 0.24)	0.02 (−0.26 to 0.3)	0.03 (−0.25 to 0.31)
Canopy: Upper Green Cover	**Reference: Upper Green Cover**			
Lower Green Cover		−0.07 (−0.43 to 0.3)	−0.08 (−0.45 to 0.29)	−0.08 (−0.44 to 0.29)
Mineral		−0.01 (−0.26 to 0.24)	0.00 (−0.26 to 0.25)	0.01 (−0.25 to 0.26)
Material Deprivation		−0.03 (−0.15 to 01.1)	−0.02 (−0.15 to 0.1)	−0.03 (−0.15 to 0.1)
Social Deprivation		−0.15 (−0.29 to 01)	−0.12 (−0.26 to 0.03)	−0.12 (−0.26 to 0.03)
Major road density		−0.01 (−0.12 to 0.11)	0.00 (−0.11 to 0.11)	−0.01 (−0.12 to 0.1)
Distance To Closest Park		−0.05 (−0.18 to 0.08)	−0.05 (−0.18 to 0.07)	−0.05 (−0.17 to 0.08)
Mean Temperature (°C)		0.07 (−0.19 to 0.34)	0.21 (−0.01 to 0.43)	0.21 (−0.01 to 0.43)
Total Precipitation (mm)		−0.05 (−0.15 to 0.06)	−0.06 (−0.16 to 0.05)	−0.06 (−0.16 to 0.05)
Gender* Social Interaction (Man*Alone)	**Reference: Man*Alone**			
Woman: Alone, but people around				**−0.63** (−1.17 to −0.09) *
Other: People Around				0.60 (−1.17 to 2.37)
Woman: Friend(s)				0.11 (−0.78 to 1.01)
Other: Friend(s)				0.71 (−1.85 to 3.26)
Woman: Family				−0.02(−0.53 to 0.5)
Other: Family				−0.53 (−2.39 to 1.34)
Woman: Colleague				0.67 (−0.08 to 1.33)
Other: Colleague				0.14 (−2.74 to 3.01)
Social Interaction * Education* (Alone *University Degree)	**Reference: Alone * University Degree ***			
Alone, but People Around: Trade/ Technical				−0.14 (−0.98 to 0.7)
Friend(s): Trade/ Technical				−0.54 (−1.79 to 0.71)
Family: Trade/ Technical				−0.04 (−0.75 to 0.68)
Colleague: Trade/ Technical				−0.93 (−2 to 0.15)
People around: Primary/Secondary School				0.60 (−0.89 to 2.1)
Friend(s): Primary/ Secondary School				1.07 (−1.14 to 3.28)
Family: Primary/ Secondary School				−1.57 (−3.33 to 0.19)
Colleague: Primary/ Secondary School				0.96 (−0.91 to 2.82)
People Around: Other				3.83 (−5.47 to 13.12)
Family: Other				4.25 (−3.9 to 12.4)
Colleague: Other				4.29 (−6.56 to 15.14)

Sig. codes: ***<0.001, **<0.01, *<0.05.
M1: model with just individual variables, **M2**: model with just momentary environment variables, **M3**: Model with individual and Environment Variables, **M4:** model M3 + Interaction of momentary social interaction with gender and education levels variables.

positively linked to well-being, compared to not interacting with anyone and being alone. Being alone, having people around without interacting, or interacting with colleagues showed similar associations with well-being.

To test the second hypothesis, we examined the cross-level interaction between gender and social interaction and education and social interaction on well-being. Women who were not interacting with anyone but with people around reported significantly lower well-being levels than men who were alone (β = −0.66, 95% CI: −1.17 to −0.09). No other social interaction − gender interaction was significant. Similarly, educational attainment did not modify the relationship between social interaction and well-being.

4. Discussion

This study investigated how momentary well-being varied over the time of day and during the week, as well as across environmental and social interaction contexts, in a sample of 889 participants living in the Montreal region who participated in a geographic ecological momentary assessment study with three prompts per day for seven consecutive days. Our results contribute to the growing GEMA literature by suggesting, within the current measurement framework, momentary affect appeared more closely associated with social interaction and time-structured daily rhythms than with relatively stable neighborhood characteristics. Statistically significant findings highlighted associations between momentary well-being and age, time of day, day of week, and social interactions, whereas no significant associations were observed for proximity-based built environment indicators such as greenness, parks, or major roads.

4.1. Comparison with the literature

Age was the only individual-level variable associated with momentary well-being, with older individuals reporting higher levels. Several studies report that well-being increases with age, although most of these studies did not use a momentary design (Biermann et al., 2022; Jivraj et al., 2020; Mayungbo, 2017). The association between age and well-being is frequently attributed to decreased levels of stress, anger, worry, and sadness (Stone et al., 2010) and mindfulness (Shook et al., 2017). Unlike earlier research, the current study did not find significant associations between momentary well-being and education (Cuñado and de Gracia, 2012), gender (Bossmann et al., 2013; Tomczyk et al., 2021), or ethnic group. Research conducted in the US highlighted lower well-being among Black and Hispanic adults than among Whites (Crowe and Kim, 2020; Williams, 2018). In contrast to previous research findings (Bejarano et al., 2019; MacKerron and Mourato, 2013), our results suggest that weather conditions were not significantly associated with momentary well-being. The coefficient for temperature indicated a positive trend, with an estimated 0.21-point increase in well-being per additional degree Celsius, although this association did not reach statistical significance. One possible explanation for these differences is that our study relied on real-time ecological momentary assessment in naturalistic settings, which may reduce recall bias but capture more transient fluctuations than retrospective survey data. Additionally, the relatively narrow variability in environmental and individual-level characteristics—including temperature, precipitation, educational attainment, and ethnic background—may have limited our ability to detect effects that were observed in broader or more diverse samples. The urban Canadian context of the study may also have contributed to these differences.

Regarding within-day variations, our findings indicate well-being increases in the afternoons and decreases in the evenings. Previous studies have reported this pattern (Birenboim, 2018; Bryson and MacKerron, 2017; Itzhacki et al., 2019; Stieger and Reips, 2019). However, some studies report differing trends, with calmness and valence declining until around 1:00 pm, followed by an increase, while the level of energy decreases (Giurgiu et al., 2019). Observed higher levels of well-being on weekend days have also been reported before (Birenboim, 2018; Ram et al., 2014; Stieger and Reips, 2019). Weekend days are non-workdays for many people, when more time is spent on travel, entertainment, leisure, eating, shopping, and social activities (Zhong et al., 2008).

Contrary to our hypothesis, we did not observe any significant relationship between momentary well-being and proximity-based indicators of the built environment, including greenness, parks, or major roads. Previous EMA research has often reported positive associations between contact with natural environments and momentary happiness or stress reduction (Bakolis et al., 2018; Hammoud et al., 2024; MacKerron and Mourato, 2013) although systematic reviews highlight that these effects are generally small, context −dependent, and sensitive to study design (Rautio et al., 2018; Roberts et al., 2019).

Although all environmental exposures were operationalized at the momentary level using GPS-linked locations, some contextual indicators such as deprivation and gentrification exhibit limited short-term variability. These indicators may therefore function more plausibly as background contextual conditions shaping general emotional tone rather than as drivers of within-day affective fluctuations. As a result, their associations with momentary well-being may appear weaker when examined alongside rapidly changing situational factors. This difference in temporal dynamics, rather than a mismatch in measurement level, should be considered when interpreting null or attenuated environmental effects. Although our environmental hypotheses are theory-informed, analyses regarding time-varying modulation of built environment exposure should be interpreted as partly exploratory. Future GEMA studies incorporating direct sensory exposure, indoor/outdoor classification, and activity context could more rigorously test these mechanisms.

Our GEMA approach links momentary affect with GPS-derived spatiotemporal context, enabling assessment of environmental, temporal, and social influences on well-being in daily life. In this study, environmental exposure was operationalized using location-based proximity indicators at the time of EMA completion. While this approach captures momentary contextual exposure, other GEMA implementations using continuous GPS tracking can additionally characterize recent or cumulative exposure to environments preceding each prompt (Fancello et al., 2023). Incorporating such exposure histories, as well as contextual information such as activity patterns or indoor/outdoor status, may further improve estimation of environmental effects in future studies.

Finally, we found interesting results regarding the role of social interactions. Interacting with friends and family members was associated with higher well-being compared to being alone. This supports previous findings emphasizing the positive influence of companionship on well-being (Birenboim, 2018; Bryson and MacKerron, 2017) and the positive role of interactions with family members on momentary well-being (Ram et al., 2014). Social connections play a pivotal role in enhancing well-being, as supported by empirical studies and *meta*-analytical evidence (Liu et al., 2019). Interestingly, we noted differences in the associations between social interactions, or their absence, and well-being between men and women. Compared to men who reported being alone, women reported lower levels of well-being when they were surrounded by others but did not engage with them. These findings suggest that women may be more responsive to social interactions—or their absence—than men, which aligns with previous research highlighting the differential effects of social interactions on men's and women's well-being more generally (Okabayashi and Hougham, 2014; Uziel and Schmidt-Barad, 2022). Our study does not explain why people having around but not interacting with them would lower well-being among women. Yet gender is crucial in understanding how social dynamics shape momentary well-being, with societal norms, communication patterns, and role expectations potentially contributing to this finding. Taken together, these findings suggest that while environmental context remains theoretically relevant, current proximity-based GEMA measures may be insufficient to support direct urban design or planning recommendations without more refined exposure assessment.

4.2. Limitations and future research directions

One of our study's strengths lies in our approach to real-time data capture through Ecological Momentary Assessment, as well as the addition of contextual data through temporal and spatial linkage. This approach enables an environmentally authentic exploration of the relationship between environmental contexts, momentary social interactions, and momentary well-being. Although our sample size exceeded that of most GEMA studies, enhancing statistical power, the composition of our participants was not representative of the wider population. The sample was disproportionately younger, White, female, and highly educated, consistent with demographic patterns often observed in EMA research (Kahneman et al., 2004; Murray et al., 2023; Stone et al., 2023; Stone and Mackie, 2013; Turner et al., 2017). Such characteristics may shape social interaction patterns and well-being, which restricts the generalizability of our findings beyond similar populations. While this study examined in-person interactions, we did not account for digital interactions, which have the potential to shape emotions and perceptions.

Another limitation relates to the distinction between spatial proximity and actual environmental experience. Location-based indicators capture what is present around an individual at a given time, but not whether participants actively engaged with, perceived, or were exposed to these features. Our EMA application did not provide information on indoor versus outdoor status or activity type, which may have led to exposure misclassification. Such misclassification likely attenuated associations and may partly explain the null findings observed for built environment variables. While some mobile sensing approaches attempt to infer indoor versus outdoor contexts, these methods are often device-specific and insufficiently documented, limiting their reliability (Esmaeili Kelishomi et al., 2019; Wang et al., 2016). EMA compliance averaged approximately 57%, consistent with comparable mobile-based designs. Nevertheless, selective response patterns may have occurred, as participants may have been less likely to respond during periods of high activity, stress, or limited device access. Such missingness may not be completely random and could bias momentary well-being estimates toward episodes when individuals were more available or less burdened. Although we were unable to formally assess correlates of non-response or conduct sensitivity analyses within the scope of this revision, this limitation should be considered when interpreting the findings. Future GEMA studies may incorporate response-time modeling, compliance-weighted analyses, or other approaches to account for selective participation.

We used GPS data to identify and characterize the location where participants responded to the prompts, but we did not characterize the type of place (e.g., home, coffee shop, work, travelling). Some places might affect well-being more profoundly than others through different processes, including attachment or sense of place. Using location data to characterize the type of place is difficult and asking participants to self-report their location type adds to the protocol burden. Similarly, we did not collect data on activities engaged in before the prompt. Accounting for activities and activity place types might help further explain momentary well-being. Because EMA prompts could be answered with delay, momentary affect may not perfectly align with environmental exposure at the time of prompt delivery. Finally, we did not distinguish indoor from outdoor locations, which could improve the identification of potential impacts of environmental exposures (Fancello et al., 2023).

Finally, our multilevel models included random intercepts at the participant and day levels but did not incorporate random slopes for time-varying predictors such as time of day, weekday versus weekend, or social interaction. While this modeling strategy allowed us to account for baseline differences between individuals and days, it may have limited our ability to capture individual variability in reactivity to contextual and temporal factors. As a result, heterogeneity in these effects may be underestimated, and uncertainty around fixed-effect estimates may be conservative. This modeling choice was driven by model complexity and convergence constraints given the large number of EMA observations. Future studies may explore random-slope specifications or alternative estimation approaches, such as Bayesian hierarchical models, to better characterize person-specific responses to environmental and social contexts.

While data were pooled from two parent studies with similar protocols, recruitment contexts differed. Future work could model study source effects more explicitly, although here both samples were combined to increase ecological variability and statistical power.

5. Conclusion

This study examined momentary well-being in relation to temporal rhythms, social interactions, and GPS-linked environmental context using a geographic ecological momentary assessment design. Our findings indicate that momentary well-being is more consistently shaped by social interactions and temporal patterns of daily life than by static built environment characteristics. While exposure to greenness, parks, road density, deprivation, and gentrification was operationalized at the momentary level, these contextual indicators showed predominantly null or weak associations with momentary well-being. These results should be interpreted cautiously, as they may reflect limitations in exposure measurement and the limited short-term variability of certain environmental features rather than the absence of contextual relevance.

In contrast, social interaction context and temporal rhythms emerged as robust correlates of momentary well-being, with notable gender differences in responses to social presence and interaction. Together, these findings underscore the importance of social and temporal dimensions in shaping daily emotional experience and suggest that these domains may represent more immediately actionable targets for well-being interventions under current measurement conditions. Future GEMA research incorporating more refined environmental exposure measures will be essential before translating built environment findings into urban planning or design recommendations.

CRediT authorship contribution statement

Sadun Khezri: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Benoît Thierry:** Writing – review & editing, Writing – original draft, Data curation. **Daniel Fuller:** Writing – review & editing, Writing – original draft. **Meghan Winters:** Writing – review & editing, Writing – original draft. **Martina Kanning:** Writing – review & editing, Writing – original draft. **Ahmed El Geneidy:** Writing – review & editing, Writing – original draft. **Yan Kestens:** Writing – review & editing, Writing – original draft, Supervision, Data curation, Conceptualization.

Ethics approval and consent to participate

Our research was approved by the ethics board of the au Comité d'éthique de la recherche en sciences et en santé (CERSES) de l'Université de Montréal, ensuring compliance with ethical standards.

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Declaration of competing interest

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.

Data availability

Data will be made available on request.

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