Journal of *Parks*

MDPI

Article

Air Quality, Heat, and Visitor Experience in Lumpini Park, Bangkok: An AI-Enabled Evaluation of an Iconic Urban Park

Eain Dray Aung [1], Nophea Sasaki [1,*] and Issei Abe [2]

[1] ESG and Sustainability, Sasin School of Management, Chulalongkorn University, Bangkok 10330, Thailand; eain.aung@sasin.edu
[2] Faculty of Sociology, Kyoto Koka University, Kyoto 615-0882, Japan; i_abe@koka.ac.jp
* Correspondence: nophea.sasaki@sasin.edu

Abstract

Urban parks provide recreation, cultural ecosystem services, microclimate regulation, and benefits for well-being, but their realized value may vary with air pollution and heat. This exploratory study linked 2947 Google Maps reviews posted in 2024–2025 to daily PM2.5, temperature, humidity, and precipitation and assessed a BERT-based workflow for classifying star-linked sentiment and dominant emotion text labels. Star-linked sentiment classifications were highly favorable (mean score of 4.86/5; 88.39% very positive). Independent weighting of the rounded air-quality and heat-stress subgroup summaries yielded consistent approximate overall shares for provisional joy (28.9%) and anger (32.5%), but the full seven-class distribution could not be reconstructed from the archive. All emotion-label analyses remain provisional. All 25 tested environmental correlations were negligible (absolute Spearman $\rho \leq 0.049$), and none met the Bonferroni-corrected significance threshold ($\alpha = 0.002$). Posting dates classified as heat-stress days showed descriptive differences in provisional anger and joy labels, but posting date is an uncertain proxy for the visit date. The findings do not establish individual-level exposure associations. They instead illustrate the methodological safeguards needed before user-generated park feedback and environmental monitoring can support climate-responsive management.

Keywords: urban parks; park evaluation; visitor experience; PM2.5; heat stress; sentiment analysis; BERT; Google Maps reviews; Bangkok; climate-responsive park management

1. Introduction

Parks are increasingly understood as ecological infrastructure rather than passive open lands. They provide regulating services such as cooling, stormwater retention, and air-quality moderation; cultural services such as recreation, learning, tourism, heritage, and social interaction; and indirect well-being benefits through contact with nature [1–5]. In rapidly urbanizing cities, these functions matter because residents and visitors often face high density, traffic exposure, urban heat, and limited access to quiet outdoor space [6–9]. For park science and planning, the central question is therefore not only whether parks exist but also how well they perform under real environmental conditions. However, the value of a park is conditional. A large and attractive park may still deliver a weaker visitor experience when users encounter polluted air, excessive heat, crowding, poor maintenance, or other stressors. This conditionality has become more important as climate change and urban air pollution increasingly shape outdoor recreation and public space use [9–12]. Static indicators such as park area, vegetation cover, or distance to green space remain

Check for updates

Academic Editor: Hongxu Wei

Received: 5 June 2026
Revised: 1 August 2026
Accepted: 6 August 2026
Published: 14 August 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

useful, but they do not fully capture the experience of using a park on a hot, polluted, crowded, or seasonally unusual day.

Urban vegetation can help cool cities and contribute to particulate deposition, but these benefits are not unlimited. The effect of vegetation on particle concentrations depends on canopy structure, wind, street geometry, local emissions, and pollution intensity [10]. Park cooling also varies with park size, tree cover, water bodies, surrounding built form, and meteorological conditions [11]. In tropical cities, the same park may therefore provide different levels of comfort and perceived environmental quality across seasons. Against this background, fine particulate matter (PM2.5) and extreme heat are major public-health stressors. Global assessments link PM2.5 with respiratory and cardiovascular disease burdens [13,14], while temperature extremes are associated with heat-related morbidity and mortality [15,16]. This study does not measure clinical outcomes. It uses star-linked sentiment and provisional discrete emotion labels as descriptive signals of park-related expression. This distinction is important: the analysis can examine how daily environmental conditions correspond with review outputs by posting date, but it cannot diagnose individual health effects or establish causal exposure pathways.

Traditional park evaluation relies on visitor counts, field observation, questionnaire surveys, expert audits, maintenance records, and environmental monitoring. These approaches remain essential, but they are often episodic, costly, and difficult to repeat frequently across many locations. User-generated content provides a complementary data stream because online reviews contain unsolicited descriptions of scenery, activities, accessibility, amenities, safety, crowding, wildlife, maintenance, and discomfort [17–19]. Complementary to these approaches, computational urban studies have used sentiment analysis, machine learning, deep learning, and multimodal models to examine public perceptions of green spaces and urban environments [19–24]. These methods can process thousands of narratives, but they require careful interpretation. Online reviews do not represent all park users; reviewer demographics are often unknown, and text classifications may reflect platform culture, translation, tourism, sarcasm, or review-writing conventions. AI-enabled review analysis should therefore support, rather than replace, representative surveys, fieldwork, and direct environmental measurement.

Bangkok provides a relevant context for examining environmentally conditioned park experiences because heat, humidity, rainfall, and particulate pollution vary seasonally [12]. Against this citywide setting, Lumpini Park offers a focused case for exploring how environmental monitoring and public review text may be considered together without treating review posting dates as confirmed visit dates. Lumpini Park is located in the Pathum Wan district in central Bangkok at approximately 13°43′49″ N, 100°32′30″ E and covers about 57.6 hectares. Its landscape includes lawns, mature tree cover, walking and jogging routes, water bodies, recreational facilities, and habitats for urban wildlife [24–27].

As a long-established and prominent urban public park, Lumpini is used by residents, office workers, domestic visitors, and international tourists. Its central location, public-transport access, historic status, exercise use, tourist visibility, and event functions make it one of Bangkok's most visible and intensively used parks. This mixed user base is analytically useful but requires caution because Google Maps reviews may combine routine local use with retrospective accounts from tourists. Accordingly, the present study treats Lumpini Park as a single illustrative case of a high-profile urban park, not as a representative sample of all Bangkok parks. Findings should not be generalized to smaller neighborhood parks, pocket parks, peri-urban green spaces, or parks serving different social groups without comparative analysis.

The study is informed by three complementary theories. Appraisal Theory suggests that emotions arise from how people evaluate environments in relation to goals, expectations, and well-being [28]. In a park setting, visitors may appraise shade, air quality, temperature, crowding, wildlife, cleanliness, facilities, and safety as supportive or disruptive. Stress Reduction Theory and Attention Restoration Theory explain why natural settings can support recovery, positive affect, and attentional restoration [29,30]. Affective Events Theory explains how specific events during a visit, such as pleasant scenery, uncomfortable heat, visible haze, crowding, or facility problems, can trigger emotional responses that shape overall evaluations [31]. Together, these perspectives suggest that visitor experience is not fixed; it is shaped by the environmental and social conditions under which park use occurs.

The aim of this study is to explore how daily air-quality and thermal conditions correspond with sentiment and provisional emotion labels when public reviews of Lumpini Park are linked to environmental records by posting date and to assess the usefulness and limitations of AI-enabled review analysis for climate-responsive park evaluation. Four research questions guide the analysis: (1) What star-linked sentiment profile is present, and what limitations are revealed by the archived emotion outputs? (2) What descriptive posting-date differences appear in provisional emotion labels under PM2.5 and heat-stress conditions? (3) How do environmental conditions and provisional label summaries vary across posting-date seasons? (4) What do these patterns and limitations imply for park planning, management, and AI-supported park evaluation?

2. Materials and Methods

2.1. Study Design

This research used a retrospective observational design based on digital trace data. Publicly available Google Maps reviews were analyzed as user-generated evidence of visitor experience and were linked to daily environmental records by review posting date. The design can identify descriptive and correlational patterns, but it cannot establish causality or confirm individual exposure, clinical health outcomes, or population representativeness. The workflow included review extraction and screening, text preprocessing, AI-based sentiment and emotion classification, environmental data acquisition, review-date matching, and statistical analysis (Figure 1).

2.2. Study Area

The study site is Lumpini Park (approximately 13.731° N, 100.541° E), located in the Pathum Wan district in central Bangkok, Thailand (Figures 2 and 3). The park covers approximately 57.6 hectares and includes lawns, mature tree cover, walking and jogging routes, water bodies, recreational facilities, and habitat for urban wildlife. It functions as a central recreational landscape for walking, jogging, tai chi, social gatherings, tourism, birdwatching, and informal contact with nature. Lumpini Park was selected because it is a high-use, historically significant, centrally located, and internationally visible urban park. Its position in Bangkok's central business district gives it a mixed user base that includes nearby residents, office workers, domestic visitors, and international tourists. This diversity is valuable for studying public-facing park experience, but it also limits inference: Google Maps reviews may capture occasional tourist impressions as well as routine local use, and the balance between these groups cannot be determined from the public review record.

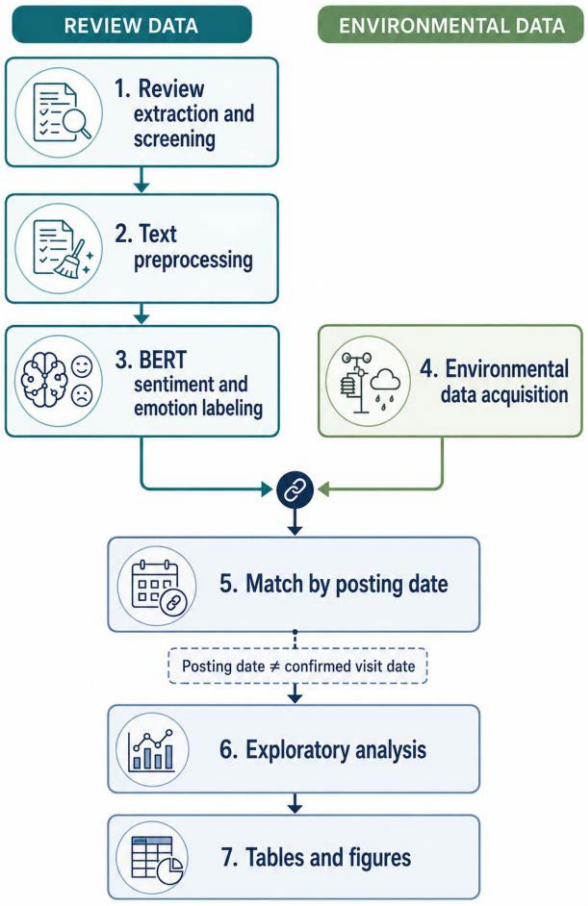


Figure 1. Workflow for linking review posting dates to daily environmental data and exploratory analyses. Note: The workflow summarizes the analytical sequence and uses review posting date as the only linkage key. It does not imply that posting date equals visit date; findings are therefore treated as exploratory associations with timing limitations.

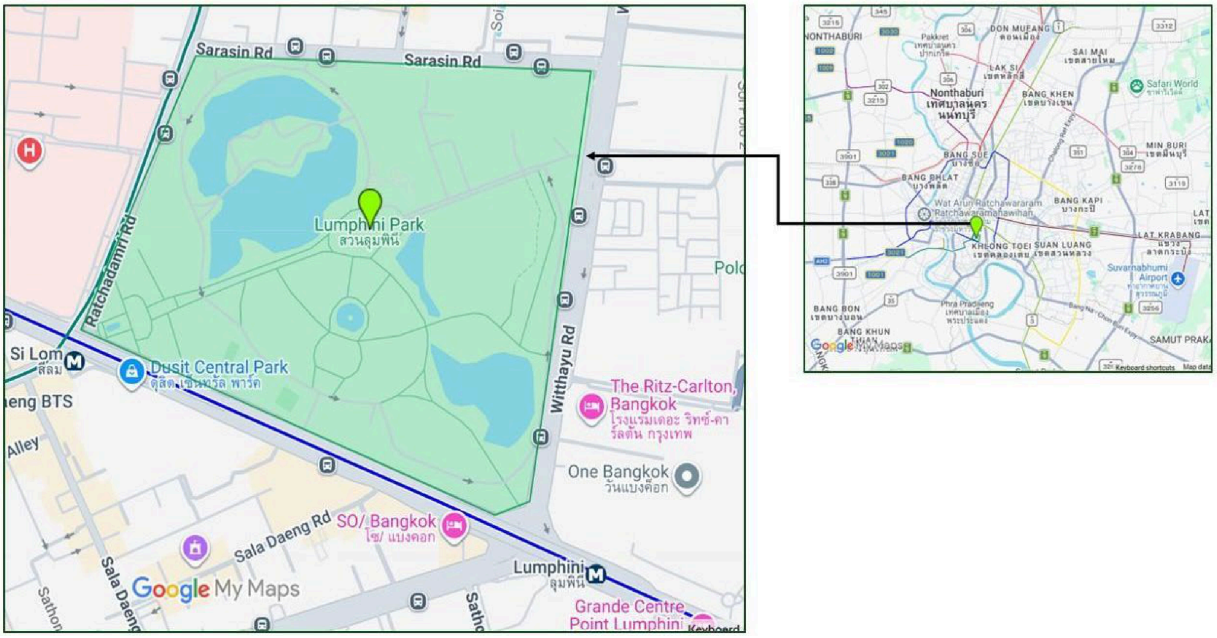


Figure 2. Location of Lumpini Park in central Bangkok. Note: The map was prepared using Google My Maps. Lumpini Park is treated as a single iconic urban-park case, not as a representative sample of all Bangkok parks.



Figure 3. Photographic overview of Lumpini Park: (**A**) mature trees and canal; (**B**) lake and surrounding urban skyline; (**C**) park users walking and jogging; and (**D**) adjacent local fresh produce market. Note: Photographs taken by Nophea Sasaki at Lumpini Park and its immediate surroundings, Bangkok, Thailand, in April, June, and July 2026.

2.3. Review Data Collection and Preprocessing

The empirical text dataset consisted of publicly available Google Maps reviews of Lumpini Park. Google Maps was selected because it is widely used for place-based evaluations and contains star ratings, posting dates, review text, and language information [32]. The archival scrape captured available reviews dated 2015–2025; the present analysis was restricted to reviews posted in 2024–2025 to represent recent visitor experience and to match the environmental-data window. The screening process excluded reviews outside the analytical period, duplicate records, entries without usable text or date information, and records that were noninformative after cleaning. The final analytical dataset contained 2947 valid reviews. Text preprocessing included language detection, Thai-to-English translation where needed, lowercasing, removal of URLs and excessive punctuation, and basic text normalization. The analysis used anonymized review text and did not retain personal identifiers. Two limitations follow directly from the data source. First, Google Maps reviewers are self-selected and may not represent all park users. Second, the posting date may differ from the actual visit date. The posting date was used because visit dates are not available in

the public review record. This may introduce exposure misclassification, especially among tourists or users who post retrospective reviews.

2.4. Environmental Data

Daily environmental data were collected for the Lumpini Park area (13.731° N, 100.541° E) from January 2024 to December 2025. Meteorological variables included daily maximum, minimum, and mean temperature, relative humidity, and precipitation from the Open-Meteo Historical Weather API. Open-Meteo describes its historical weather data as reanalysis-based and constructed from weather station, aircraft, buoy, radar, and satellite observations [33]. Air-quality variables, including daily PM2.5 and PM10 concentrations, were obtained from the Open-Meteo Air Quality API, which uses CAMS atmospheric composition products; for Bangkok, the documentation identifies the global CAMS product at an approximate 45 km spatial resolution [34]. The environmental series covered 731 days. Days were classified into Bangkok's hot (March–May), rainy (June–October), and cool (November–February) seasons. Heat-stress days were defined as days with maximum temperature $\geq$ 35 °C. Poor air-quality days were operationally defined as daily mean PM2.5 > 35.4 $\mu g/m^3$, the upper bound of the current US EPA Moderate 24-hour PM2.5 AQI category [35]. This cutoff is an analytical grouping threshold, not a Bangkok-specific exposure standard.

2.5. Sentiment and Emotion Classification

The archived analysis used a BERT-based natural language processing workflow [36]. It mapped sentiment to five ordinal categories (very negative, negative, neutral, positive, and very positive) and assigned one dominant text label from joy, anger, sadness, fear, surprise, disgust, and neutral, informed by discrete emotion resources [37]. The workflow notes transfer learning and a manually checked subset but does not identify the exact pretrained checkpoint or software version. However, the retained study records did not include the training and validation corpora, class balance, training-validation-test split, optimizer, learning rate, batch size, epoch count, decision thresholds, random seed, or model weights. No independent, manually annotated gold-standard sample from this corpus was available, so corpus-specific per-class precision, recall, F1 scores, and a confusion matrix could not be reproduced. The previously cited aggregate F1 score above 0.90 was not documented for these 2947 reviews and has been removed. All emotion labels, especially those assigned after Thai-to-English translation, are therefore provisional and not independently validated.

2.6. Data Integration and Variables

Each review was matched to the corresponding daily environmental record using the review posting date. The main review-level variables were star rating, star-linked sentiment score, and provisional dominant emotion label. The main environmental variables were daily mean PM2.5, daily maximum temperature, mean temperature, humidity, precipitation, season, heat-stress indicator, and poor air-quality indicator. Importantly, the posting-date linkage is an approximation rather than a measure of personal exposure. It is most plausible for reviews posted immediately after a visit and least plausible for retrospective reviews, but Google Maps does not expose the visit date or posting lag. A defensible restriction or lag-based sensitivity analysis could therefore not be implemented from the public records: imposing an arbitrary lag would not identify the actual visit day. Environmental findings are consequently framed as exploratory associations between review timing and daily conditions.

2.7. Statistical Analysis

Descriptive statistics summarized environmental conditions, star-linked sentiment scores, and provisional emotion labels. Stratified comparisons used the review posting date to define normal versus poor air-quality days and heat-stress versus non-heat-stress days. Chi-square tests compared categorical label distributions, and Spearman rank correlations assessed ordinal or non-normally distributed variables. For the environmental-correlation family, 25 comparisons were tested using a Bonferroni-corrected two-sided alpha of 0.002. For the star-rating-correlation family, seven comparisons were tested using a corrected alpha of 0.0071. Raw *p*-values are retained where available, but inferential statements follow the corrected thresholds and emphasize effect magnitude. As a documentation cross-check, approximate corpus-level joy and anger shares were reconstructed separately from the air-quality and heat-stress partitions by weighting each reported subgroup percentage by the subgroup sample size. Because the source percentages were rounded and review-level predictions were unavailable, these values are approximate derived summaries. For reproducibility, the archived analysis was conducted in Python using packages including scikit-learn, SciPy, and statsmodels. Missing environmental values were checked during dataset construction, and records without matchable posting dates were excluded. The raw review-level prediction file and executable model artifacts were not available in the retained archive, preventing re-estimation, multivariable modeling, or corpus-specific validation during this revision.

3. Results

3.1. Environmental Conditions During the Study Period

The environmental dataset covered 731 days from January 2024 to December 2025. Mean daily temperature was 28.5 °C (SD = 1.5), and mean daily PM2.5 concentration was 23.9 μg/m^3 (SD = 18.0). Across the full period, 81 days (11.1%) met the heat-stress definition and 128 days (17.5%) met the poor air-quality definition. Within this period, seasonal differences were clear (Table 1). The hot season had the highest daily maximum temperature and the highest number of heat-stress days. The rainy season had the highest humidity and precipitation and the lowest mean PM2.5. The cool season had the lowest mean temperature but the highest PM2.5 and the largest number of poor air-quality days.

Table 1. Environmental characteristics of the study period by season (2024–2025).

Variable	Overall	Hot (Mar–May)	Rainy (June–October)	Cool (November–February)
Days (*n*)	731	184	306	241
Mean temperature (°C)	28.5 ± 1.5	30.0 ± 1.4	28.1 ± 0.9	27.8 ± 1.5
Maximum temperature (°C)	32.4 ± 1.9	34.2 ± 1.7	31.6 ± 1.3	32.0 ± 1.8
Minimum temperature (°C)	25.3 ± 1.8	26.9 ± 1.5	25.5 ± 0.8	23.4 ± 1.6
Mean PM2.5 (μg/m^3)	23.9 ± 18.0	22.6 ± 13.3	16.6 ± 15.9	34.2 ± 18.7
Humidity (%)	73.2 ± 11.8	74.0 ± 8.3	81.0 ± 5.0	62.8 ± 11.5
Precipitation (mm/day)	4.8 ± 7.4	4.2 ± 8.4	8.0 ± 8.1	1.2 ± 3.5
Heat-stress days	81 (11.1%)	63 (34.2%)	4 (1.3%)	14 (5.8%)
Poor air-quality days	128 (17.5%)	26 (14.1%)	23 (7.5%)	79 (32.8%)

Note: Values are mean ± SD for continuous variables and *n* (%) for categorical variables. PM2.5 = particulate matter with an aerodynamic diameter ≤ 2.5 μm. Heat-stress days were defined as daily maximum temperature ≥ 35 °C. Poor air-quality days were defined as daily mean PM2.5 > 35.4 μg/m^3. Percentages may not total 100% because of rounding.

3.2. Sentiment Profile and Emotion-Output Audit

Public sentiment toward Lumpini Park was strongly positive (Table 2). Very positive reviews accounted for 88.39% of the dataset, positive reviews for 9.26%, and neutral reviews for 2.34%. In the cleaned analytical dataset, no reviews were classified as negative or very negative by the five-category sentiment model. The mean sentiment score was 4.86 (SD = 0.40; SE = 0.007; 95% CI: 4.85–4.87).

Table 2. Sentiment distribution of Lumpini Park reviews (n = 2947).

Score	Category	Count (N)	Percentage (%)
5	Very positive	2605	88.39
4	Positive	273	9.26
3	Neutral	69	2.34
2	Negative	0	0.00
1	Very negative	0	0.00

Note: Sentiment score was treated as an ordinal review-level indicator. Percentages may not sum exactly because of rounding.

The archived emotion outputs did not permit reconstruction of the complete seven-class corpus-level distribution. However, the two independent subgroup partitions provide a limited internal consistency check. Weighting the rounded air-quality subgroup percentages by their sample sizes (n = 2431 and 516) yielded approximate overall shares of 28.9% for joy and 32.5% for anger; applying the same procedure to the heat-stress partition (n = 339 and 2608) yielded the same values when rounded to one decimal place. This agreement indicates that the retained joy and anger subgroup summaries are internally consistent across partitions. Because the review-level predictions, unrounded counts, and complete class totals were unavailable, these are approximate derived summaries rather than independently reproduced prevalence estimates, and the full seven-class distribution remains unreconstructed. Table 3 records this qualified audit outcome.

Table 3. Audit of archived sentiment and emotion outputs.

Output	Archived Summary	Audit	Decision
Sentiment	88.39% very positive	Imbalanced	Descriptive
Emotion	Subgroup summaries; archive totals conflict	Joy/anger partitions agree (28.9%; 32.5%)	Partial descriptive summary
Validation	Undocumented F1 > 0.90	No corpus metrics	Exploratory only

Note: The audit is based on the manuscript and files supplied for revision. It does not substitute for validation against an independently annotated sample from the current corpus. The joy and anger shares were approximated by weighting rounded subgroup percentages by subgroup sample size across two independent partitions; they do not reconstruct the full seven-class distribution or establish label validity.

3.3. Provisional Emotion Labels by Air-Quality Posting Date

Reviews were grouped by the daily mean PM2.5 value on the review posting date, not a confirmed visit date. The archived stratified summary reported provisional joy labels for 29.4% of reviews on normal-air-quality posting dates (n = 2431) and 26.7% on poor air-quality posting dates (n = 516); provisional anger labels were 32.1% and 34.3%, respectively (Figure 4). Mean star-linked sentiment scores differed by 0.080 points (4.875 versus 4.795). These are descriptive contrasts subject to unknown visit-posting lag and model error. Consistent with these contrasts, the unadjusted PM2.5–anger coefficient was $\rho = +0.049$ (reported $p < 0.05$), while the PM2.5-joy coefficient was $\rho = -0.026$. Neither met the Bonferroni-corrected alpha of 0.002 for Table 4; their magnitudes were negligible.

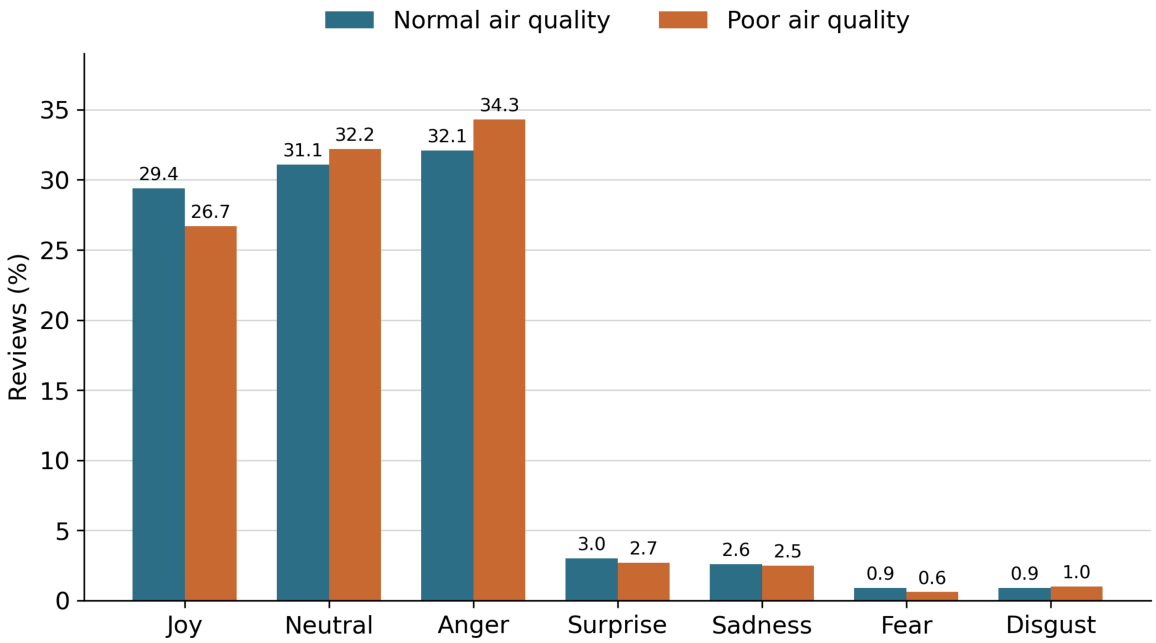


Figure 4. Distribution of provisional dominant emotion labels by air-quality category on review posting dates. Note: Reviews were grouped by daily mean PM2.5 on the review posting date, not a confirmed visit date. Poor air-quality days were defined as daily mean PM2.5 > 35.4 μg/m^3. Labels are provisional model outputs.

Table 4. Spearman rank correlations between environmental variables and sentiment or provisional emotion indicators.

Variable	Sentiment	Joy	Anger	Sadness	Fear
PM2.5	−0.040	−0.026	+0.049	−0.001	−0.030
Temperature (mean)	−0.007	−0.047	+0.029	−0.003	+0.005
Temperature (max)	−0.032	−0.049	+0.040	+0.012	+0.002
Humidity	+0.011	+0.031	−0.035	−0.006	+0.016
Precipitation	+0.015	+0.044	−0.044	−0.005	+0.000

Note: Coefficients are Spearman rank correlations. Sentiment score was treated as ordinal; emotion indicators were binary provisional labels. Bonferroni correction for 25 comparisons set $\alpha = 0.002$. None of the archived coefficients met that threshold. PM2.5 = particulate matter with an aerodynamic diameter $\leq$ 2.5 μm.

3.4. Provisional Emotion Labels by Heat-Stress Posting Date

Among reviews posted on heat-stress dates (daily maximum temperature at or above 35 °C; $n = 339$), the archived provisional anger share was 41.0%, compared with 31.4% on other posting dates ($n = 2608$); provisional joy shares were 23.0% and 29.7%, respectively. The chi-square statistic was 17.71 (df = 6, unadjusted $p < 0.01$). This posting-date contrast is exploratory because actual visit dates and corpus-specific label validity are unknown.

3.5. Seasonal Posting-Date Patterns

The archived posting-date summaries also varied by season. The rainy season had the lowest mean PM2.5 and the highest provisional joy share, whereas the cool season had the highest mean PM2.5 and the highest provisional anger share (Figure 5). Mean star-linked sentiment scores were similar across the hot (4.865), rainy (4.863), and cool (4.854) seasons. Nevertheless, the maximum seasonal difference in mean sentiment was 0.011 points. No seasonal value identifies a visitor's actual exposure because grouping was based on posting date.

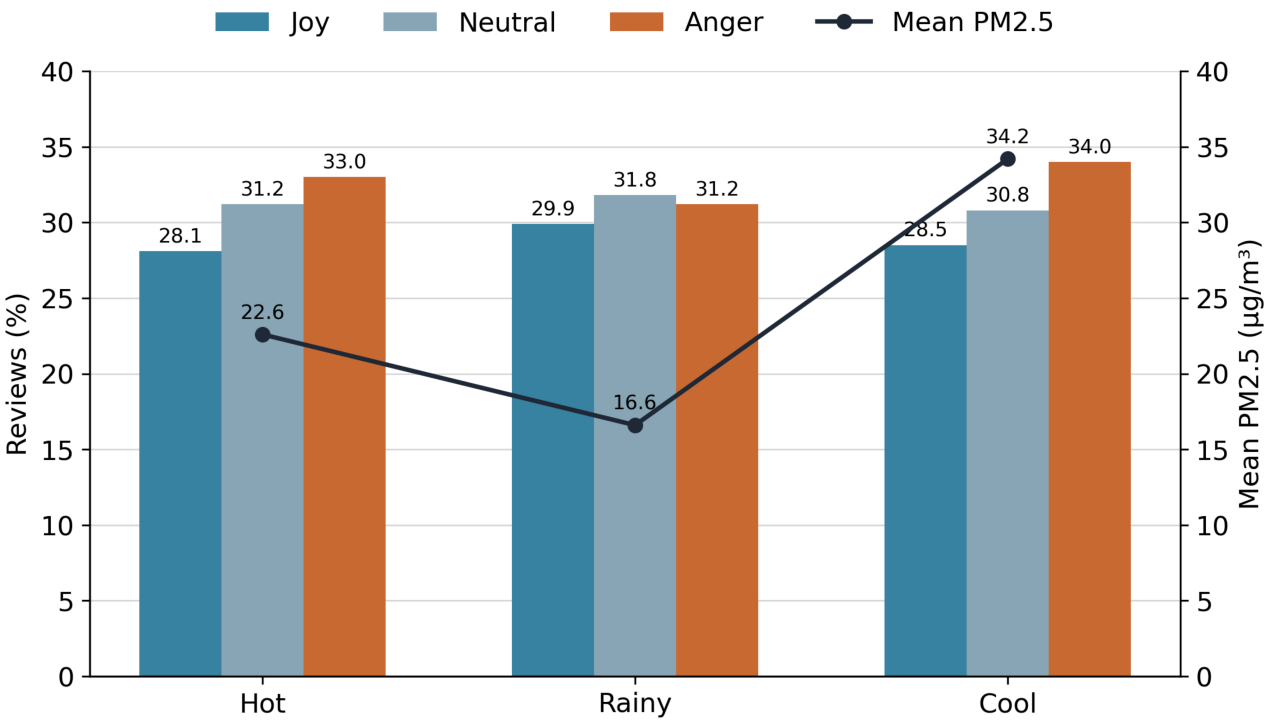


Figure 5. Seasonal variation in provisional dominant emotion labels and mean PM2.5 by review posting date. Note: Emotion-label values are percentages of reviews grouped by posting-date season and are provisional model outputs. PM2.5 values are seasonal means in micrograms per cubic meter. Seasons were classified as hot (March–May), rainy (June–October), and cool (November–February).

3.6. Environmental and Star-Rating Correlations

Table 4 summarizes 25 Spearman correlations between environmental variables and review-level outputs. All coefficients were very small (absolute $\rho \leq 0.049$). Several met unadjusted $p < 0.05$ in the archived analysis, but none met the Bonferroni-corrected alpha of 0.002; they are therefore not treated as statistically reliable associations.

After Bonferroni correction for seven comparisons, the unadjusted *p*-values (Table 5) for the archived correlations of star rating with anger ($\rho = +0.095$), disgust ($\rho = -0.055$), sadness ($\rho = -0.228$), and surprise ($\rho = -0.100$) were below the corrected alpha of 0.0071; the *p*-value for neutral expression was not. The small positive anger-rating coefficient, together with the broader output inconsistencies, is treated as a model-diagnostic warning rather than evidence that highly rated visits contained validated anger.

Table 5. Spearman rank correlations between star ratings and provisional dominant emotion indicators.

Emotion	Spearman ρ	Unadjusted *p*
Anger	+0.095	<0.001
Disgust	–0.055	0.003
Fear	–0.020	0.278
Joy	–0.009	0.635
Neutral	+0.037	0.042
Sadness	–0.228	<0.001
Surprise	–0.100	<0.001

Note: Emotion indicators were provisional binary model labels. Reported *p*-values are unadjusted. Bonferroni correction for seven comparisons set $\alpha = 0.0071$; anger, disgust, sadness, and surprise met this threshold, whereas fear, joy, and neutral did not. Statistical significance does not establish label validity or practical importance.

4. Discussion

4.1. Interpreting Environmental and Emotion-Label Outputs

Lumpini Park received highly positive star-linked sentiment, confirming that the review corpus is dominated by favorable evaluations. Across the two independent subgroup partitions, the reconciled approximate shares were 28.9% for provisional joy and 32.5% for provisional anger. However, the full seven-class distribution remains unreconstructed, and corpus-specific validation is unavailable. These limited derived summaries should not be interpreted as validated emotion prevalence until the original predictions are recovered and tested against independently annotated Thai and English reviews. By comparison, the environmental correlations were negligible in magnitude (absolute $\rho \leq 0.049$), and none survived correction for 25 comparisons. Coupled with uncertain visit-posting lag, these results provide no evidence of a plausible individual-level exposure association. The larger heat-stress posting-date contrast may be useful for generating a management hypothesis, but it remains vulnerable to seasonality, reviewer composition, translation, and model error.

Methodologically, this study belongs to a growing literature that uses social-media content, online reviews, and computational models to characterize affective responses to urban green spaces and place-based experience [18–24]. The present analysis differs by linking review posting dates to daily environmental series, but it cannot claim a validated exposure–effect estimate because visit timing and corpus-specific classifier performance were unavailable. Its defensible contribution is therefore procedural and diagnostic: it illustrates both the scalability of digital-trace linkage and the need for verified timing, reconciled predictions, reproducible model reporting, and local multilingual validation before environmental interpretation is made.

4.2. Bangkok's Seasonal Park-Experience Paradox

The environmental series shows a management-relevant seasonal tradeoff: Bangkok's cool season had lower mean temperature than the hot season but higher mean PM2.5. This pattern can inform the timing of air-quality communication and park programming independently of the preliminary emotion labels. It should not be interpreted as evidence that pollution was systematically associated with reported emotions. For a journal focused on parks, the contribution is not a clinical morbidity or individual exposure claim. The environmental series instead highlights a management question: thermal comfort and air quality may not improve together across seasons. Park evaluation should therefore consider environmental conditions dynamically alongside static measures of area, accessibility, vegetation cover, and amenities. The present posting-date analysis does not estimate the association of those conditions with individual visitors.

4.3. AI-Enabled Visitor Feedback as a Tool for Park Evaluation

The study illustrates a scalable workflow for combining user-generated review text with daily environmental data. With validated models and verified timing, such a workflow could help managers screen for periods when visitors discuss satisfaction, discomfort, frustration, or appreciation and could complement visitor counts, maintenance records, surveys, and sensors. At present, the AI component is suitable only for exploratory screening. The exact model checkpoint, fine-tuning configuration, validation split, per-class metrics, and review-level predictions were not available for audit. Translation, short text, sarcasm, cultural language use, platform conventions, and class imbalance may all shift label assignments. The positive anger-rating correlation, unavailable review-level predictions, and inability to reconstruct the full seven-class distribution are concrete warnings that apparently plausible labels can be misleading without local validation.

4.4. Implications for Park Planning and Management

The practical implications are precautionary management considerations rather than effects estimated by the posting-date analysis. Park authorities could integrate independently verified air-quality and heat information into entrance signage, mobile notices, or programming calendars. Heat-sensitive design priorities include shade, drinking water access, rest areas, tree canopy continuity, and appropriate surface materials. Cool-season programming should consider air quality as well as thermal comfort. Visitor feedback may complement environmental monitoring, surveys, counts, and maintenance records, but the provisional emotion labels should not determine management decisions on their own. In the Bangkok context, linking verified environmental information with multiple forms of visitor evidence is consistent with climate-responsive urban governance. Within the present corpus, Lumpini Park was highly rated; the study does not establish that air quality or heat caused particular visitor responses.

4.5. Strengths and Limitations

The study has several strengths. It uses a large digital-trace corpus of 2947 public reviews, links review posting dates with daily environmental data, examines star-linked sentiment and provisional emotion outputs, and focuses on a tropical megacity where air pollution and heat are relevant constraints for outdoor park use. It also makes the model, timing, and multiplicity limitations explicit, providing a transparent basis for designing stronger multi-park studies.

The limitations are substantial and govern interpretation. The study concerns one iconic, tourism-facing park, and Google Maps reviewers are self-selected. Demographics, residence status, visit purpose, activity, actual visit date, and posting lag were unavailable. Matching by posting date may therefore produce substantial exposure misclassification that cannot be corrected with an arbitrary lag. Daily gridded environmental data do not capture hourly variation, within-park microclimate, or personal exposure. The emotion workflow lacks an identified checkpoint, reproducible hyperparameters, a corpus-specific gold standard, per-class performance, review-level predictions, and a fully reconstructed seven-class distribution; Thai-to-English translation may further alter nuance. Correlations are observational, very small, and sensitive to multiple testing. No direct health outcome was measured. The results are therefore exploratory signals about review timing, not evidence of causal exposure, verified emotion, or clinical morbidity.

4.6. Future Research

Future work should compare parks that differ in size, design, neighborhood context, and user composition and combine online reviews with surveys, counts, on-site sensors, and time-stamped visit data. Before re-estimating environmental relationships, researchers should archive the raw predictions and code, specify the exact multilingual checkpoint and hyperparameters, and create an independent stratified gold standard with per-class precision, recall, F1, and a confusion matrix. Multivariable models should then account for season, language, rating, and meteorological covariation, while embedding-based topic or aspect analyses could move beyond unsupported word-count plots. Tourist–resident differences should be evaluated when user status can be ethically and reliably measured.

5. Conclusions

This study explored a posting-date linkage between 2947 Google Maps reviews of Lumpini Park and daily environmental data for 2024–2025. The corpus was overwhelmingly favorable, but the environmental correlations were negligible, and none survived Bonferroni correction across Table 4. Heat-stress and seasonal posting-date groups showed

descriptive differences in provisional emotion labels, yet actual visit dates were unknown. Independent subgroup partitions yielded consistent approximate overall joy and anger shares (28.9% and 32.5%, respectively), but the full seven-class distribution could not be reconstructed and corpus-specific validation remained unavailable. These patterns must not be interpreted as individual-level exposure inferences for park visitors. Taken together, the study's defensible contribution is a transparent assessment of an AI-enabled park-monitoring workflow: Public reviews can be linked with environmental series at scale, but credible inference requires verified visit timing, reproducible model documentation, multilingual corpus validation, reconciled predictions, effect-size emphasis, and multiplicity control. For climate-responsive park management, environmental monitoring and visitor feedback may complement each other, but neither provisional AI labels nor posting-date correlations should replace surveys, field observation, or direct measurement.

Author Contributions: Conceptualization, N.S. and E.D.A.; methodology, E.D.A. and N.S.; formal analysis, E.D.A.; writing—original draft preparation, E.D.A. and N.S.; writing—review and editing, N.S. and I.A.; supervision, N.S. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially supported by the Second Century Fund (C2F), Chulalongkorn University, under the Sustainable Development Goals initiative, Project No. 21.

Data Availability Statement: Environmental data are publicly available from Open-Meteo. Google Maps review text is not redistributed in full because of user privacy and platform restrictions. Review-level prediction files, model artifacts, and corpus-specific validation data are not available in the retained study records; consequently, the provisional emotion-label results cannot be independently reproduced from the current archive.

Acknowledgments: AI tools, including GPT and Gemini, were used to support coding, language refinement, and manuscript editing. The authors reviewed, revised, and verified the manuscript content, analysis, interpretation, and references, and remain fully responsible for the final submitted work.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

BERT	Bidirectional Encoder Representations from Transformers
API	Application Programming Interface
CAMS	Copernicus Atmosphere Monitoring Service

References

1. Chiesura, A. The role of urban parks for the sustainable city. *Landsc. Urban Plan.* **2004**, *68*, 129–138. [CrossRef]
2. Tan, P.Y.; Zhang, J.; Masoudi, M.; Alemu, J.B.; Edwards, P.J.; Grêt-Regamey, A.; Richards, D.R.; Saunders, J.; Song, X.P.; Wong, L.W. A conceptual framework to untangle the concept of urban ecosystem services. *Landsc. Urban Plan.* **2020**, *200*, 103837. [CrossRef] [PubMed]
3. Hunter, R.F.; Nieuwenhuijsen, M.; Fabian, C.; Murphy, N.; O'Hara, K.; Rappe, E.; Sallis, J.F.; Lambert, E.V.; Sarmiento, O.L.; Sugiyama, T.; et al. Advancing urban green and blue space contributions to public health. *Lancet Public Health* **2023**, *8*, e735–e742. [CrossRef] [PubMed]
4. Hartig, T.; Mitchell, R.; de Vries, S.; Frumkin, H. Nature and health. *Annu. Rev. Public Health* **2014**, *35*, 207–228. [CrossRef] [PubMed]
5. Wang, R.; Helbich, M.; Yao, Y.; Zhang, J.; Liu, P.; Yuan, Y.; Liu, Y. Urban greenery and mental wellbeing in adults: Cross-sectional mediation analyses on multiple pathways across different greenery measures. *Environ. Res.* **2019**, *176*, 108535. [CrossRef] [PubMed]

6. Bratman, G.N.; Anderson, C.B.; Berman, M.G.; Cochran, B.; de Vries, S.; Flanders, J.; Daily, G.C. Nature and mental health: An ecosystem service perspective. *Sci. Adv.* **2019**, *5*, eaax0903. [CrossRef] [PubMed]
7. Kabisch, N.; Qureshi, S.; Haase, D. Human-environment interactions in urban green spaces-A systematic review of contemporary issues and prospects for future research. *Environ. Impact Assess. Rev.* **2015**, *50*, 25–34. [CrossRef]
8. Markevych, I.; Schoierer, J.; Hartig, T.; Chudnovsky, A.; Hystad, P.; Dzhambov, A.M.; de Vries, S.; Triguero-Mas, M.; Brauer, M.; Nieuwenhuijsen, M.J.; et al. Exploring pathways linking greenspace to health. *Environ. Res.* **2017**, *158*, 301–317. [CrossRef] [PubMed]
9. Janeka, P.; Foellmer, J.; Martinez, J.; Schrammeijer, E.A.; Hertig, E.; van Rompay, T.J.L.; Cerrone, D.; Sawungrana, A.R.; Anthonj, C. How green and blue spaces promote health among vulnerable urban populations facing climate hazards: A scoping review. *Wellbeing Space Soc.* **2025**, *9*, 100304. [CrossRef]
10. Janhall, S. Review on urban vegetation and particle air pollution: Deposition and dispersion. *Atmos. Environ.* **2015**, *105*, 130–137. [CrossRef]
11. Meng, Q.; Gao, J.; Zhang, L.; Hu, X.; Qian, J.; Jancsó, T. Coupled cooling effects between urban parks and surrounding building morphologies based on the microclimate evaluation framework integrating remote sensing data. *Sustain. Cities Soc.* **2024**, *102*, 105235. [CrossRef]
12. Ta, A.T.; Promchan, N. A relationship between urban green space and PM2.5 levels in urban and suburban areas of Bangkok. *IOP Conf. Ser. Earth Environ. Sci.* **2024**, *1368*, 012004. [CrossRef]
13. Cohen, A.J.; Brauer, M.; Burnett, R.; Anderson, H.R.; Frostad, J.; Estep, K.; Balakrishnan, K.; Brunekreef, B.; Dandona, L.; Dandona, R.; et al. Estimates and 25-year trends of the global burden of disease attributable to ambient air pollution: An analysis of data from the Global Burden of Diseases Study 2015. *Lancet* **2017**, *389*, 1907–1918. [CrossRef] [PubMed]
14. World Health Organization. *WHO Global Air Quality Guidelines: Particulate Matter (PM2.5 and PM10), Ozone, Nitrogen Dioxide, Sulfur Dioxide and Carbon Monoxide*; World Health Organization: Geneva, Switzerland, 2021.
15. Gasparrini, A.; Guo, Y.; Hashizume, M.; Lavigne, E.; Zanobetti, A.; Schwartz, J.; Tobias, A.; Tong, S.; Rocklöv, J.; Forsberg, B.; et al. Mortality risk attributable to high and low ambient temperature: A multicountry observational study. *Lancet* **2015**, *386*, 369–375. [CrossRef] [PubMed]
16. Mora, C.; Dousset, B.; Caldwell, I.R.; Powell, F.E.; Geronimo, R.C.; Bielecki, C.R.; Counsell, C.W.W.; Dietrich, B.S.; Johnston, E.T.; Louis, L.V.; et al. Global risk of deadly heat. *Nat. Clim. Change* **2017**, *7*, 501–506. [CrossRef]
17. Werder, E.; Lawrence, K.; Deng, X.; Jackson, W.B., II; Christenbury, K.; Buller, I.; Engel, L.; Sandler, D. Residential air pollution, greenspace, and adverse mental health outcomes in the U.S. Gulf Long-term Follow-up Study. *Sci. Total Environ.* **2024**, *946*, 174434. [CrossRef] [PubMed]
18. Roberts, H.; Resch, B.; Sadler, J.P.; Chapman, L.; Petutschnig, A.; Zimmer, S. Investigating the emotional responses of individuals to urban green space using Twitter data. *Urban Plan.* **2018**, *3*, 21–33. [CrossRef]
19. Plunz, R.; Zhou, Y.; Vintimilla, M.I.C.; Mckeown, K.; Yu, T.; Uguccioni, L.; Sutto, M.P. Twitter sentiment in New York City parks as a measure of well-being. *Landsc. Urban Plan.* **2019**, *189*, 235–246. [CrossRef]
20. Delmelle, E.; Gao, X. Emotional landscapes: Mapping urban park sentiments using natural language processing. *Abstr. Int. Cartogr. Assoc.* **2025**, *10*, 56. [CrossRef]
21. Wang, Y.; Zhou, S.; Guan, Q.; Fang, F.; Yang, N.; Li, K.; Liu, Y. Enhancing place emotion analysis with multi-view emotion recognition from geo-tagged photos: A global tourist attraction perspective. *ISPRS Int. J. Geo-Inf.* **2024**, *13*, 256. [CrossRef]
22. Aman, J.A.J.; Matisziw, T.C. Urban sentiment mapping using language and vision models in spatial analysis. *Front. Comput. Sci.* **2025**, *7*, 1504523. [CrossRef]
23. Wu, Y.; Liu, J.; Quevedo, J.M.D.; Cheng, H.; Yu, K.; Kohsaka, R. Critical factors influencing visitor emotions: Analysis of restorativeness in urban park visits in Fuzhou, China. *Front. Public Health* **2023**, *11*, 1286518. [CrossRef] [PubMed]
24. Li, Y.; Zhu, M.; Shen, H.; Yang, Y.; Lange, E.; Lu, X. Could there be negative sentiments toward urban parks? An analysis of internal and external factors. *Urban For. Urban Green.* **2025**, *112*, 128920. [CrossRef]
25. Thaiutsa, B.; Puangchit, L.; Kjelgren, R.; Arunpraparut, W. Urban green space, street tree and heritage large tree assessment in Bangkok. *Urban For. Urban Green.* **2008**, *7*, 219–229. [CrossRef]
26. Bangkok Metropolitan Administration. *Bangkok Green Space Development Plan*; Bangkok Metropolitan Administration: Bangkok, Thailand, 2019.
27. Suwannapuk, N. Management Guidelines for Urban Public Parks: A Case Study of Lumpini Park. Master's Thesis, Chulalongkorn University, Bangkok, Thailand, 2018.
28. Lazarus, R.S. Progress on a cognitive-motivational-relational theory of emotion. *Am. Psychol.* **1991**, *46*, 819–834. [CrossRef] [PubMed]
29. Ulrich, R.S.; Simons, R.F.; Losito, B.D.; Fiorito, E.; Miles, M.A.; Zelson, M. Stress recovery during exposure to natural and urban environments. *J. Environ. Psychol.* **1991**, *11*, 201–230. [CrossRef]
30. Kaplan, S. The restorative benefits of nature: Toward an integrative framework. *J. Environ. Psychol.* **1995**, *15*, 169–182. [CrossRef]

31. Weiss, H.M.; Cropanzano, R. Affective Events Theory. In *Research in Organizational Behavior*; Staw, B.M., Cummings, L.L., Eds.; JAI Press: Greenwich, CT, USA, 1996; Volume 18, pp. 1–74.
32. Filieri, R. What makes online reviews helpful? A diagnosticity-adoption framework. *J. Bus. Res.* **2015**, *68*, 1261–1270. [CrossRef]
33. Open-Meteo. Historical Weather API Documentation. Available online: https://open-meteo.com/en/docs/historical-weather-api (accessed on 4 June 2026).
34. Open-Meteo. Air Quality API Documentation. Available online: https://open-meteo.com/en/docs/air-quality-api (accessed on 4 June 2026).
35. U.S. Environmental Protection Agency. AQI Breakpoints: PM2.5 24-Hour Categories. Available online: https://aqs.epa.gov/aqsweb/documents/codetables/aqi_breakpoints.html (accessed on 22 July 2026).
36. Devlin, J.; Chang, M.-W.; Lee, K.; Toutanova, K. BERT: Pre-training of deep bidirectional transformers for language understanding. In *Proceedings of NAACL*; ACL: Minneapolis, MN, USA, 2019; pp. 4171–4186.
37. Mohammad, S.M.; Turney, P.D. Crowdsourcing a word-emotion association lexicon. *Comput. Intell.* **2013**, *29*, 436–465. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.