Introduction
Cities in the United States have announced initiatives to become more sustainable, healthy, resilient, livable, and environmentally friendly.

However, indicators for measuring all outcomes related to these targets and the synergies between them have not been well defined or studied. One such relationship is the linkage between air quality with emotional well-being (EWB) and neighborhood infrastructure. Here, regulatory monitoring, low-cost sensors (LCSs), and air quality modeling were combined to assess exposures to PM2.5 and traffic-related NOx in 6 Minneapolis, MN, neighborhoods of varying infrastructure parameters (median household income, urban vs suburban, and access to light rail). Residents of the study neighborhoods concurrently took real-time EWB assessments using a smart phone application, Daynamica, to gauge happiness, tiredness, stress, sadness, and pain. Both LCS PM2.5 observations and mobile-source-simulated NOx were calibrated using regulatory observations in Minneapolis. No statistically significant (α = 0.05) PM2.5 differences were found between urban poor and urban middle-income neighborhoods, but average mobile-source NOx was statistically significantly (α = 0.05) higher in the 4 urban neighborhoods than in the 2 suburban neighborhoods. Close proximity to light rail had no observable impact on average observed PM2.5 or simulated mobile-source NOx. Home-based exposure assessments found that PM2.5 was negatively correlated with positive emotions such as happiness and to net affect (the sum of positive and negative emotion scores) and positively correlated (ie, a higher PM2.5 concentration led to higher scores) for negative emotions such as tiredness, stress, sadness, and pain. Simulated mobile-source NOx, assessed from both home-based exposures and in situ exposures, had a near-zero relationship with all EWB indicators. This was attributed to low NOx levels throughout the study neighborhoods and at locations were the EWB-assessed activities took place, both owing to low on-road mobile-source NOx impacts. Although none of the air quality and EWB responses were determined to be statistically significant (α = 0.05), due in part to the relatively small sample size, the results are suggestive of linkages between air quality and a variety of EWB outcomes.

KEYWORDS: Air quality, low-cost PM2.5 sensor, R-Line, subjective well-being, neighborhood infrastructure
studies of EWB track a range of positive and negative emotions such as happiness, anger, aggression, pleasure, fatigue, stress, and sadness.16,17

Emotional well-being has often been associated with health as the 2 influence each other; better health often leads to higher EWB and vice versa.19 High EWB involves frequent pleasant emotions, infrequent unpleasant emotion, the net of which is one measure of EWB called net affect; high well-being also includes cognitive aspects, that is, high levels of life satisfaction/evaluation. Poor health, separation (encompassing widowhood, divorce, or separation), unemployment, and lack of social contact are factors of strong, negative associations to EWB.19 Intra-personal personality traits can also influence subjective self-assessments of well-being. In addition, neighborhood-level infrastructure has also been shown to impact health and EWB.20-22 Access to convenient and affordable transportation enables participation in activities that can improve life, including gainful employment, improved education, and social interactions.23,24 Exposure to poor air quality, particularly PM_{2.5}, has been found to be one of the largest factors leading to disease burden globally, as it has both chronic and acute adverse health outcomes.25-29 In addition, PM_{2.5} affects visibility, which is an additional socioeconomic burden that influences EWB.30

Traditionally, air pollution has been measured using expensive, bulky, and sparsely located monitors.31 New techniques to generate fine-scale measurements have been developed and studied in recent years, including the use of low-cost sensing technologies.32 Low-cost sensors (LCSs) have advantages as they are cheaper and smaller, providing widespread spatial coverage that has not been viable in the past, and are easier to transport and operate than regulatory or research-grade instruments. However, evaluation of their performance is inconsistent.33-36 City-scale modeling of air pollutants is often done using dispersion models, but the modeled concentrations do not always agree with observations, due in part to emission uncertainties, omission of complex atmospheric chemistry, and no default depositional loss mechanisms in the model. Much of the local gradients of pollution concentrations, particularly NO_{x} (a combustion byproduct), are driven by on-road mobile sources in cities,37 so fine-scale dispersion simulations from on-road mobile sources can provide additional understanding of neighborhood air pollution levels and their impacts on EWB.

Historically, EWB was measured using retrospective self-reports, in which participants would reflect on certain past events and attempt to recall their feelings. The results from these studies were accordingly limited due to recall bias. Following self-reporting, the next advancement in measuring EWB was with experience sampling methods (ESMs). Experience sampling methods involve repeated sampling of subjects’ behaviors in real time in natural environments.38 Experience sampling methods assess specific events in subjects’ lives or assess subjects at periodic intervals by random time sampling.39 While ESMs allow for advancements of studying EWB, they do not offer continuous measurements of it.

The day reconstruction method (DRM) asks the respondent to reconstruct the entire sequence of daily activities and emotional experiences during each activity, which offers a more comprehensive measurement of EWB than ESMs and captures more completely the time-variant nature of EWB.40 Recent mobile technology advancements, including smartphone applications, allow for opportunities to collect EWB data near real time (survey subjects often fill the responses throughout the day and not necessarily following each event, so their real-time EWB emotions may not be fully captured) using the DRM approach.41-44 Smartphone-enabled DRM approaches allow for comprehensive data acquisition throughout the day as opposed to single snapshots. Using smart phones for the surveys provides additional benefits including (1) accurate location identification using the Global Positioning System (GPS),45 (2) additional characterization of activity attributes using smartphone built-in sensors for user inputs (eg, transportation mode, companionship/event partnerships), and (3) for information on the temporal sequence of activities and experiences.46-49

Recent studies have addressed environmental justice and air pollution exposure based on socioeconomic status (SES) and have generally found that poor and racial minority communities are disproportionately affected with lower air quality.41-46 And while the linkages between air pollution and health risks (mortality and morbidity) is known,7,47 linkages to EWB are just emerging. Some studies48-50 have noted correlations with negative emotions, such as feelings of sadness/depression, but such studies have not evaluated a full range of EWB outcomes and their variation within cities in the United States. This first-of-its-kind study explored the relationship between air quality (measured using LCS sensors and simulated with a mobile-source dispersion model) with EWB (assessed using a novel phone application) and neighborhood infrastructure (assessed from census-level data) in Minneapolis, MN, using a combination of low-cost air pollution sensors, air quality modeling, and dynamic well-being sampling using a phone-based application.

Methods
This study examined the relationship between ambient air quality with neighborhood infrastructure and individual’s emotional well-being (EWB) using concurrent air quality measurements, mobile source modeling of a traffic-related air pollutant (TRAP), and individual’s EWB assessments in 6 neighborhoods of varying infrastructure parameters in Minneapolis, MN.

Neighborhood selection
The study’s 6 Minneapolis neighborhoods included Phillips, Near North, Brooklyn Center, St. Anthony Park, Blaine, and Prospect Park (Table 1 and SI Figure 1). Infrastructure quality
was assumed to be correlated with median household income (with income class breaks designated from literature on income and health-based disparities),\(^5\) access to light rail (access defined as the neighborhood either containing a light rail station or one block away from at least 2 light rail stations), and urban or suburban (urban defined as inside the city boundaries of Minneapolis and St. Paul, MN, and suburban considered outside the boundaries; Table 1 and SI Figure 1). Because the intensity of the data collected limits the size of the panel to be studied, only 6 neighborhoods were used in this study; however, these 6 neighborhoods still allowed for studying combinations of the infrastructure criteria. The study period was from October 2016 to April 2017.

### Air pollution measurements and modeling

This study focuses on PM\(_{2.5}\) and NO\(_2\) air quality as these pollutants show more heterogeneity than a secondary pollutant like ozone and both are found to contribute significantly to the overall health burden.\(^6\)\(^,\)\(^5\)\(^2\)\(^,\)\(^5\)\(^3\) There are 9 regulatory PM\(_{2.5}\) monitors in the study domain and 4 are defined to capture pollutant concentrations representative of neighborhoods\(^5\)\(^4\) (SI Table 1). However, the neighborhoods housed by 3 of these 4 monitors did not meet our other neighborhood criteria, so to measure suitable neighborhood PM\(_{2.5}\) levels we use low-cost air quality sensors that were deployed and evaluated during a number of previous studies.\(^5\)\(^5\)\(^-\)\(^5\)\(^8\) In this study, the monitors were deployed in the backyards of residents’ homes. The selection criteria for the homes included no close-proximity (within 10s of meters) sources (eg, fire pit, back alleyways for cars/parking, lawn mowing; the study was conducted from October to April, limiting lawn mowing and similar activities), no nearby construction (also limited by the choice of study period), and being at least one house away from a street intersection. Differences in PM\(_{2.5}\) concentrations will exist on the neighborhood scale and within neighborhood microenvironments (eg, on the driveway vs a remote spot over the lawn) in US cities;\(^5\)\(^9\)\(^-\)\(^6\)\(^1\) the location of the LCSs in this analysis should be treated as representative neighborhood background levels. The monitors were zip-tied to fences or posts approximately at the inhalation height, \(~1.5\) m off the ground (SI Figure 2). The LCS measured PM\(_{1/2/5}\) using a Plantower PMS3003 with no upstream drier (SI Figure 3 for schematic) and relative humidity (RH) and temperature with a Sensiron SHT 15 (Figure 1).

The sensors were calibrated using a co-location approach with an EPA Near-Road (monitoring) Network (NRN) site in Minneapolis (Minneapolis—Near Road I-35/I-94). The LCS were co-located with a dry PM\(_{2.5}\) measurement (Beta Attenuation Monitor [BAM]) at the NRN site. Initial PM\(_{2.5}\) calibration (using the manufacturer reported PM\(_{2.5}\) output) results showed a piecewise continuous response that split at \(~10\) µg m\(^{-3}\), which has been observed in other studies.\(^6\)\(^2\) A RH correction to the sensor PM\(_{1/2/5}\) data (level 2A correction)\(^6\)\(^3\) was employed,\(^5\)\(^8\) which provided an estimate of dry PM\(_{1/2/5}\) from the LCSs. Calibrations lasted 2 days and were conducted every 2 weeks during the study period to account for any drifts that occur. A linear fit was then used to calibrate the LCSs with the reference site measurements. The sensors’ calibration data were then applied to the neighborhood sampling data by time-weighted averaging. The sampling frequency used in these samples was minute data; however, to be consistent with the NRN monitor data, levels were averaged hourly. A recent evaluation of the Plantower PMS3003 with a BAM in a US city

### Table 1. Neighborhoods used in this study, including neighborhood infrastructure characteristics, study-average observed PM\(_{2.5}\) concentrations (95% confidence interval) from low-cost sensors (LCS), and R-Line-simulated on-road mobile-source NO\(_x\) concentrations (95% confidence interval).

| NEIGHBORHOOD       | URBAN STATUS | LOW-INCOME STATUS | RAIL ACCESS | DISTANCE TO CENTRAL CITY (ML.) | POPULATION DENSITY (PEOPLE/ ACRE) | MEDIAN HOUSEHOLD INCOME (US$/HH) | LOW-COST SENSOR PM\(_{2.5}\) (µG M\(^{-3}\)) | R-LINE NO\(_x\) (PPB) |
|--------------------|--------------|-------------------|-------------|-------------------------------|-----------------------------------|---------------------------------|---------------------------------|------------------|
| Prospect Park      | X            | X                 | 3.5         | 6.0                           | 75800                             | 7.8 (7.5-8.2)                   | 8.2 (7.8-8.6)                  |
| St. Anthony Park   | X            |                   | 4.4         | 5.2                           | 79800                             | 7.5 (7.2-7.7)                   | 8.0 (7.7-8.4)                  |
| Phillips           | X X          |                   | 1.8         | 20.8                          | 32200                             | 7.5 (7.2-7.9)                   | 8.2 (7.8-8.6)                  |
| Brooklyn Center    | X            |                   | 7.4         | 6.1                           | 56300                             | 7.6 (7.2-7.9)                   | 6.4 (6.1-6.7)                  |
| Near North         | X X          |                   | 2.5         | 12.5                          | 36200                             | 7.5 (7.1-7.8)                   | 7.4 (7.1-7.7)                  |
| Blaine             | 15.3         | 5.1               | 90400       | 6.4 (6.2-6.7)                 | 3.8 (3.6-4.0)                    |

The PM\(_{2.5}\) concentrations were only considered for hours where observations existed in all 6 neighborhoods. See SI Figure 1 for a detailed spatial map of the study neighborhoods and SI Table 5 for entire sampling average concentrations.
showed the BAM to have a high noise-to-signal ratio at low concentrations, similar to levels that would be observed in
Minneapolis; future work with the Plantower sensors may con-
sider longer averaging times during the calibrations to smooth
out the noise. Uncertainty was assessed from the slope and
intercept uncertainty from the co-location calibration.

Uncertainties were propagated through the sampling period
for each hour’s pollutant measurement.

While LCS can provide additional monitoring, they still do
not provide comprehensive spatial coverage, so R-Line was
used to simulate on-road mobile source NOx impacts for the
same hours that the EWB assessments were conducted. Model-
ing of mobile-source impacts on PM2.5 was not used be-
cause PM2.5 impacts from on-road mobile sources are under-
stood to be low, leading to issues with relying on R-Line
results. Mobile sources contribute to 18% of primary PM2.5
emissions in Minneapolis.64,65

R-Line uses a similar approach to AERMOD, the EPA
recommended regulatory dispersion model. R-Line is formu-
lated specifically to address line (vs point or area) sources. In
addition, R-Line has updated plume spread (σx, σy, σz) param-
eterizations, specific for near-surface dispersion.64,66

National
land cover data from the multi-resolution land characteristic
(MRLC) consortium were used in AERSURFACE to gener-
ate monthly surface properties in Minneapolis to estimate the
Bowen ratio, surface roughness length, and albedo. This, in
combination with surface data from the Minneapolis airport
and upper air data from nearby Chanhassen, MN (WMO# 72649), was then processed in AERMET to generate meteoro-
logical fields, including hourly boundary layer heights.

On-road mobile source emission estimates were generated
using annual average daily traffic (AADT) counts from the
Minnesota Department of Transportation (MNDOT; http://
www.dot.state.mn.us/traffic/data/data-products.html) in com-
bination with representative emission factors used in the EPA
National Emission Inventory (NEI). The AADT counts for
each road link were from 2017 counts or from the most recent
estimates on each road if 2017 data did not exist. Fleet com-
position data were available for 1040 links in Minneapolis. A
weighted average by vehicle type and vehicle count was then
used to estimate the fleet composition for the remaining road
links used in the simulations (N=34,459). Diurnal and day-of-
the-week trends measured in Minneapolis68 were used along-
side the AADT data to develop hourly vehicle counts for each
link. Emission factors used to convert activity data to emissions
were from the NEI and were a function of vehicle type, season
gasoline formulation), temperature, and RH. A 380 m (E-W) ×
500 m (N-S) resolution receptor network spanning 46 km
(E-W) × 60 km (N-S) was used in R-Line.

The R-Line simulations gave hourly on-road mobile source
NOx estimates, and concentrations were determined for each of

the study neighborhoods. R-Line modeling has been found to
lead to unrealistically high simulated pollutant values, which
may be attributed to the model itself, that is, due to no default
loss mechanisms or an overestimation of modeled emissions,69,70
both of which led to approaches to calibrate simulated values.71
Here, 24 correction factors were generated, one for each hour of
the day. The correction was developed from linear fits between
the R-Line simulation results for each hour of the day and an
estimate of the true on-road mobile source impact from obser-
vations, (ie, the difference between the I-35/I-94 NRN moni-
toring site [AQS Site IDs# 27-053-0962] and a background,
regulatory EPA site observation [AQS Site IDs# 27-003-
1002]). The correction approach resulted in the reduction of the
model’s initial, high-simulated concentrations (see SI Section 1
for more details on the correction methodology).

Emotional well-being assessments

Emotional well-being assessments were recorded using
Daynamica™, a smart phone application available on Android phones (SI Figure 4). Neighborhood residents took entry and egress surveys for demographic and personal charac-
teristics. Survey respondents were not informed of the ongoing
air pollution study. Residents of the 6 homes in which the
LCSs were housed did not participate in the EWB assess-
ments. Daynamica™ scaled EWB on a scale from 1 (not at all)
to 7 (strongly), and 5 emotions were assessed: happiness, sad-
ness, stress, pain, and tiredness.36 The net affect, defined as the
positive category (happiness) less the average of the 4 negative
ones (sadness, stress, pain, and tiredness), was also assessed.
This was the same approach that has been used in other studies
to determine the U-index, an oft-applied misery index (ie, a
measure of time that people spend in an unpleasant state).72

The application tracked the users’ movements for a period
of 7 consecutive days. Next, users would subsequently identify
the activity completed and when it occurred and then respond
to a series of EWB questions. There were 371 users, and 26,313
responses were gained from all users (see SI Section 2 for more
details on the respondent selection criteria and respondent
demographic and SES background). More detailed assessment
of the EWB results can be found in Fan et al.37 Oftentimes,
the event to which the EWB recording was associated lasted over
multiple hours. The midpoint of the start time and end time
was used as the hour of the EWB recording for analysis.
Because multiple responses existed in a given hour from a sin-
gle person or from a person in the same neighborhood, the
EWB assessment results in the same hour were averaged.

Linking air quality with neighborhood
ingrastructure and EWB

We analyzed the relationships between the EWB assessments
with the neighborhood PM2.5 measurements (home-based
LCS exposure), the R-Line NOx model results evaluated at the
Results and Discussion

Low-cost sensor PM<sub>2.5</sub> performance and neighborhood concentrations

The RH-corrected, ambient LCS PM<sub>2.5</sub> observations resulted in a linear relationship between the LCS data and regulatory instrument (BAM) at the NRN site, and Pearson correlation coefficients were consistently between 0.8 and 0.9 (see SI Table 2 for calibration fits for the entire study period). Elevated PM<sub>2.5</sub> levels were observed at the beginning of the study period in October/November and toward the end of the study period in April. Minnesota Pollution Control Agency (MPCA) sites within the study domain showed similarly elevated levels during the same hours (SI Figure 6). High concentrations are typically driven by meteorology (eg, low inversion heights, low wind speeds) though they also reflect increased emission events (eg, rush-hour traffic and residential wood burning, a common approach to home heating throughout Minneapolis). The calibrated LCS observations were compared against the reference measurements for the entire study domain, and rough agreement was found between the neighborhood levels and the reference sites ($R^2 = 0.30-0.61$; SI Figures 6 and 7 and SI Table 4).

The LCS measurements showed similar average PM<sub>2.5</sub> concentrations in 5 of the 6 neighborhoods, with Blaine (the middle-income, suburban neighborhood) being statistically significantly ($α = 0.05$) cleaner than each of the other 5 neighborhoods. Here, concentrations were compared only when observational data existed for all 6 neighborhoods. The highest observed average PM<sub>2.5</sub> concentration was in Prospect Park (the middle-income, urban with access to light rail neighborhood), but there was no statistical difference between the mean PM<sub>2.5</sub> in Prospect Park and each of the other neighborhoods except Blaine (Table 1). Although Brooklyn Center is a suburban neighborhood, it showed similar measured levels as the urban neighborhoods. Brooklyn Center is just outside the Minneapolis city boundary (SI Figure 1) and would thus be subject to similar urban emissions. The neighborhood PM<sub>2.5</sub> observations followed similar time series (SI Figure 6), which further supports that much of the particulate pollution in the area was from regional sources and/or driven by meteorological factors. The results suggest that there were no noticeable rail access impacts on PM<sub>2.5</sub> levels. It is understood that current-day PM<sub>2.5</sub> emissions from mobile-sources are generally low; the displacement of vehicles from riders choosing light-rail over personal vehicles will not affect local PM<sub>2.5</sub> levels. In addition, public transportation only accounts for 13% of Minneapolis’ commute modeshare, of which 68% is by bus commute and 29% by the light rail. The light-rail system does not displace a large fraction of personal use vehicles.

R-Line on-road mobile source NO<sub>x</sub> modeling calibration results and simulated concentrations

The re-scaling of on-road mobile source NO<sub>x</sub> contributions resulted in improved agreement between the simulated mobile-source impact and the true mobile-source impact evaluated at the NRN site (SI Section 1). As expected, the modeled on-road mobile source impacts closely followed the major roadways in Minneapolis (Figure 2). A small NO<sub>x</sub> concentration difference...
was found between urban neighborhoods with access to light rail (Phillips and Prospect Park) and neighborhoods without such access (Near North and St. Anthony Park). Access to light rail was expected to reduce mobile-source NOx impacts considering the proximity of alternative-fuel transportation modes, that is, electric light rail. However, this can be offset by increased traffic arriving at the light-rail stations or because these 4 study neighborhoods were centrally located and thus subject to high vehicle counts along common routes. Phillips, Prospect Park, St. Anthony Park, and Near North (the urban neighborhoods) had the highest average simulated NOx impacts with higher simulated NOx concentrations than the 2 suburban neighborhoods (Brooklyn Center and Blaine; Table 1). This is due to the higher vehicle counts in the urban areas.

**Linking R-Line NOx (home-based and in situ exposures) and EWB**

Stress, sadness, and pain were positively correlated with simulated neighborhood on-road mobile-source NOx levels, while tiredness and happiness were negatively associated with home-based NOx concentrations (Figure 3). Net affect was also negatively associated with mobile-source NOx concentrations (home-based exposure). For the in situ on-road mobile-source NOx exposures, we found tiredness, sadness, and net affect to be positively associated with simulated NOx concentrations and happiness, stress, and pain to be negatively associated. Happiness and net affect were expected to be EWB indicators negatively correlated with mobile-source NOx concentrations. There were 4732 and 5126 hourly EWB responses used in comparisons with home-based and in situ NOx simulations, respectively (see Table 2 for neighborhood breakdown).

All of the regression relationships between NOx and EWB, for both home-based and in situ exposures were near zero, suggesting that the influence of mobile source pollution had little impact on immediate EWB (Figure 3). Although the majority of anthropogenic NOx emissions (~59%) come from on-road mobile sources in the United States, on-road mobile-source NOx emissions have reduced ~80% as the Clean Air Act was passed in 1970, resulting in relatively low average concentrations in the 6 study neighborhoods and at the locations where the associated activity for the EWB response took place (Table 1 and Figure 3). The range of average NOx concentrations was 3.8-8.2 ppb in the 6 study neighborhoods, far below the annual NO2 NAAQS standard of 53 ppb. Thus, the average NOx levels might not have been high enough for its effects on EWB to be observed, and further, NO2 has little impact on visibility at such low levels.

Other factors that can influence the findings presented have not been controlled for in the analysis. The respondent took the survey at various times during the day (they could take the questionnaire right after completing an activity or hours after the activity), which could bias results. Confounding variables that could have major impacts on EWB assessments against a single indicator using this dataset are discussed further in Fan et al. Briefly, EWB is a function of many factors in addition to air quality, including personality, age, sex, ethnicity, companionship, employment, and health. Recent work using the same survey data to carry out individual-level analyses has shown that general happiness and life satisfaction of a person predicts EWB during various activities. For example, Fan et al. used the same survey data and found that an individual’s general happiness is associated with the individual’s emotional experiences during daily trips. Ambrose and colleagues (https://www.sciencedirect.com/science/article/pii/S0169204619307297) used the same survey data and found that high levels of life satisfaction and optimism (personality traits) are associated with emotional experiences during gardening activities. This article aims to examine the air quality and EWB connection at the neighborhood level. Controlling for...
individual attributes is out of the scope of the comparisons presented here. Future work should explore the effects of air quality on EWB at the individual level and the use of the sampling approach applied here can provide a fine time-series relating EWB to air quality, for example, at the hourly level. Furthermore, the EWB outcomes were not mutually exclusive of one another, that is, if someone is feeling pain, it is possible they feel stressed, too. This inter-relationship among the indicators was difficult to quantify and can influence results. Also, we have not included any correction or re-scaling of the data due to personality or...
Table 2. The number of emotional well-being (EWB) responses that aligned with an air quality (low-cost sensor PM$_{2.5}$, home-based R-Line on-road mobile-source NO$_x$, or in situ R-Line on-road mobile-source NO$_x$) data point during the same hour for each of the 6 study neighborhoods.

| NEIGHBORHOOD | LCS PM$_{2.5}$ COMPARISON | HOME-BASED R-LINE MOBILE SOURCE NO$_x$ COMPARISON | IN SITU R-LINE MOBILE SOURCE NO$_x$ COMPARISON |
|--------------|----------------------------|-----------------------------------------------|---------------------------------------------|
| Phillips     | 102                        | 271                                           | 406                                         |
| Near North   | 612                        | 858                                           | 897                                         |
| Prospect Park| 520                        | 833                                           | 861                                         |
| St. Anthony Park | 677                    | 1172                                          | 1297                                        |
| Blaine       | 496                        | 805                                           | 778                                         |
| Brooklyn Center | 399                   | 793                                           | 887                                         |
| **Total**    | **2806**                   | **4732**                                      | **5126**                                    |

Other demographic (eg, age, sex, ethnicity) effects. The relationships found in this manuscript should be interpreted with caution considering the high uncertainty associated with the variability in the air pollutant concentrations, uncontrolled factors of estimating personal EWB, and potential time lags in the response of EWB to air quality.

High-pollution events and EWB impacts

No noticeable trends were found when exploring the top 10% of neighborhood PM$_{2.5}$ concentrations, home-based mobile-source NO$_x$ levels, or in situ mobile-source NO$_x$ levels, including a 2-day lag, on any of the EWB outcomes (Tables 3, 4, and 5, and SI Figure 7). The PM$_{2.5}$ finding was likely due to the little difference between PM$_{2.5}$ concentrations in the top 10% of hours with the remaining concentrations (SI Table 5), while the NO$_x$ finding could be explained from the low mobile-source NO$_x$ to EWB relationship. There were no noticeable trends of EWB impacts from high NO$_x$ or PM$_{2.5}$ events in the 6 neighborhoods with respect to access to light rail, income levels, or urban versus suburban.
Conclusions

This exploratory research used a novel approach to characterize the relationships between air quality with EWB and neighborhood infrastructure. This study integrates low-cost sensing for PM$_{2.5}$ and R-Line modeling for mobile-source NO$_x$ with a novel phone application for near real-time EWB assessments. From the observational data in 6 neighborhoods of varying SES and light-rail access, poorer neighborhoods tended to have higher PM$_{2.5}$ concentrations than their mid-SES counterparts in Minneapolis, MN, raising environmental justice concerns. Simulated NO$_x$ levels from on-road mobile sources were significantly ($\alpha = 0.05$) higher in the urban neighborhoods than the suburban ones, which was expected, considering higher average traffic counts in the urban neighborhoods. There was little influence of light rail access on neighborhood air quality (for both measured PM$_{2.5}$ and modeled mobile-source NO$_x$). When compared to concurrent EWB assessments from neighborhood respondents, neighborhood PM$_{2.5}$ had a negative response (ie, a higher PM$_{2.5}$ concentration resulted in a lower EWB outcome) for

| EWB INDICATOR | PHILLIPS | NEAR NORTH | PROSPECT PARK | ST. ANTHONY PARK | BLAINE | BROOKLYN CENTER |
|---------------|----------|------------|---------------|------------------|--------|-----------------|
| Happiness     | $-0.95^*$| $-4.2 \times 10^{-2}$ | $-0.18$       | $-0.51^*$        | $1.2 \times 10^{-2}$ | $0.15$ |
| Tiredness     | 0.21     | 0.49$^*$   | 1.0$^*$       | $-0.23^*$        | $-0.16$ | $-6.6 \times 10^{-2}$ |
| Stress        | 0.18     | 0.26       | 0.65$^*$      | $-2.3 \times 10^{-2}$ | $-0.16^*$ | $1.3 \times 10^{-2}$ |
| Sadness       | 0.11     | 0.12       | 0.41$^*$      | $-7.3 \times 10^{-2}$ | $-3.6 \times 10^{-2}$ | $-1.9 \times 10^{-2^*}$ |
| Pain          | 0.33$^*$ | $-3.8 \times 10^{-2}$ | 0.34$^*$     | $-0.13$ | 0.35$^*$ | $-7.3 \times 10^{-3}$ |
| Net affect    | $-1.23^*$| $-0.13$    | $-0.69^*$    | $-0.34^*$        | $-0.19$ | 0.13 |

Abbreviation: EWB, emotional well-being.
See SI Table 6 for the cutoff concentrations. Positive values indicate the top 10% EWB average value was higher than the bottom 90% value (ie, a positive score means the EWB outcome was higher in the high PM$_{2.5}$ days). The asterisk (*) indicates the difference is statistically significant ($\alpha = 0.05$).

Table 4. Average difference between EWB indicators for the top 10% of mobile-source NO$_x$ hourly concentrations (including a 2-day lag) and the 90% cleanest hours in each neighborhood.

| EWB INDICATOR | PHILLIPS | NEAR NORTH | PROSPECT PARK | ST. ANTHONY PARK | BLAINE | BROOKLYN CENTER |
|---------------|----------|------------|---------------|------------------|--------|-----------------|
| Happiness     | 0.16     | $-0.28^*$  | $-0.25^*$     | $-0.36^*$        | $-0.14$ | 0.37$^*$        |
| Tiredness     | $-0.18$  | 0.35$^*$   | 0.20$^*$      | $-1.6 \times 10^{-2}$ | $-0.16$ | $-0.20$        |
| Stress        | $-0.37^*$| 0.30$^*$   | $7.3 \times 10^{-2}$ | $-1.6 \times 10^{-2}$ | $-6.0 \times 10^{-2}$ | 7.9$ \times 10^{-2}$ |
| Sadness       | $-0.12$  | 0.59$^*$   | $8.9 \times 10^{-2}$ | $-7.6 \times 10^{-2}$ | $-9.8 \times 10^{-2}$ | 0.13$^*$        |
| Pain          | $-0.32^*$| 0.23$^*$   | $-0.16^*$     | $-0.42^*$        | 1.8$ \times 10^{-2}$ | $-0.10$ |
| Net affect    | 0.64$^*$ | $-0.41^*$  | $-0.21^*$     | $-0.23^*$        | $-0.23$ | 0.26 |

Abbreviation: EWB, emotional well-being.
See SI Table 6 for the cutoff concentrations. Positive values indicate the top 10% EWB average value was higher than the bottom 90% value (ie, a positive score means the EWB outcome was higher in the high NO$_x$ days). The asterisk (*) indicates the difference is statistically significant ($\alpha = 0.05$).

| EWB INDICATOR | HAPPINESS | TIREDNESS | STRESS | SADNESS | PAIN | NET AFFECT |
|---------------|-----------|-----------|--------|---------|------|-----------|
|               | $-0.24^*$ | $-0.13^*$ | $-0.19^*$ | $-6.7 \times 10^{-2}$ | 1.5$ \times 10^{-2}$ | $-0.11$ |

Abbreviation: EWB, emotional well-being.
Positive values indicate the top 10% EWB average value was higher than the bottom 90% value (ie, a positive score means the EWB outcome was higher in the high NO$_x$ days). The asterisk (*) indicates the difference is statistically significant ($\alpha = 0.05$).
happiness and net affect, but a positive response (ie, a higher PM$_{2.5}$ concentration resulted in a higher EWB outcome) for tiredness, stress, sadness, and pain. None of the air pollution relationships were found to be statistically significant ($\alpha = 0.05$) with EWB, and though from a relatively small sample size associated with this exploratory research, these results are suggestive of more measureable affects given larger sample sizes or greater pollutant variability. Both mobile-source and in situ NO$_x$ had a minimal and near-zero regression relationship with all EWB indicators, which may have been a result of reductions in mobile source emissions as well as increased exposure measurement error versus having observed levels.

Future work linking air quality to EWB should consider personal pollution exposures with on-body monitors and consider personality, age, sex, ethnicity, companionship, employment, and health to better characterize environment impacts (ie, air quality) on EWB. The findings from this work and the novel methods introduced here may be used for policy directives specifically in Minneapolis and in other cities with similar neighborhood characteristics. Local interventions (eg, cleaner heating practices in the winter seasons), particularly in lower SES communities, may offer air quality improvements, which from the results presented here may results in improved well-being. More detailed assessments on the emission sources and activities will be needed to directly intervene in cities, but the methods presented here can be applied in other cities. The findings from this study are only applicable to relatively clean environments with similar infrastructure characteristics, but the relationship between air quality with neighborhood infrastructure and EWB may have more pronounced effects in developing countries (eg, Asian, African, and South American countries) where PM$_{2.5}$ levels can vary be 100s of $\mu$g m$^{-3}$ within the same day. Such studies would offer a unique opportunity to assess the relationship between air quality, infrastructure, and well-being.

**Author Contributions**

RML set up the LCSs in Minneapolis and analyzed their data, estimated mobile-source NO$_x$ emissions and simulated NO$_x$ impacts using R-Line in Minneapolis, linked EWB results with air quality, and wrote the manuscript. KD led the EWB sampling in Minneapolis. KKB designed and manufactured the LCSs. All authors assisted with manuscript preparation. AR, AGR, YF, and NB conceptualized the research.

**ORCID iD**

Raj M. Lal https://orcid.org/0000-0001-6024-0629

**Data Availability**

All data used in this study are openly available. Please email ral6@gatech.edu or anu@princeton.edu for any data needs.

**Supplemental Material**

Supplemental material for this article is available online.

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