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Indoor environmental quality and learning outcomes: protocol on large-scale sensor deployment in schools

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ABSTRACT

Introduction Exposure to poor environmental conditions has been associated with deterioration of physical and mental health, and with reduction of cognitive performance. Environmental conditions may also influence cognitive development of children, but epidemiological evidence is scant. In developed countries, children spend 930 hours per year in a classroom, second only to time spent in their bedroom. Using continuous sensing technology, we investigate the relationship between indoor environmental quality (IEQ) and cognitive performance of school-aged children. The proposed study will result in a better understanding of the effects of environmental characteristics on cognitive performance, thereby paving the way for experimental studies.

Methods and analysis A study protocol is presented to reliably measure IEQ in schools. We will monitor the IEQ of 280 classrooms for 5 years, covering approximately 10 000 children. Each classroom in the sample is permanently equipped with a sensor measuring air quality (carbon dioxide and coarse particles), temperature, relative humidity, light intensity and noise levels, all at 1 min intervals. The location of sensing equipment within and across rooms has been validated by a pilot study. Academic performance of school-aged children is measured through standardised cognitive tests. In addition, a series of health indicators is collected (eg, school absence and demand for healthcare), together with an extensive set of sociodemographic characteristics (eg, parental income, education, occupational status).

Ethics and dissemination Medical Ethical Approval for the current study was waived by the Medical Ethical Committee azM/UM (METC 2018-0681). In addition, data on student performance and health stems from an already existing data infrastructure that are granted with ethical approval by the Ethical Review Committee Inner City faculties (ERCIC_092_12_07_2018). Health data are obtained from the 'The Healthy Primary School of the Future' (HPSF) project. Medical Ethical Approval for HPSF was waived by the Medical Ethical Committee of Zuyderland, Heerlen (METC 14 N-142). The HPSF study protocol was registered in the database ClinicalTrials.gov on 14-06-2016 with reference number NCT02800616, this study is currently in the Results stage. Data collection from Gemeentelijke Gezondheidsdienst Zuid-Limburg (GGD-ZL) is executed by researchers of HPSF, this procedure has been fully approved by the Medical Ethical Committee of Zuyderland. The questionnaires on level of comfort will be filled in anonymously by students and teachers. The study will follow the EU General Data Protection Regulation (EU GDPR) and Dutch data protection law to ensure protection of personal data, as well as maintain proper data management and anonymisation.

The protocol discussed in this paper includes significant efforts focused on integrating results and making them available to both the scientific community and the wider public, including policy makers. The results will lead to multiple scientific articles that will be disseminated through peer-reviewed international journals, as well as through conference presentations. In addition, we will exploit ongoing collaboration with project stakeholders and project partners to disseminate information to the target audience. For example, the results will be presented to school boards in the Netherlands, through engagement with the Coalition for Green Schools, as well as to school boards in USA, through engagement with the Center for Green Schools.

Trial registration number NCT02800616; Results.

Strengths and limitations of this study

- ► This is a longitudinal study in which the environmental conditions in the classrooms of more than 10 000 children will be monitored during five academic years, allowing for quasi-experimental research design.
- ► State-of-the-art sensor technology to objectively and continuously measure five different aspects of indoor environmental quality, which enables the decomposition of results into long-term learning effects (average air quality) and short-term testing effects (point in time air quality).
- ► Data infrastructure allows for measurement of cognitive performance at the individual level (instead of class level), based on standardised tests, as well as for objective assessment of health status and socioeconomic background through administrative data.
- ► We have no influence on the allocation of students across classrooms, limiting our ability to randomly expose students to varying environmental conditions over time, and instead rely on the variation over time in environmental conditions to which students are exposed.
- ► The study depends on the existing framework of standardised tests, rather than using a set of tests tailored specifically to the purpose of measuring cognitive performance, and the development thereof.

INTRODUCTION

Exposure to poor environmental conditions has been associated with depreciation of physical health, mental health and cognitive performance.[1] However, most evidence relies on outdoor measurements and is based on adult samples. There is a dearth of reliable and accurate evidence on the impacts and distribution of indoor environmental conditions on human performance in general, and children's cognitive development in particular. Children are especially vulnerable to poor environmental conditions, and these conditions might well be a significant determinant of outcomes in later life.

Children in developed countries spend an average of 7450 hours in school buildings during their primary and lower secondary education.[2] After their home, schools are the most frequented place for children on any given weekday. Schools are also a major consumer of public funds. USA alone invested \$49 billion per year in school facilities from 2011 to 2013. Yet, a recent study reports that 53% of US public schools are in urgent need of repairs, renovation and/or modernisations,[3] providing some indication that indoor conditions may be adversely affected. Understanding better the relationship between the variation in indoor environmental conditions and cognitive performance of children may have important implications for academia and society alike.

In this paper, we present an overview of studies that address the impact of environmental conditions on children's health and performance. We then present a description of the study protocol, which aims to investigate the relationship between indoor environmental quality (IEQ) and cognitive performance of school-aged children. We provide detailed insight into the deployment of continuous sensing technology, as well as the health measures and socioeconomic indicators used in the analysis.

LITERATURE

The effects of ambient environment on health and cognitive functioning

There is extensive evidence in the health science literature on the damaging effects of ambient environmental stressors, such as extreme temperatures or air pollution, on physical and mental health of individuals. For instance, heat waves or the presence of air pollutants, such as ozone or fine particles, both have been associated with respiratory or cardiovascular diseases in humans.[4 5] More recently, empirical evidence shows that air pollution can also cause serious damage to human nervous systems, impairing proper cognitive functioning of people. In particular, research in the field of neuroscience suggests that exposure to air pollution is related to ischaemic stroke risk, depression and mood disorders in adult populations.[6 7]

These hazards are expected to create even more severe damage among infants and young children, as the immune systems, central nervous systems and respiratory systems are not yet fully developed at a young age.[8] Quasi-experimental evidence shows that moderate levels of pollution in developed countries are associated with significant drops in birth weight, increases in school absences, and infant mortality and morbidity. Currie[9] provides an extensive review of the effect of air pollution on children's health, and Graff Zivin *et al*[10] provide an extensive review of the effect of extreme temperature on children's health and human capital development. Furthermore, children's behavioural responses to environmental hazards differ from adults, since children have limited decision power on how and where they spend their time. Exogenous shocks in environmental conditions might well have detrimental consequences for individual human capital accumulation and labour outcomes later in life.

Air quality

Recent evidence suggests that the impact of air pollution on human performance goes beyond direct health channels. A recent study of 39 schools in southern Europe finds strong associations between the level of traffic-related pollution (ie, fine particles) and slower cognitive development among children.[11 12] Similarly, Ebenstein *et al*[13] show that air pollution may also lead to immediate impairment of cognitive performance of individuals. The authors link a longitudinal data set of 400 000 high-stake test examinations in Israel to ambient levels of pollution on the test day, documenting that a student taking an exam on a day with high pollution (measured by levels of fine particles) scores, on average, 2.3% lower.

Indoor air quality (IAQ) is not purely a by-product of outdoor air pollution, or purely generated by outdoor sources alone. Rather, it is the result of a complex process affected by building conditions and occupant-related factors.[14] The most commonly used indicator of IAQ is the concentration of carbon dioxide (CO_2), a colourless, odourless gas that is metabolically produced by humans. CO_2 is also used as a metric to evaluate the performance of ventilation systems in buildings. The inhalation of high levels of CO_2 has been associated with respiratory and cardiovascular problems in humans.[15–17] The health science literature documents multiple physiological symptoms related to poor ventilation in rooms, such as fatigue, headaches and prevalence of asthma episodes.[18] These health issues, ultimately, have also been associated with an increase in absence from work and school for adults and children, respectively.[19 20]

Studies in the field of epidemiology and neuroscience show significant impairments in cognitive performance associated with poorly ventilated rooms (ie, high levels of CO_2). Experimental evidence from functional MRI in the field of neuroscience documents reduction in brain activity following inhalation of 5% (50 000 ppm) CO_2.[21]

Recent lab evidence suggests significant effects of moderate CO_2 concentrations on the cognitive performance of individuals beyond the aforementioned health channels. These studies typically evaluate the performance of healthy adults in different cognitive tasks in rooms where CO_2 levels have been manipulated. Zhang *et al*[22] show significant reductions in the speed of addition, increased response time in a redirection task, and an increase in the number of errors made by adults when undertaking those tasks in rooms with a CO_2 level of 3000 ppm (relative to 500 ppm). Satish *et al*[23] find that, relative to a baseline of 600 ppm of CO_2 (close to outdoor levels), healthy adults exposed to 2500 ppm of CO_2 for 2.5 hours scored 44%–94% lower along different cognitive dimensions, such as crisis response, or information usage. Using a similar study design, Allen *et al*[24] document a 50% reduction in cognitive performance after being exposed for 6 hours to CO_2 levels of 1400 ppm (relative to 550 ppm).

Temperature

The literature highlights the role of temperature in human health and performance. In particular, strong links have been found between extreme temperatures and morbidity and mortality in developed and developing countries.[25] In addition, there is increasing evidence from quasi-experimental field studies concerning the health and cognitive implications of sharp variations in day-to-day temperatures. Hancock *et al*[26] construct a meta-analysis of 49 studies, exploring the effect of thermal stressors on human cognitive performance, showing a significant negative effect on cognitive performance associated with thermal stressors. Park[27] studies the effects of outdoor temperature on the exam day on student performance, using 4.6 million high school exit tests in New York. The author finds that students taking an exam on a day with temperatures higher than 32°C score up to 15% lower. Cho[28] explores the effect of temperature on student learning. In a cohort study including 1729 high schools in Korea (some 1.6 million students during 5 years) the author explores the changes in student test scores within schools associated with heat waves during the academic year. The estimates show a drop in math and English tests of 0.0042 and 0.0064 SD for days with a maximum daily temperature above 34°C, relative to days with a maximum daily temperature between 28°C and 30°C.

Lab experiments equally show detrimental effects of passive heat on stress and human cognitive function. These studies experimentally manipulate the exposure to high temperatures (50°C, 50% relative humidity) over short periods (45 mins) and look at changes in performance on cognitive tasks. The results indicate that individuals under heat stress perform worse in complex tasks such as working memory or executive function.[29,30] Studies in the area of neuroscience suggest that these drops might be a consequence of alterations in blood flow and brain activity associated with heat stress.[31] The effects of extreme temperatures on performance and health are likely to be even more damaging when coinciding with other environmental factors, such as high relative humidity[32] or air pollutants such as ozone.[33]

Existing studies on IEQ in schools

Schools are commonly regarded to have poor indoor air quality, resulting from a combination of high occupancy and poorly ventilated spaces. Numerous studies show that CO_2 concentrations in schools frequently go beyond the levels that facilitate proper cognitive functioning of occupants—as proposed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers or any of the studies in epidemiology or neuroscience discussed in the previous section.[34] However, the evidence on the implications of deficient environmental conditions in classrooms for learning outcomes is still rather scarce, and the magnitude and distribution of the impact of IEQ on children's school performance remains an open question.

The most recent review of the literature identified 27 studies exploring the link between ventilation rates and CO_2 on children's academic achievement or health.[34] The current analyses tend to focus on one unique measure of environmental conditions (eg, average temperature in a classroom or average CO_2 over the measurement period) as the main explanatory variable. Thus, the authors are not able to differentiate between the effects of indoor climate on learning and testing performance. This differentiation is critical for the interpretation of results and policy implications of the study.

The current evidence on indoor environmental conditions in schools and student performance mostly relies on between-subject comparisons and do not contain information on health outcomes at the individual level. The limited number of students in the typical sample, the use of classroom-aggregated variables and the lack of background information about students hinder examination of channels or heterogeneous effects of climate on student achievement. The lack of availability of testing measures for younger children make all of the available studies, with one exception,[35] rely on samples of pupils at the end of their primary/elementary education (age 10–12 years). The systematic exclusion of younger children from studies might well have important consequences for the estimated effects of poor environmental conditions. Children's developing bodies experience significant changes in respiratory, immune and neurological systems. In addition, learning goals and challenges differ between the ages 4–5 years and 10–12 years, impeding the direct extrapolation of findings from older children to the younger children.

Examining the relationship between air quality or temperature and cognitive performance or health is a challenging task, as there are many confounding factors. The presence of unobserved school or classroom characteristics that are potentially correlated with indoor conditions is likely to pollute any estimate on the effect of indoor air quality on health or academic outcomes. Thus, it is necessary to measure indoor environmental conditions for a large number of classrooms over multiple years to let participants be exposed to different indoor environmental conditions while undertaking comparable tasks.

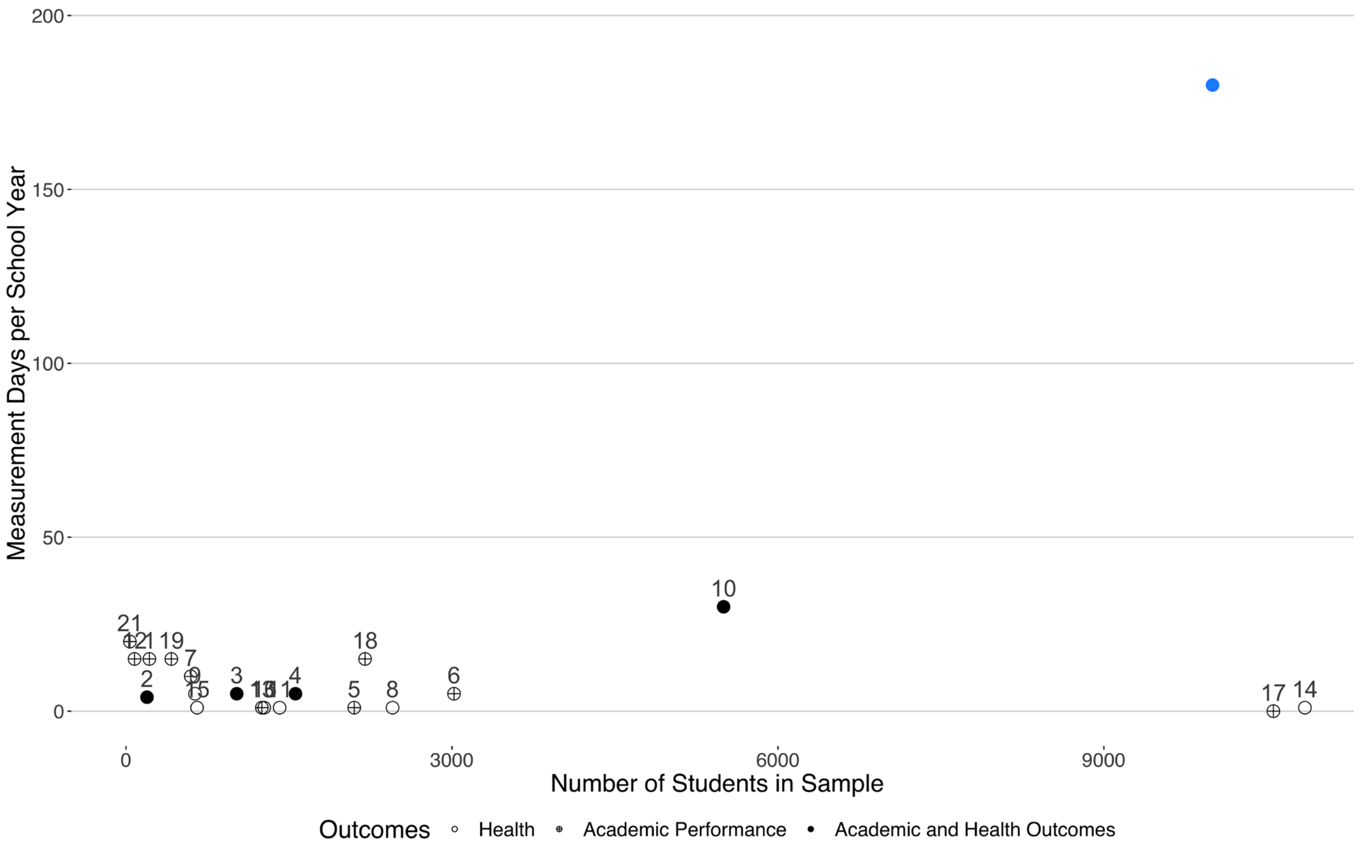

Figure 1 Current studies on indoor environmental quality (IEQ) and cognitive performance of children. The references of the studies included in the graphs are included in the appendix. The blue dot represents the study design presented in this paper.

The current studies often highlight the lack of statistical power in their tests due to the low number of observations in their analysis. This is the result of a low number of individuals in the sample (typically less than 2500 individuals) and the collection of one testing outcome per child.[36] The low number of observations leads to wide CIs, often resulting in a failure to reject the null effect of deficient climate conditions affecting academic achievement.

Finally, the current literature lacks data on individual health profiles and sociodemographic characteristics of children. Most studies have access to absence days or gender ratios at the grade or classroom level only.[36] The lack of individual characteristics in the analysis hinders the examination of potential heterogeneous effects of climate conditions on children's academic achievements. This is critical for the policy recommendations of a study, since it allows for the identification of specific target groups (eg, asthmatic kids) and ultimately advice on more effective interventions or investments (eg, ventilation system vs heating system).

For a graphic overview of the existing literature, and to provide a comparison with our own research setup, we collected information on the number of measurement days and number of individuals in all current studies investigating the effects of indoor school environment on health and/or academic performance (see online supplementary appendix A for references to all studies included in figure 1). Operational limitations typically make researchers face a trade-off between measurement time and sample size (ie, classrooms monitored). Over 90% of the studies rely on short-term measurements (less than 10 days) and no study performs analyses on measurement periods longer than 30 days. Stability in occupancy rates and usage of classrooms within the academic year tend to reduce variance in environmental conditions in classrooms. However, the changes in ambient conditions (outdoor climate or pollution) and in the built environment (ie, building modification or depreciation) create meaningful deviations in environmental conditions over time. Each dot in figure 1 represents one study, and we distinguish between studies that focus on health, academic performance or both. For comparison, our own study is depicted in the larger blue dot in the upper right-hand corner. Since the graph depicts observations days per school year and since our study will cover at least four school years, it understates the difference between our study and the existing literature.

METHODS

The elementary education system in the Netherlands

In a typical Dutch elementary school, children attend class from 08:30 hours until 15:15 hours. Children have the option to consume their lunch at home during the

1 hour lunch break, or eat their self-brought lunch at school. The amount of time that children spend in the classroom is second only to the time they spend in their bedroom, and it generally increases as children progress in elementary school.

The elementary education in the Netherlands consists of 8 years, from the age of 4 years to the age of 12 years, being compulsory from the age of 5 years only. The education system is ruled under the principle of 'freedom of education', where elementary schools are granted a high degree of autonomy, giving the right to any natural or legal person to set up a school and to organise its teaching programme. At the same time, the central government sets learning objectives and quality standards that apply to all schools and monitors school quality and compliance with central rules and regulations. Nearly all schools participate in the well-developed nationally standardised assessment system, the *Leerling Volg Systeem* (LVS), a longitudinal student tracking system comprised of multiple tests per grade, covering the main knowledge areas and developed by the Central Institute for Test Development (*Centraal Instituut voor Toetsontwikkeling, Cito*). The tests take place throughout the academic year, with clear testing peaks in January, February and June. By the end of the primary education, in the eighth grade, Cito's *Entreetoets* supports elementary schools in their recommendations regarding the level of high school education most suitable for each student. A recent report by the Organisation for Economic Co-operation and Development (OECD) provides a comprehensive description of the Dutch primary education system.[37]

Study sample and study design

Our study is designed to monitor the indoor environmental conditions and learning outcomes in approximately 280 classrooms, including about 10 000 pupils. The 29 schools involved are a random sample of the schools belonging to an educational board with 47 schools under management, in the Parkstad region, located in the south of the Netherlands. Some of the schools are situated in an area that is slightly deprived, but differences in median income and unemployment are small. For example, the median net household income in the sample ranges from €21.9k to €25.6k, as compared with €25.8k in the Netherlands, on average. Unemployment in the sample ranges from 3.3% to 4.7%, compared with 3.8% in the Netherlands.[38 39]

All schools in the sample teach all grades (ie, grades 1–8) in their elementary school education programme. The average number of groups per school is 11. The sample is quite heterogeneous in terms of building characteristics. Online supplementary appendix B provides an overview of the sample typology. The average school building in the sample was built in 1987, and the date of construction ranges from 1932 to 2016. All classrooms have internet connection and multimedia boards for teaching practices. The buildings are also heterogeneous in terms of ventilation system. Approximately half of the buildings have a ventilation system (52%), and 23% of the school buildings have a ventilation system that was installed in the last 5 years.

The levels of CO_2, particles, temperature, relative humidity, background noise and light intensity of each classroom, as well as student performance in the sample will be continuously monitored for five academic years.

Monitoring environmental conditions in classrooms

Sensor network

Environmental conditions in each classroom will be monitored using the Aclima measurement system (Aclima, San Francisco, California, USA). Spatially and temporally resolved indoor data are collected using a sensor network consisting of individual wall-mounted stationary nodes, all equipped with a number of individual sensor modules. For this study, the nodes will measure CO_2 (ppm), coarse particles (counts/L), temperature (C), relative humidity, light intensity (lux) and sound (dBA). The node captures and transmits all data to a cloud-based server, where the data are processed, analysed and stored. See table 1 for the sensor performance characteristics. The frequency of raw data collection ranges from 1 s to 30 s. However, we implement a smoothing protocol that aggregates all measures at the 1 min level, using moving averages.

Table 1 Sensor characteristics

	Sensing method	Accuracy	Resolution	Sample frequency
Carbon dioxide (CO_2)	Non-dispersive infrared	50 ppm + 3%	10 ppm	17 s
Coarse particles (PM)	Optical, scattered light	250 count/L+ 20%	250 count/L	30 s
Relative humidity (rh)	Complementary metal oxide semiconductor	4%	0.3%	5 s
Light (lux)	Photodiode	3 lux	NA	1 s
Temperature (°C)	Solid state integrated circuit	1°C	0.2°C	1 s
Sound (dB)	Back electret	5 dBA	3 dBA	1 s

Coarse particle counts will be aggregated at 15 min intervals due to the high variance of the series.

Sensor placement

Before the deployment of the sensor network, we carried out a pilot study in multiple classrooms across two schools. The aim of the pilot study was to test the spatial and time series variations of indoor environmental conditions in schools. Two schools with heterogenous physical characteristics were selected for the pilot, with the aim to maximise differences in environmental conditions (see online supplementary appendix C for a complete description of the pilot study). For the purpose of the pilot study, we deployed 3 sensors in 4 classrooms (12 sensors in total), monitored for a period of 5 months (August 2016–January 2017).

The sensors were deployed at the same height (1.50 m) and in three separate locations covering the perimeter of the classrooms (photos of sampling locations in the classrooms of the pilot schools are shown in online supplementary appendix C, figure 1). The height was chosen following current guidelines for air quality monitoring in schools.[40] In one of the classrooms at Pilot School 2, we further investigated the differences in measurements at different heights (1.50 m vs 2.00 m) and the results showed high correlations between the measurements of the sensor mounted at 2 m versus the other two sensors installed in the same classroom.

Figure 2 presents the Pearson correlation coefficients between the respective sensors and CO_2, coarse particles and temperature for the pilot study. The results indicate that the correlations for CO_2, coarse particles and temperature between the three sensors within one classroom are on all occasions very high (over 0.98). Correlations of indoor environmental metrics are always higher between the sensors within a classroom than with sensor measurements across different classrooms within a school. Especially the variation in indoor temperature and CO_2 levels is highly heterogenous between classrooms, as can be observed from figure 2. The correlation between sensors in different classrooms in the same schools is higher in Pilot School 1, the newly constructed school with a mechanical ventilation system, suggesting a higher degree of homogeneity in the school. During the academic year, it became also apparent that IEQ shows high temporal variation in our sample of schools (see online supplementary appendix C, figures 2 and 3). Finally, the indoor environmental conditions are strongly associated with the status of building conditions, as illustrated by the effects on the CO_2 levels of a breakdown and modification of a ventilation system (see online supplementary appendix C, figures 4 and 5).

These graphs provide important information on the heterogeneity of indoor environmental conditions within a room, and the heterogeneity across rooms. From a measurement perspective the results suggest that there is unique information to obtain from each node, thus reinforcing the need to measure each room individually. However, deploying more than one sensor per room seems to be redundant. With respect to node positioning, based on the pilot we decided to position each node at the same height (1.50 metres), to obtain a good representation of the inhalation area. The nodes are located on the wall opposite from where the teacher tends to undertake the teaching activities (we avoid locations next to operable windows and doors). This combination of height and location represents the typical exposure level in the rooms occupied by the pupils.

An important channel for IEQ on place and occupant performance is the perceived quality of the environment. To explore the level of comfort at different schools and classrooms, we assess[1] teachers and[2] students, by completing annual questionnaires validated by previous studies. For teachers, we use the Occupant Indoor Environmental Quality Survey developed by the Centre for the Built Environment at the University of California, Berkeley.[41] The questionnaire includes questions about thermal comfort, perceived air quality and noise. For students, we ask a cohort of 1000 pupils (all pupils in group 6 in the sample) to report annually their perceptions of odour intensity and acceptability starting at age 10 years by using a series of visual scales, as previously used in the literature.[42]

Sensor calibration

Prior to deployment, both the CO_2 and particulate matter (PM) sensors are calibrated to reference-grade instrumentation at Aclima's facilities. Sensors that pass sensor-reference performance metrics for precision, bias and R-squared (ie, goodness of fit) are deployed.

During the first 2 weeks of deployment, background concentrations characterised by limited influence from CO_2 sources are calculated for each sensor using the lowest concentrations measured. These sensor-specific, in situ baselines are applied to correct any observed drift over time in the sensor response. This correction assumes that the derived reference value in any specific building and location is characteristic of that space over time. Analysis of the first year of data from the schools in the pilot study demonstrated stable values, with the sensors needing no drift correction.

To ensure proper measurement during the sensor deployment period, we developed a protocol to check the status and performance of the sensors. This protocol includes regularly monitoring network health and checking sensor response. This also includes regular checks of the data from the set of sensors to identify if any of the sensors look to be outliers. Following up on outliers should provide sufficient information to identify any failed sensors.

Monitoring outdoor environmental conditions

We will also monitor continuously the outdoor air pollution (PM10, PM2.5 and PM1) for each school building in the sample using PurpleAir devices (PurpleAir, Draper, Utah, USA). The sensors will be deployed on the roofs

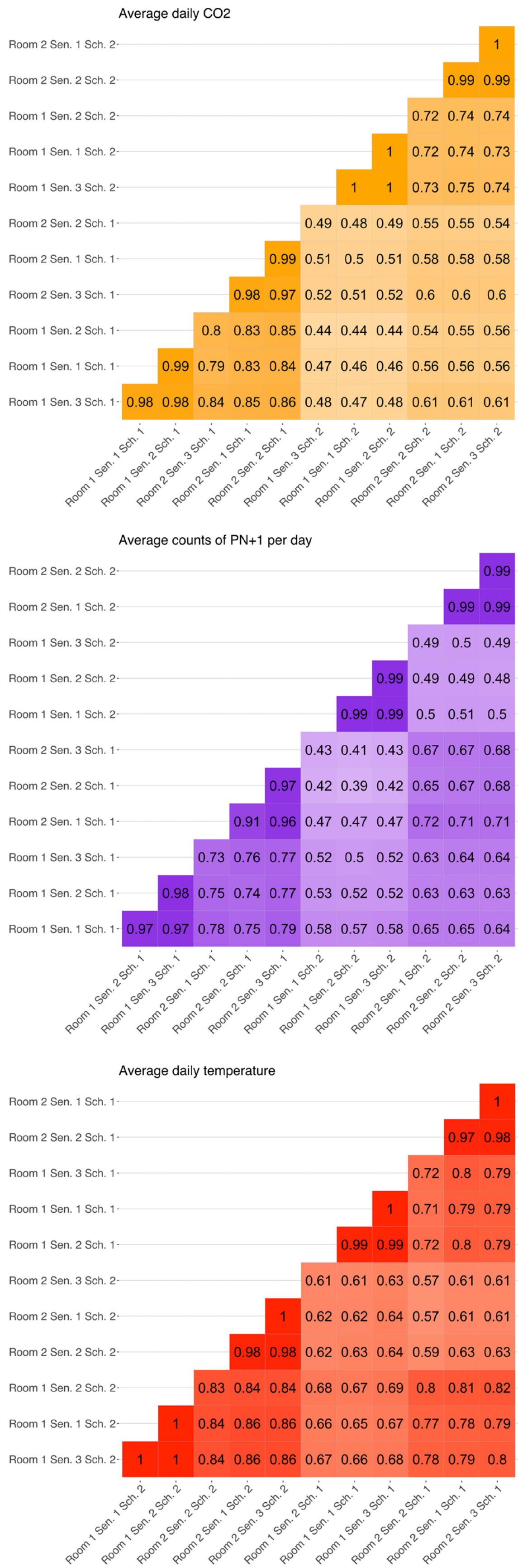

Figure 2 Correlation in carbon dioxide (CO_2), coarse particles and temperature within and across classrooms. The figure presents the Pearson correlation matrixes of the peaks of CO_2, the daily average of coarse particles (PN), and temperature, measured at different locations within four classrooms: two classrooms in a relatively new school ('school 1') and two classrooms in an older school ('school 2').

Table 2 Student performance assessments

National tests	School tests	Study tests
► Cito *Leerling Volg Systeem* (LVS) tracking tests groups 3–8 ► Cito final test group 7	► Grades (four times/year) ► School advice on secondary education ► Actual ongoing education	► Self-efficacy pupils ► Strengths and difficulties questionnaire

of each the schools, and will be intercalibrated with the indoor particle sensors. Even though outdoor sensing technology is relatively novel, there are already a number of studies using the PurpleAir sensors and comparing their values against official air quality monitoring stations.[43 44]

In addition, daily information on ambient temperature is obtained from the Global Historical Climatology Network of the National Oceanic and Atmospheric Administration, and information on outdoor levels of air pollution is obtained from the Dutch National Air Quality Monitoring Network.

Student performance

For our study, we use an already existing infrastructure on student performance that is based on standardised tests (LVS tracking system), regular evaluations by the teachers, the Cito final test, student and teacher attendance, student sociodemographics and their attitudes towards the school (see table 2 for an overview of the data). This data set is part of *OnderwijsMonitor Limburg* (OML) within the Educational Agenda Limburg that monitors educational development and teacher quality.[45] Borghans *et al*[46 47] are two examples of previous studies using these data for the evaluation of factors affecting cognitive development of primary school children.

In our sample of schools, the data set contains a total of approximately 36 000 standardised tests per year (six tests per child). Each child takes an average of two tests per year per subject. The tests comprise a wide variation of educational areas, such as reading, math, language and foreign language tasks (English). The data set includes individual identifiers for each child in the data set, allowing to follow children over the entire study period, and to explore changes in the test scores of a child. The panel structure of the data set allows for the exploitation of variation in environmental conditions, linking it to test scores at the individual level. In addition, the final data set will include accurate information of the time and place of each of the tests in the sample, allowing us to differentiate between contemporaneous effects (ie, at the time of testing) and permanent effects (learning).

Individual characteristics

Individual health outcomes

We gather data on health outcomes for children in the sample from multiple sources. Daily absence days of individual children will be collected by OML and the registration records by the educational board. Note the absence data are available at the student level, although anonymised. For students enrolled in five sample schools, we will complete the student profile with general health measures of the child, combining multiple sources. All health outcome measures originate from an already existing longitudinal study on health and lifestyle of pupils.[48] Willeboordse *et al*[48] provide a detailed description of all general health measures (see table 3 for the list of health outcomes). Information on general health outcomes will be derived from an online parental questionnaire covering: disease status since birth, hospital admissions (number and duration), healthcare visits (number), and medication use in the previous 12 months (see online supplementary appendix D for the English translation of the exact questions in the questionnaire.). Anthropometric measurements including height, weight, hip, and weight circumference will be objectively collected in children. Information on birth weight and additional information on disease status will be collected via the regional public health services (Gemeentelijke Gezondheidsdienst Zuid Limburg,(GGD ZL)).

Household socioeconomic characteristics

In addition to academic and health outcomes, we gather a complete profile of household socioeconomic characteristics of the pupil. These factors have been shown to be important mediators on the link between pupil health and academic achievement.[49] This information is available for every pupil in the data set and contains information on parental income, occupational status, education and health.

Empirical model

In the main analysis, we examine the association between the environmental conditions in classrooms and the test scores of students in our sample. We base our empirical approach on the existing field studies linking

Table 3 Health outcomes

Health measure	Source
Birth weight (subsample of five schools)	Regional public health services (GGD ZL)
Disease status, hospital admissions, medicine use, healthcare visits (subsample of five schools)	Parental questionnaire and GGD ZL
Anthropometrics (subsample of five schools)	Objective measurement in children
Absence days	OnderwijsMonitor Limburg (OML)
Frequency of pupil absence and sick leave	Educational board

environmental factors, such as air pollution or temperatures, to test scores.[50 51] For identification, we rely on the panel structure of the data and the repeated nature of the school exams. Since we have individual identifiers assigned to students and we know the subject of the test, we can include individual and subject fixed effects. We therefore use the variation in environmental conditions across exams taken by the same student in the subject. We exploit the fact that the differences in environmental conditions across testing periods are likely uncorrelated with differences in other factors that might affect academic achievements.

Patient and public involvement

No patients are involved in the study.

CONCLUSIONS

There is extensive evidence that exposure to poor environmental conditions is associated with reduced physical and mental health and cognitive performance. However most of the studies rely on outdoor measurements of environmental conditions and adult samples. Scientific evidence on the relationship between indoor environmental conditions and student achievement and health outcomes is scarce, generally suffers from small samples and relies on between-subject comparisons rather than within-subject comparisons, making it hard to establish causality. This paper describes the design of a longitudinal study in which the environmental conditions of more than 10 000 children will be monitored during five academic years and linked to individual measures of academic performance and health. The study presented has a robust design to measure IEQ in a school setting, using state-of-the-art sensor technology to objectively measure the environmental conditions at high frequency.

From the first pilot study, we conclude that the exact placement of sensors in a classroom does not affect the ability of the sensor to accurately measure indoor environmental conditions. The additional information content from installing multiple sensors, relative to a singular sensor, to accurately measure IEQ within a classroom is low. Placement of one sensor at briefing height provides robust measurements of the indoor environment in a classroom setting. At the same time, indoor climate conditions differ considerably across classrooms, indicating that sensors need to be installed in each individual classroom in a school. The pilot study also showed that the variation of various indoor environmental quality characteristics over the course of one academic schoolyear is high. The findings in our pilot study are in line with the findings of previous studies, which generally document that indoor climate depends on building conditions, outdoor environmental conditions and occupant-related factors. Due to the high variation in IEQ during the schoolyear, a longitudinal design of at least one academic year is necessary to robustly measure the impact of IEQ on health and academic outcomes.

The current study will clarify to which degree different environmental characteristics influence cognitive performance, considering the health of pupils. The correct placement of sensors was thoroughly pilot-tested, and the longitudinal design and large number of pupils included in the study will add valuable knowledge to the current research area. If it turns out that IEQ is indeed salient for the performance of young schoolchildren, the next stage will be to design field experiments. By optimising air, light and sound in classrooms, cognitive performance can possibly be improved. As changes in indoor environment are often low cost and easily implementable, the direct societal and scientific importance of the findings in this study is substantial. Indirectly, this study may affect how school buildings are built, managed and maintained, both in the Netherlands and across the globe.

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