Air pollution and age: Do older persons suffer more?

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Abstract

Background: Air quality is known to aggravate cardiopulmonary disease. The aim of this work was to examine the extent to which air pollution, underlying illness, and age influenced 30-day inhospital mortality outcomes.
Methods: All emergency medical admissions, between 2002 and 2018, to St. James's Hospital, Dublin, Ireland (113,807 episodes in 58,126 patients) and particulate matter (PM_{10}) level on the day of admission were studied; we determined 30-day mortality outcomes for older (≥70 years) persons and whether outcomes were conditionally dependent on the underlying illness severity or comorbidity score. We employed a logistic multiple variable regression model to calculate PM_{10} influence on the outcome adjusted for other predictors.
Results: PM_{10} levels fell over time; the daily median was 15.8 μg/m^3 (interquartile ranges [IQR]: 12.1, 21.0) prior to 2010 but 11.5 μg/m^3 (IQR: 8.3, 15.7) in subsequent years. A higher admission day PM_{10} level predicted a worse 30-day mortality – odds ratios 1.09 (95% confidence intervals: 1.05, 1.2) for those >70 years, while for younger patients, this was not significant. The influence of PM on outcomes appeared largely confined to older persons; comparisons between increasing PM_{10} quintiles with Q1 median values of 7.5 μg/m^3 had a model predicted mortality of 10.8% but 15.0% at Q5 median values of 29.3 μg/m^3. An explanation for such difference in outcomes between older and younger may lie in the computed comorbidity and illness severity scores that were quantitatively markedly more severe with advancing age.
Conclusion: PM_{10} levels on the day of admission predicted an increased 30-day in hospital mortality risk, with older patients identified to be more susceptible to poor air quality. The disproportionate impact on older persons may be due to their higher concomitant illness severity and comorbidity scores.

Keywords: Air pollution, hospital mortality, particulate matter, PM10

INTRODUCTION

Conditions such as asthma, rhinosinusitis, respiratory tract infection, lung cancer, and cardiopulmonary disease are widely regarded as exhibiting susceptibility to poor air quality.[1] According to the World Health Organization, 3.8 million premature deaths are attributable to air pollution, approximately 80% of which are due to heart disease and stroke, while the remaining result from respiratory illnesses and cancers related to exposure to fine particulate matter.[1] In Dublin, concern was raised in past decades regarding the public health implications of urban air pollution,[2] which subsequently led to national legislation controlling the marketing, sale, and distribution of bituminous coals. As a result, the average black smoke concentration fell by a

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significant 35.6 μg/m^3, with an associated estimated 15.5% and 10.3% reduction in cardiovascular and respiratory deaths, respectively.[3]

Whether older persons might be more sensitive to the effects of air pollutants is uncertain. Saldiva *et al*.[4] found that PM_{10} levels were more predictive of mortality than other measures of pollution (SO_2 and NO_x) for persons aged >65 years, with an increase in PM_{10} of 100 μg/m^3 associated with an increase in overall mortality to approximately 13%.[4] Di *et al*. found that the effect of $PM_{2.5}$ exposure was greatest among male, black, and Medicaid-eligible persons (>65 years), with an increase of 10 μg/m^3 leading to increase of 7.3% in all-cause mortality.[5] Indeed, the influence of $PM_{2.5}$ air pollution has been shown to affect cognitive function for middle-aged and older adults in Los Angeles, with increasing $PM_{2.5}$ exposure associated with lower verbal learning.[6] The issue, however, of a differential effect based on age is undetermined.

Comorbidity has an important influence on human health, especially in older people; however, efforts to establish standardized instruments to assess levels of multimorbidity have proven to be a challenge.[7] Algorithms have been proposed to identify the presence of chronic conditions toward facilitating the study and surveillance of multimorbidity.[8] For emergency medical admissions, both the comorbidity burden and the Acute Illness Severity Score (AISS)[9,10] can be anticipated as important modifiers of mortality outcomes. In this work, we sought to investigate whether we could, firstly, relate PM_{10} particulate matter levels on the day of admission of an emergency medical patient to subsequent 30-day mortality outcomes. Furthermore, we sought to determine whether background acute illness severity, comorbidity scores, and/or age were more susceptible to such environmental influences.

METHODS

St. James's Hospital, Dublin, serves as a secondary care center for emergency admissions in a catchment area with a population of 270,000 adults. All emergency medical admissions (113,807 episodes in 58,126 patients) from the emergency department (ED) to an acute medical admission unit, between 2002 and 2018, were examined in this work, according to methods described elsewhere.[11,12] As a city center hospital, St. James's Hospital admits persons who are resident elsewhere but working in the capital in addition to visitors to Dublin who become acutely ill.

Data collection

An anonymous patient database was employed, collating core information of clinical episodes from the patient administration system, the national hospital in-patient enquiry (HIPE) scheme, the patient electronic record, the emergency room, and laboratory systems. HIPE is a national database of coded discharge summaries from acute public hospitals in Ireland.[13,14] The International Classification of Diseases, Ninth Revision, Clinical Modification (ICD-9-CM) has been used for both diagnosis and procedure coding from 1990 to 2005, with ICD-10-CM used since then. Data included parameters such as the unique hospital number, admitting consultant, date of birth, gender, area of residence, principal and up to nine additional secondary diagnoses, principal and up to nine additional secondary procedures, and admission and discharge dates. Additional information cross-linked and automatically uploaded to the database includes physiological, hematological, and biochemical parameters.

Air quality data (2002–2018) from three stations within the St. James's Hospital catchment area (Winetavern and Coleraine Street or Rathmines stations) were assessed and hourly PM_{10} measurements were acquired using gravimetric mass concentration measurements with low flow Partisol 2000 air samplers using an impaction type PM_{10} inlet and 47 mm diameter glass fiber filters. The Partisol sampler is a US Environmental Protection Agency reference method for the measurement of PM_{10} mass concentrations. In addition, finer time resolution measurements were made using a tapered element oscillating microbalance PM_{10} mass monitor. More information on these methods may be found elsewhere.[15] A single average value for each day was calculated for the analyses with the daily levels divided into equally spaced quintiles – the PM_{10} quintile cut-points were 9.3, 12.5, 16.1, and 22.2 μg/m^3. The data represented the average daily level across all three stations; where a value was missing, the average of the remaining stations was taken.

Comorbidity instrument

HIPE codes[13,14] were used to construct a measure of multimorbidity. To devise the score, we searched ICD9 hospital episode discharge codes (back-mapping ICD10 codes to ICD9 as appropriate) based on the definition proposed by the US Department of Health and Human Services for chronic physical or mental health disorders that limit people "in activities that they generally would be expected to be able to perform." These ICD codes were similar to those proposed by the Canadian group for multimorbidity[8] and the work of Quan;[16,17] they were grouped by the system into the following ten groups: (i) cardiovascular, (ii) respiratory, (iii) neurological, (iv) gastrointestinal, (v) diabetes, (vi) renal, (vii) neoplastic disease, (viii) others (including rheumatological disabilities), (ix) ventilatory assistance required, and (x) transfusion requirement. We have previously detailed the ICD9 codes utilized, based on the definition proposed by the US Department of Health and Human Services.[18] In addition, we searched other hospital databases for evidence of diabetes (Diamond database), respiratory insufficiency based on forced expiratory volume (FEV) (FEV in 1 s <2 L from data pulmonary function laboratory), troponin status (high-sensitivity troponin >25 ng/L),[19] low albumin (<35 G/dL), and anemia (hemoglobin levels <10 G/dL) or chronic renal insufficiency – Modification of Diet in Renal Disease (MDRD) <60 mL/min × 1.73 m^2.[20] The "morbidity score" for each individual's clinical episode during the study was weighted by its relative importance against the 30-day mortality outcome in the multiple variable regression analysis. This study had no interventional component, used anonymized data, and complied with data protection legislation.

Statistical methods

Descriptive statistics were calculated for background demographic data, including means/standard deviations, medians/interquartile ranges (IQR), or percentages. Comparisons between categorical variables and mortality were made using Chi-square tests. We adjusted the outcome (30-day inhospital mortality) for other known predictor variables that included the multimorbidity score, including the AISS,[9,10] chronic disabling disease score,[21] the Charlson Comorbidity Index,[22] and the sepsis status.[23] Over the prolonged observation period of 17 years, many patients were admitted more than once; for example, those admitted more than once, twice, or three times were 48.8%, 31.2%, and 22.2%, respectively, with 5.3% admitted >10 times each. There will, thus, be a difference in mortality rates if calculated by episode or by the patient (only last admission considered if >1); calculated mortality is therefore explicitly stated as per the episode or as per the patient. National deprivation metrics as determined by the Small Areas Health Research Unit of Trinity College Dublin using methodology similar to Townsend[24] and Carstairs and Morris[25] were used to derive a deprivation score using principle components analysis, a weighted combination of four indicators, relating to unemployment, social class, type of housing tenure, and car ownership.[26] Seasonality and temperature were also adjusted for.

We employed a logistic model with a robust estimate to allow for clustering; the correlation matrix thereby reflected the average discrete risk attributable to each of these predictor variables.[9] Logistic regression analysis identified potential mortality predictors and then tested those that proved to be significant univariate predictors ($P < 0.1$ by the Wald test) to ensure that the model included all variables with predictive power. Stata v. 15 (Stata Corporation, College Station, Texas) statistical software was used for the analysis. We used the margins command in Stata to estimate and interpret adjusted predictions for subgroups, while controlling for other variables such as time, using computations of average marginal effects. Margins are statistics calculated from predictions of a previously fitted model at fixed values of some covariates and averaging or otherwise over the remaining covariates. In the multiple variable logistic regression model, we adjusted univariate estimates of effect, using the previously described outcome predictor variables. The model parameters were stored; postestimation intramodel and cross-model hypotheses could thereby be tested.

Adjusted odds ratios (OR) and 95% confidence intervals (CI) were calculated for those predictors that significantly entered the model ($P < 0.10$). Statistical significance at $P < 0.05$ was assumed throughout.

RESULTS

Patient demographics

There were a total of 113,807 emergency medical admissions in 58,126 patients over a 17-year study period (2002–2018). This included patients admitted directly into the intensive care unit or high dependency unit. The proportion of males was 48.8%. The number of emergency medical admissions resident from the catchment area was 74.5%; this compares with a figure of 59% for ED presentations where the social influences on ED visitations on two London hospitals have been examined.[27] The median (IQR) length of stay (LOS) was 5.0 (2.1, 9.7) days. The median (IQR) age was 63.3 (43.3, 77.8) years, with the upper 10% boundary at 85.3 years. We set a cutoff point for the comorbidity score of ≥10 points, representing high versus low comorbidity burden. Patients with high comorbidity scores were older at a median (IQR) of 75.1 years (64.4, 82.6) versus 60.8 years (41.2, 76.6). They were more likely to be male 53.4% versus 46.7% and had a longer median (IQR) LOS at 9.1 days (5.1, 16.0) versus 4.6 days (1.9, 8.7).

The demographic characteristics [Table 1] are outlined with a division of age at the time of hospital admission (lower/higher age cutoff at 70 years at presentation and tabulated to allow group comparisons) by our comorbidity score, Charlson Index,[22] and sepsis status.[23] Older persons aged 80.3 years (IQR: 75.4, 85.2) compared with younger persons aged 47.9 years (IQR: 34.4, 60.0) had a longer hospital stay (6.7 day [IQR: 3.1, 12.1] vs. 4.1 day [1.7, 8.0]) and a higher 30-day episode mortality (8.2% vs. 2.0%) outcome. These older admissions were more likely to have high AISS (Group VI – 72.6% vs. 18.5%), a higher comorbidity scores (≥10 points – 19.3% vs. 7.2%), and Charlson Index (Grade 2–39.3% vs. 18.9%) but had similar sepsis scores.

Air pollution levels at admission and 30-day mortality outcome [Figures 1 and 2]

The overall level of environmental particulate matter PM_{10} fell over time; on average prior to 2010, the daily median PM_{10} across the measurement stations was 15.8 μg/m^3 (IQR: 12.1, 21), but in later years, the corresponding PM_{10} levels were 11.5 μg/m^3 (IQR: 8.3, 15.7). The overall 30-day mortality was lower for younger admissions at 2.0% (95% CI: 1.9, 2.1), compared with 8.2% (95% CI: 7.9, 8.5) for older persons. In the logistic multiple variable models, an increasing PM_{10} pollutant level on the day of the hospital admission predicted a higher mortality – OR (1.09) (95% CI: 1.05, 1.12). While various short-term time lag exposures were examined, in addition to maximum, minimum, and ranges of pollutant levels, it was found that only the influence of the average pollutant level on the day of admission was predictive. Adjusted for the other predictive variables of AISS,[9,10] comorbidity score, the Charlson Comorbidity Index,[22] and sepsis status,[23] the model predicted [Figure 2] that the PM_{10} influence on adjusted episode 30-day mortality rates would largely be confined to older persons, with little impact for younger admissions [Figure 2]. For example in older subjects, compared with Q1 PM_{10} values of

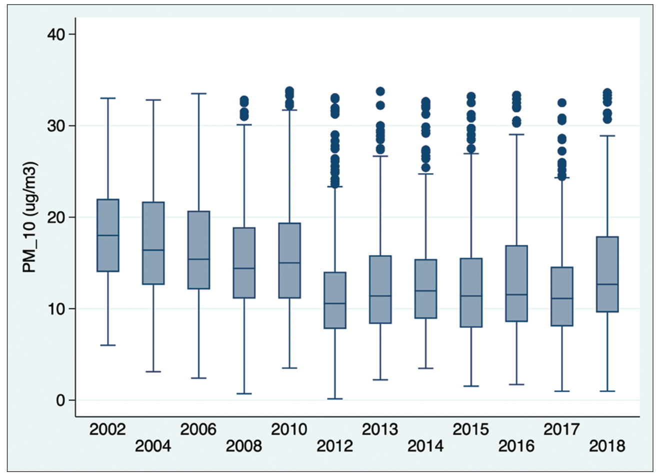

Figure 1: The environmental particulate matter (PM10) present on the day of hospital admission on average declined over time. The predicted probabilities were derived from the multiple variable logistic model; the effect is plotted based on the latter prediction. The data in the model predicted patient mortality adjusted for deprivation status, comorbidity, and Acute Illness Severity Scores

Table 1: Characteristics of emergency medical admission episodes by age

	<70 years (*n*=61,816)	≥70 years (*n*=40,668)	*P*
Age (years)			
Mean (SD)	46.7 (14.92)	80.7 (6.51)	<0.001
Median (Q1-Q3)	47.9 (34.4-60.0)	80.3 (75.4-85.3)	
Length stay (day)			
Mean (SD)	6.0 (5.9)	8.5 (7.1)	<0.001
Median (Q1-Q3)	4.1 (1.7-8.0)	6.7 (3.1-12.1)	
Gender, *n* (%)			
Male	33,036 (53.4)	17,110 (42.1)	<0.001
Female	28,780 (46.6)	23,558 (57.9)	
30 days hospital mortality, *n* (%)			
Alive	60,579 (98.0)	37,328 (91.8)	<0.001
Dead	1237 (2.0)	3340 (8.2)	
Acute illness severity, *n* (%)			
1	3060 (5.7)	8 (0.0)	<0.001
2	6734 (12.6)	6 (0.0)	
3	11,037 (20.6)	218 (0.6)	
4	12,798 (23.9)	2258 (6.2)	
5	9990 (18.7)	7570 (20.6)	
6	9917 (18.5)	26,623 (72.6)	
Comorbidity score, *n* (%)			
<6	40,058 (64.8)	12,843 (31.6)	<0.001
≥6<10	17,338 (28.1)	19,979 (49.2)	
≥10<13	3249 (5.3)	6239 (15.4)	
≥13<16	780 (1.3)	1207 (3.0)	
≥16	369 (0.6)	375 (0.9)	
Charlson index, *n* (%)			
0	32,279 (55.8)	11,721 (31.0)	<0.001
1	14,625 (25.3)	11,258 (29.8)	
2	10,960 (18.9)	14,848 (39.3)	
Sepsis group, *n* (%)			
1	47,078 (76.2)	31,609 (77.7)	<0.001
2	12,833 (20.8)	7550 (18.6)	
3	1905 (3.1)	1509 (3.7)	

SD: Standard deviation

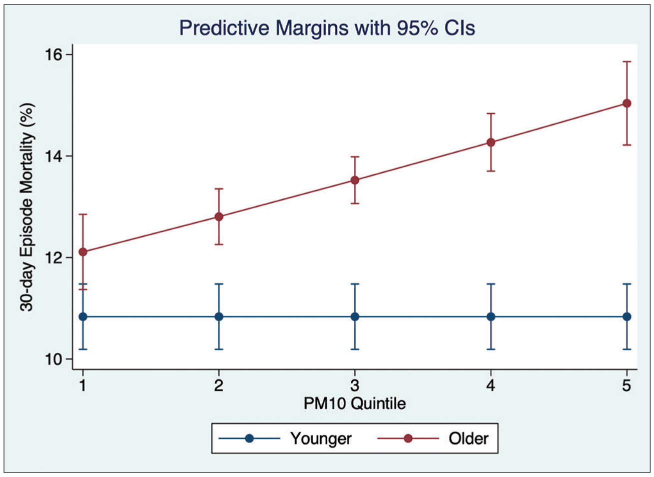

Figure 2: The 30-day hospital mortality outcome was increased linearly in older (unlike younger) persons, proportionate with the quintile of environmental particulate matter (PM10) present on the day of hospital admission. The predicted probabilities were derived from the multiple variable logistic model; the effect is plotted based on the latter prediction. The data in the model predicted patient mortality adjusted for deprivation status, comorbidity, and Acute Illness Severity Scores

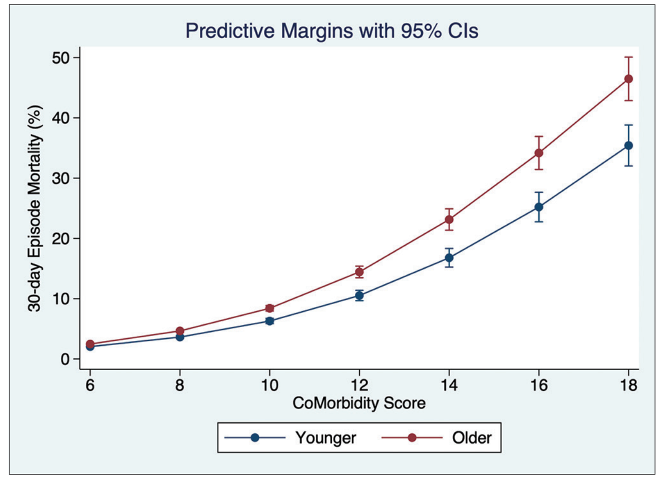

Figure 3: The 30-day hospital episode mortality increased nonlinearly in older and younger persons, with the comorbidity score. The predicted probabilities were derived from the multiple variable logistic model; the effect is plotted based on the latter prediction. The data relates to the predicted episode mortality adjusted for deprivation status, co-morbidity and Acute Illness Severity Scores. However, at any given score, the outcome was worse for older persons

7.5 μg/m^3 (95% CI: 6.1, 8.3) with model predicted mortality of 10.8% (95% CI: 10.2%, 11.5%), mortality would increase at Q3 PM_{10} values of 14.2 μg/m^3 (95% CI: 13.3, 15.1) to 12.1% (95% CI: 11.4%, 12.9%) and Q5 PM_{10} values of 29.3 μg/m^3 (95% CI: 25.1, 38.3) to 15.0% (95% CI: 14.2%, 15.8%).

Comorbidity construct and age [Figure 3]

The comorbidity score increased as a function of age – the median morbidity scores for the three cohorts of (i) <40 years, (ii) ≥60 years, and (iii) ≥85 years were 4.8, 6.5, and 7.6 points. Within these three cohorts, older persons had much higher scores in comparison to the younger admissions, in the ≥6 and <10 points range the (49.2% vs. 28.1%) and the higher ≥10, <13 points ranges (15.4% vs. 5.3%). Overall, although high comorbidity scores >10 and 15 points, for example, were not that common (12% and 1.2% of episodes, respectively), there was a steep and linear rise in 30-day hospital mortality outcomes above the 10 point cut value. In contrast, the laboratory score (AISS) – a major outcome predictor – was remarkably different in older persons accounting for 72.6% of the highest Grade VI risk group versus 18.5% for the younger cohorts. In the multiple variable logistic regression model, the comorbidity score was predictive of 30-day mortality – OR: 1.35 (95% CI: 1.33, 13.7) but less so than the AISS – OR: 2.76 (95% CI: 2.54, 3.0). The interaction of the PM_{10} days of admission level and age (<70 years or ≥70 years) was significant – OR: 1.10 (95% CI: 1.07, 1.13), as was interaction with the AISS – 1.04 (95% CI: 1.04, 1.05) and with the comorbidity score – 1.03 (95% CI: 1.02, 1.03). At any level of comorbidity and adjusted for AISS and other predictive variables, older patients had worse outcomes.

DISCUSSION

There are little data on the selective impact of environmental particulate matter on older versus younger persons. Our data suggested that the adverse impact of elevated day of admission particulate matter in emergency medical admissions was largely confined to older subjects. Among older persons, long-term exposure to traffic-related air pollution increases the risk for asthma hospitalization, those with previous asthma or chronic obstructive pulmonary disease (COPD) admission being most susceptible.[28] Exposure to particulate matter has been associated with an accelerated cognitive decline in older women.[29] Brazilian data on the effects of air pollution in persons aged >65 years found that the PM_{10} levels were more predictive than other measures of pollution (SO2 and NOx) – size (ORs) 1.03, 1.06, and 1.12 although at PM_{10} levels 46 of 79, 93, and 127 μg/m^3, considerably higher than the 47 Dublin exposure level, considerably higher than the Dublin exposure level.[4] This would be consistent with our model adjusted value of 1.09, although their population data would not imply any negative survival impact at the level of our patient exposure (75 and 90 centiles of 20.3 and 29.3, respectively, μg/m^3). Di *et al.* found that the effect size for $PM_{2.5}$ exposure was greatest among male, black, and Medicaid-eligible persons (>65 years), an increase of 10 μg/m^3 in $PM_{2.5}$ with increase in all-cause mortality of 7.3%.[5] The absolute mortality increase for our cohort was

2.9% and 6.9%, adjusted and unadjusted, respectively, for Acute Illness Severity and Comorbidity status, over a PM_{10} median range of 12.9 μg/m^3 – these data appear consistent with the earlier reports. The levels of air pollution in our environment are somewhat lower as compared with levels in other European cities[30] and have been falling also over time[31] but, nonetheless, predicted an adverse inhospital outcome. Despite considerably lower current air pollution levels, pollution below international standards may still prove detrimental to health.[30,32-34] The World Health Organization has proposed air quality guidelines of 50 μg/m^3 and 20 μg/m^3 for 24-hour averages and an annual mean PM_{10}, respectively, while it is acknowledged that guidelines cannot completely protect against adverse health effects.[35,36]

For older persons, long-term exposure to traffic-related air pollution increases the risk of asthma hospitalization, those with previous asthma or COPD hospitalizations being most susceptible.[28] Exposure to particulate matter has been associated with an accelerated cognitive decline in older women.[29] A review of the main health effects of pollutants in the elderly indicated higher risks compared to the rest of the population. Increased pollution exposures have been associated with increased mortality for cardiopulmonary or respiratory causes (mainly COPD and pneumonia), with an increased number of hospital admissions and emergency-room visits (mainly due to exacerbations of COPD and asthma or to respiratory tract infections, mainly pneumonia), with a higher incidence of respiratory diseases, and with decreased lung function.[37] Our multiple variable model, adjusted for disease acuity and complexity and comorbidities, in contrast to the lack of effect for younger patients, predicts that increasing PM_{10} day-of-admission pollutant quintiles would, over the range described, increase unadjusted 30-day mortality hospital per patient mortality from 15.6% to 22.2% and adjusted for AISS and comorbidity from 12.1% to 15.0%.

It would not be unexpected that older persons would have worse outcomes, in relation to a specific risk exposure, as other background predictors will be different dependent on age. The AISS is an age-adjusted aggregate score derived from admission laboratory parameters[9,38] that predicts clinical outcomes.[9,38] A high AISS was relatively common in this work, being present in 46.5% of patients who had a 30-day inhospital mortality rate per patient of 14.4%;[39] our data indicate that the most severe grade was present in 72.6% of older persons age >70 years compared with only 18.5% in the younger admissions. Comorbidity in the population is common and increases with age; Barnett *et al*.[40] indicated multimorbid prevalence rates of 23.2% in the population with other estimates of multimorbidity reported to be 19.0% in the general population.[41] Frailty can, in general terms, be thought of as an accumulation of deficits;[42] such age-related increasing comorbidity burden will inevitably impact on mortality outcomes. High comorbidity scores, in contrast to illness severity, are less common, with only 12% over the median of 10 points; however, when employing a 70 years age split, a comorbidity score above the median of 10 points occurred in 19.2% of the older quantile compared with only 7.1% of those <70 years. Interaction of AISS and comorbidity burden occurs such that the latter lowers the threshold effect at which the AISS alters the overall adverse outcome, which appears to be the case in this work.

Many ecologic studies of environmental equity show that groups with lower socioeconomic status (SES) are more likely to be exposed to higher air pollution levels than groups of higher SES.[43] The inner city is more densely populated than the suburbs; a Swiss cohort study linked improvements in air pollution levels over 11 years to an attenuation of the decline in lung function, providing important insight about the causality between long-term air pollution and exposure.[44] The Escape project related long-term exposure to ambient air pollution with the level of lung function across different cities and regions within Europe. Impaired lung function exhibited the most consistent association with different pollution metrics being inversely related to nitrogen oxides and PM_{10}, as well as to traffic load at the residential address.[45] Notwithstanding these considerations, the data suggested that those at increased risk from particulate matter exposure during an acute medical emergency hospital admission were older persons and that this effect was observed at relatively lower levels of pollutants and despite adjustment for other significant variables, such as AISS and comorbidity burden.

As with any study, it is important that strengths and limitations be discussed. The strengths lie in the comprehensive and extensive dataset available for the analysis and for the employed correction for confounding factors that may affect mortality in medical admissions through the use of acute illness severity and comorbidity burden. While the study includes a large general "take," it is a single-center study and as such, the findings may not translate to other sites. The limitations of this study included that there was a lack of infectious disease pandemics data which, as a result, were not corrected for. Further, given the length of the study period, therapy changes for patients have not been accounted for. Although the clinical datasets were complete where a PM_{10} value was missing among the sampled stations, the average of the remaining stations was taken. The majority of the emergency medical admission patients hailed from the catchment area, with a proportion who were not habitants of the catchment; however, the only environmental influence on the emergency medical admissions was from the average pollutant level on the day of admission. This is perhaps understandable as conditioning a worse outcome if there are high acuity and pollutant (triggering free radical attack) concurrently. As such, all emergency medical admissions were included in the analysis as, irrespective of their home address, the air quality on the day of their admission to which they were exposed was within the catchment area.

CONCLUSION

Although the pollution levels recorded in the hospital catchment area are regarded as low, the data indicated that the levels still impact our patient cohort. PM_{10} levels on the day of admission predicted an increased 30-day inhospital mortality risk, with older patients identified to be more susceptible to poor air quality. With advancing age, patients appeared to have more comorbidity and increase illness severity, which may offer as an explanation for the difference in outcomes between older and younger cohorts.

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Conflicts of interest

There are no conflicts of interest.

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