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The impact of Traffic-Related air pollution on child and adolescent academic Performance: A systematic review

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A R T I C L E I N F O

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A B S T R A C T

Background: The negative health impacts of traffic-related air pollution (TRAP) have been investigated for many decades, however, less attention has been paid to the effect of TRAP on children's academic performance. Understanding the TRAP-academic performance relationship will assist in identifying mechanisms for improving students' learning and aid policy makers in developing guidance for protecting children in school environments.
Methods: This systematic review assessed the relationship between TRAP and academic performance. Web of Science, PubMed, CINAHL, Medline, PsycINFO, SPORTDiscus, Scopus and ERIC databases were searched for relevant, peer reviewed, articles published in English. Articles assessing exposure to TRAP pollutants (through direct measurement, local air quality monitoring, modelling, or road proximity/density proxy measures) and academic performance (using standardised tests) in children and adolescents were included. Risk of bias was assessed within and between studies.
Results: Of 3519 search results, 10 relevant articles were included. Nine studies reported that increased exposure to some TRAP was associated with poorer student academic performance. Study methodologies were highly heterogeneous and no consistent patterns of association between specific pollutants, age groups, learning domains, exposure windows, and exposure locations were established. There was a serious risk of bias within individual studies and confidence in the body of evidence was low.
Conclusions: This review found evidence suggestive of a negative association between TRAP and academic performance. However, the quality of this evidence was low. The existing body of literature is small, lacks the inclusion of high-quality exposure measures, and presents limitations in reporting. Future research should focus on using valid and reliable exposure measures, individual-level data, consistent controlling for confounders and longitudinal study designs.

1. Introduction and Background

When assessing the effects of environmental exposures on children and adolescents, academic performance is an important outcome. Academic performance is interlinked with health and wellbeing and predicts adulthood thriving, civic engagement, income, and occupational status

Abbreviations: API, Academic Performance Index; AQI, Air Quality Index; CI, confidence-intervals; CPP, Capped Points Plus; ELA, English Language Arts; GPA, grade point average; HICs, high-income countries; LMICs, low and middle-income countries; LUR, Land-Use Regression; MeSH, Medical Subject Headings; NA, not applicable; NR, not reported; OHAT, Office of Health Assessment and Translation; PRISMA, Preferred Reporting Items for Systematic Review and Meta-Analysis; PROSPERO, International Prospective Register of Systematic Reviews; RoB, risk of bias; SES, socio-economic status; SR, systematic review; TRAP, traffic-related air pollution; UFP, ultra-fine particulate matter (<0.1μm in aerodynamic diameter); $PM_{2.5}$, fine particulate matter (0.1-2.5μm in aerodynamic diameter); $PM_{2.5\text{-}10}$, coarse particulate matter (2.5-10μm in aerodynamic diameter); PM_{10}, inhalable particulate matter (<10μm in aerodynamic diameter); USEPA, United States Environmental Protection Agency; WHO, World Health Organization.

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(Caro et al., 2015; Dee 2004; Degoy and Berra 2018; Milligan et al., 2004; Tabbodi et al., 2015; Tomasik et al., 2019). It is also a form of human capital, which means the unequal distribution of health risks affecting academic performance can contribute to existing patterns of social inequity (Pastor et al., 2004).

Exposure to air pollution threatens the health of children and adolescents. It is estimated that 93% of the world's children are continuously exposed to toxic air (World Health Organization, 2018). The physiology, behaviour and rapid development of children and adolescents makes them more susceptible than adults to the effects of air pollution (Bennett et al., 2007; Ginsberg et al., 2005; Saadeh and Klaunig 2014; Silbereis et al., 2016; Sly and Flack 2008). Respiratory, cardiovascular and cognitive health have all been found to be negatively impacted (Calderón-Garcidueñaset al. 2008; Chen et al., 2015; Delgado-Saboritet al. 2019; Freireet al. 2010; Iannuzziet al. 2010; Matus et al., 2019; Millman et al., 2008; Pereraet al. 2006; Salvi 2007; Suades-Gonzalez et al., 2015; Suglia et al., 2008; Sunyeret al. 2015; Tabaku et al., 2011). However, a relationship between air pollution and academic performance is yet to be firmly established.

This review focuses on traffic-related air pollution (TRAP), one of the biggest contributors to urban air pollution. TRAP includes vehicle emissions, re-suspended road dust and particles from degraded tyres and brake linings (World Health Organization Regional Office for Europe, 2005). These pollutants include particulate matter (PM) of varying aerodynamic diameters (ultra-fine PM: <0.1 µm [UFP], fine PM: 0.1–2.5 µm [$PM_{2.5}$], coarse PM: 2.5–10 µm [$PM_{2.5\text{-}10}$], and inhalable PM: <10 µm [PM_{10}]), nitrogen dioxide, carbon monoxide, black carbon, lead, volatile organic compounds, polycyclic aromatic hydrocarbons and ground level ozone (Health Effects Institute [HEI], 2010; World Health Organization Regional Office for Europe, 2005). Exposure assessment methods include personal/on site/local air quality monitoring, various modelling techniques, and road proximity/density proxy measures (Goldizen et al., 2016; HEI, 2010).

Previous longitudinal research has found a link between exposure to TRAP, specifically, and cognitive function in children – a factor closely related to academic performance (Kinget al. 2005; Sunyer et al., 2015). Furthermore, evidence suggests that low socioeconomic status (SES) and ethnic minority children experience higher risk of TRAP exposure at school (Chakraborty 2009; Korenstein and Piazza 2002; Wu and Batterman 2006). Therefore, it is important to know if TRAP is associated with academic performance in order to identify risk factors contributing to racial and SES related gaps in academic performance (Bali and Alvarez 2003; Sirin 2005). The United States Environmental Protection Agency (USEPA) provides extensive recommendations on how to protect children from TRAP exposure at school (USEPA, 2015). Finding an association between TRAP and academic performance would increase the motivation to convert these recommendations into official policy.

This systematic review (SR) synthesised the evidence examining the relationship between TRAP and academic performance in children and adolescents. The research question that guided the study was: Do children and adolescents exposed to higher levels of TRAP pollutants show poorer academic performance than those exposed to lower levels of TRAP pollutants?

2. Methods

2.1. Protocol

This SR was registered in the International Prospective Register of Systematic Reviews (PROSPERO), registration number: CRD42020176294. The protocol was written according to the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) statement (Moher et al., 2009). Risk of bias in individual studies and confidence in the body of evidence were assessed per the Office of Health Assessment and Translation (OHAT) guidelines (Rooney et al., 2014).

Table 1
Inclusion/ Exclusion Criteria for Articles.

Study Aspect	Inclusion Criteria	Exclusion Criteria
Participants: Human children and adolescents	Life stage at exposure: pre-birth up to childhood/ adolescence Life stage at outcome assessment: childhood/ adolescence. Geographic setting: worldwide. No restrictions on sex	Adulthood at outcome assessment e.g. university students
Exposure: Traffic-related air pollution (TRAP)	Exposure to TRAP pollutants including particulate matter (PM) of varying aerodynamic diameters (UFP, $PM_{2.5}$, $PM_{2.5\text{-}10}$, PM_{10}), nitrogen oxides, carbon monoxide, black carbon, lead, volatile organic compounds, polycyclic aromatic hydrocarbons and ground level ozone. Direct measurement, local air quality monitoring, modelled estimates or road proximity/density as a proxy measure	Studies exclusively testing exposure to pollution from a non-traffic source e.g. proximity to an industrial site, studies exclusively measuring hazardous air pollutants (HAPs), which include many non-TRAP pollutants
Comparators:	Unit increase in pollutants or comparison of higher and lower exposed groups	Not applicable
Outcome: Academic performance	Any measure of academic performance based on standardised tests, test or exam results, university preparatory exams, semester grades/grade point average	Behavioural tests and other tests of cognitive function
Publication type:	Original Data English Language Peer reviewed	Abstract only Conference presentations/ posters

Table 2
Search Strategy.

Component	Free search terms	MeSH terms
Population: Child/ adolescent	child* OR adolescent*	child OR adolescents
Exposure: TRAP	TRAP OR traffic OR "traffic related air pollution" OR "air pollut*" OR vehicle* OR emission* OR exhaust OR "nitrogen dioxide*" OR "nitrogen oxide*" OR "carbon monoxide" OR "black carbon" OR diesel OR ozone OR particle* OR particulate* OR "volatile organic compounds" OR "polycyclic aromatic hydrocarbons" OR "air quality" OR "air toxic*" OR "major road*" OR highway* OR freeway* OR motorway*	Traffic-Related Pollution OR Particulate Matter OR Vehicle Emissions OR Nitrogen Dioxide OR Nitrogen Oxides OR Ozone OR Carbon Monoxide OR Volatile Organic Compounds OR Polycyclic Aromatic Hydrocarbons
Outcome: Academic performance	"academic performance" OR academic OR "school performance" OR "academic achievement" OR "educational achievement" OR "education* outcome*" OR attainment OR "test score*" OR "standard* test*" OR "semester grade*" OR "grade point average*"	Academic performance

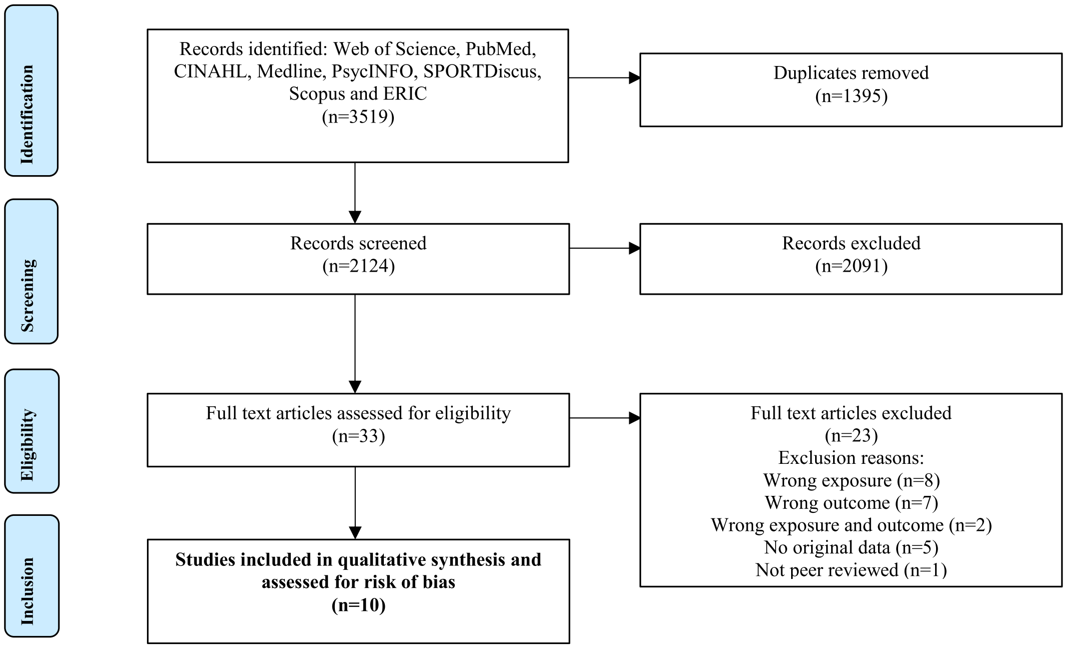

Fig. 1. PRISMA Flow Chart.

2.2. Eligibility Criteria

Eligible study designs were cross-sectional, ecological, prospective cohort, retrospective cohort, panel and case control studies. Table 1 summarises inclusion and exclusion criteria in the form of a PECO statement (participants, exposures, comparators, outcomes).

2.3. Search Strategy

The databases Web of Science, PubMed, CINAHL, Medline, PsycINFO, SPORTDiscus, Scopus and ERIC were searched from inception to June 13, 2020 for relevant, English-language, peer-reviewed articles. Reference lists of found articles were manually checked for further relevant sources.

The search terms combined three core components: population, exposure and outcome (Table 2) which were applied in appropriate formats for all databases.

2.4. Selection

Articles were uploaded into Covidence systematic review management database (www.covidence.org) which automatically removes duplicates and facilitates traceable screening and selection of articles. Article selection was conducted per the PRISMA statement (Fig. 1). Two independent reviewers screened titles, abstracts and full texts for eligibility. Conflicts were discussed and mediated by a third reviewer before reaching final inclusion decisions.

2.5. Data extraction

A data collection form was developed to extract study characteristics, methods of exposure and outcome assessment, additional independent variables included in analyses, results, and funding/ conflicts of interest. One reviewer extracted data and a second reviewer verified the extraction. The main outcome under assessment was academic performance, measured by standardised tests. Effect estimates in the form of a Beta (β) coefficient, Pearson's correlation *r,* risk ratio or odds ratio were extracted along with 95% confidence intervals (CI) or *p*-values where provided. For studies reporting multiple findings, e.g. separate analyses for different pollutants/academic domains/age groups, outcome data were extracted for each analysis.

Table 3
Justifications for selected confounders and co-exposures.

Variable	Justification
	Confounders
SES or Ethnicity	Low SES and ethnic minority groups experience higher exposure to air pollution and both factors are independently associated with academic performance (Bali and Alvarez 2003; Sirin 2005).
Geographic location	TRAP levels are higher in urban areas but rural schools may have access to fewer resources which may differentially impact academic performance (Sullivan et al., 2013).
Temperature	Ambient air temperature is associated with changes in air quality (particularly ozone levels) and impacts on academic performance (Jacob and Winner 2009; Wargocki et al., 2019).
Green space	Higher levels of green space are typically associated with lower TRAP levels, and exposure to green space is thought to improve academic performance (Browning and Rigolon 2019)
	Co-exposures
Green space	It is possible for green space and high TRAP levels to co-exist.
Non-TRAP pollution	Ambient pollutants from industrial sources may also affect academic performance (Mohai et al., 2011).
Pollen	Pollen exposure is independently associated with poorer academic performance (Bensnes 2016; Marcotte 2015).
Noise	Traffic-noise is independently associated with academic performance (Haines and Stansfeld 2003; Shield and Dockrell 2003)

2.6. Data analysis

2.6.1. Risk of bias

Risk of bias (RoB) in individual studies was assessed using an adapted version of the OHAT tool (Rooneyet al. 2014). Bias was assessed along seven domains relevant to the articles in this SR. According to the OHAT method, key confounders and co-exposures were pre-determined (Table 3). Each study was required to adjust for SES or ethnicity plus at least one other identified confounder or co-exposure which was important in relation to the primary TRAP exposure and the outcome. Studies were not penalized if other confounding variables or co-exposures were not adjusted. Two reviewers independently assessed risk of bias in individual studies. Conflicts were discussed before making

Table 4
Study Characteristics of the Articles.

Citation	Original sample	Study period	Geographic context	Grade level or age	Individual/Aggregate
Cross Sectional (n = 9)					
Berman et al 2018	158 schools	2013–2014	Baltimore, USA	3rd-8th NR	Aggregate
Clark-Reyna et al 2016	1904 children	2005–2012	El Paso, USA	4th and 5th 8–13 years	Individual
Donovan et al 2020	21,107 children	2013–2014	Portland, USA	3rd-8th NR	Individual
Gaffron & Niemeier 2015	553 schools	2008–2011	Sacramento, USA	All students	Aggregate
Grineski et al 2016	1904 children	2005–2012	El Paso, USA	4th and 5th 8–13 years	Individual
Kweon et al 2018	3660 schools	2005–2007	Michigan, USA	3rd-8th NR	Aggregate
Mizen et al 2020	18,241 children	2009–2015	Cardiff, Wales	NR 15–16 years (mean 15.71)	Individual
Retrospective cohort (n = 2)					
Shier et al 2019	9400 & 9550 children	1998–2004	USA	3rd & 5th mean age 111 months & 134.7 months	Individual
Stingone et al 2016	57,025 children	1996–2008	New York City, USA	3rd NR	Individual & Aggregate
Longitudinal (n = 1)					
Marcotte 2017	1450 children	2010–2014	USA	Kindergarten, 1st & 2nd, mean age in elementary school 81 months	Individual

Note: NR = not reported.

Table 5
Methods Used to Assign Exposure to Traffic-Related Air Pollutants and Standardised Academic Performance Tests.

	Exposure					Outcome
Citation	Location	Timing	Measure	Modelling	Spatial resolution	Outcome Assessment
Berman et al 2018	School	Time of testing	Total length of all roads/ major roads and highways only around schools	Density	100/ 200/ 300 m buffers	Proficiency in Math and Reading tests
Clark-Reyna et al 2016	Home	Estimates assume cumulative	Estimated diesel PM health risk from on-road mobile sources (hazard quotient)	USEPA's NATA 2005	Census block	GPA
Donovan et al 2020	School & Home	Time of testing	Total length of all class 1 and 2 roads around schools and homes	Density	100/ 200/ 500 m buffers	Math and Reading test scores
Gaffron & Niemeier 2015	School	Estimates assume cumulative	Estimated load of traffic-associated $PM_{2.5}$ around school	Novel method combining traffic density and emissions	150 m buffer of school land use parcel	School API score
Grineski et al 2016	School	Estimates assume cumulative	Estimated diesel PM health risk from on-road mobile sources (hazard quotient)	USEPA's NATA 2005	Census block	GPA
Kweon et al 2018	School	Time of testing	Straight line distance to nearest limited access highway	Proximity	Distance in kilometres	Failure to meet proficiency in Math and ELA tests
Mizen et al 2020	School & Home	School-term prior to examination	Estimated ambient concentration of Ozone/ Nitrogen Dioxide/ $PM_{2.5}$	Atmospheric Dispersion Modelling	20 *m*	Capped Points Plus score based on combined GCSE results
Shier et al 2019	Home	Year prior to testing & cumulative	Estimated ambient concentrations of $PM_{2.5}$, PM_{10} and ozone	Spatial interpolation of monitor data	Census tract	Math/Reading test scores
Stingone et al 2016	Home	Pre-natal	Estimated ambient concentration of Diesel PM	USEPA's NATA 1996	Census tract	Math and ELA test scores and failure to meet proficiency standards
Marcotte 2017	School & Home	Time of testing & cumulative	Air Quality Index score for $PM_{2.5}$ & Ozone	USEPA Air Quality Index	County	Math and Reading test scores

final allocations. Where necessary, a third reviewer was consulted.

Confidence in the body of evidence across all included studies was assessed per the OHAT guidelines, which involves consideration of the strengths and weaknesses of groups of studies with similar features (Rooneyet al. 2014). An overall data assessment visualisation table was developed specifically for this systematic review to assess potential publication bias (Table S11).

2.6.2. *Data synthesis*

A formal *meta*-analysis was ruled out due to a high degree of heterogeneity in terms of study design, exposure definition, outcome definition, and outcome data. Findings are presented as a systematic search with narrative synthesis.

2.6.3. *Missing data*

Authors were contacted when detailed numerical outcome data was missing.

3. Results

3.1. *Study selection and characteristics*

Fig. 1 displays the study selection process. Out of 3519 titles identified through database searching, 10 articles met the inclusion criteria.

	Risk of Bias Domains and Ratings						
	Key RoB Criteria			Other RoB Criteria			
Citation	Bias in exposure classification	Bias in outcome classification	Accounting for key confounding variables	Selection Bias	Missing Data Bias	Selective Reporting Bias	Other bias (appropriate statistical analysis)
Berman et al 2018	--	++	--	NR	++	++	--
Clark-Reyna et al 2016	--	-	+	NR	+	++	++
Donovan et al 2020	--	++	+	++	NR	--	-
Gaffron & Niemeier 2015	-	++	--	-	--	++	--
Grineski et al 2016	--	-	+	NR	+	++	++
Kweon et al 2018	--	++	+	NR	NR	++	NR
Mizen et al 2020	+	++	+	+	++	++	-
Shier et al 2019	-	++	++	++	+	++	-
Stingone et al 2016	--	++	+	+	++	+	+
Marcotte 2017	--	++	+	-	NR	++	-

--	Definitely high risk of bias
-/ NR	Probably-high risk of bias / Not reported
+	Probably-low risk of bias
++	Definitely low risk of bias

Fig. 2. Summary of Risk of Bias Assessments.

Study characteristics are summarised in Table 4, exposure and outcome assessments are summarised in Table 5. Papers were recent, with the earliest published in 2015. There were seven cross-sectional designs, two retrospective cohort studies and one longitudinal study. Original sample sizes for the studies using aggregate, school-level, outcome data ranged from 158 to 3660 schools. For studies using data at the individual child level, original sample sizes ranged from 1450–57,025 children. In cases where specific grades were selected for the study population, these were predominantly elementary grades. One study focussed only on high school students. Study populations were limited in geographic location to high income countries, primarily the USA (n = 9), with one study in Wales, UK.

There was a wide variation in the method, spatial resolution, timing and location of exposure assessments between studies. Methods used included the use of road proximity/density around schools/homes as a proxy measure; daily Air Quality Index scores assigned using the USEPA monitoring data; and other various modelled estimates.

All studies included some variation of standardised tests as outcome measures. Six studies focussed on Mathematics and Reading/English language domains specifically, while the others used more generalised outcomes combining multiple domains. Studies were split between using individual level (n = 6), aggregate level (n = 3) or a mix (n = 1) of outcome data.

3.2. Risk of bias in individual studies

Fig. 2 displays RoB ratings allocated to each of the seven bias domains in individual studies. A summary of each RoB assessment is available in Supplementary Tables S1-S10.

The overall RoB in individual studies was graded to be serious. The most common source of bias was the use of poor quality exposure assessments of TRAP. No studies used direct readings from personal, on-site, or local air quality monitors. Excluding one paper (Mizenet al. 2020), studies using road proximity/density proxy measures and modelled estimates did not support these with statistical comparison of modelled estimates of monitored data, or land-use regression [LUR] modelled data. Furthermore, three studies (Clark-Reyna et al., 2016; Grineski et al., 2016; Stingone et al., 2016) employed modelled estimates from the USEPA's National Scale Air Toxics Assessment (NATA) despite the USEPA explicitly stating on their website that these estimates should not be used as a freestanding capture of exposure or to compare exposures between neighbourhoods (USEPA, 2011).

Eight studies controlled for SES plus at least one other confounder/co-exposure relevant to the study. The studies which adjusted for more relevant confounders/co-exposures available within the study were graded lower risk of confounding bias. Two studies did not control for any confounding factors in their analysis of the TRAP-academic performance relationship and were graded with a definitely-high RoB rating (Bermanet al. 2018; Gaffron and Niemeier 2015). Other common sources of bias were low quality or unreported details in the statistical analysis and a lack of information regarding the representativeness of study samples and missing data.

3.3. Publication bias

According to OHAT (2015), when the majority of early studies in a body of evidence reject the null hypothesis, this presents a risk of publication bias. These guidelines imply that, as the field grows, more null results are likely to be presented. Therefore, potential publication bias was identified within this small and emerging body of evidence as only one study found no evidence for an association between TRAP and academic performance. Furthermore, an assessment of the frequencies of negative (decline), positive (improved) and null associations per exposure metric reveals a limited number of analysis per each different type of exposure and academic performance outcome in multiple cases (Table S11).

3.4. The relationship between TRAP and academic performance

All relevant associations between measures of TRAP and academic

Table 6
Effect Estimations for Associations between TRAP and academic performance reported in articles.

Citation	Outcome measure	TRAP measure	Type of Estimate	Association & effect estimate	95% CI/ p value
Berman et al. 2018	Grades 3–5/6–8 reading/math proficiency	Density of all roads/ major roads and highways only. 100/ 200/ 300 m buffers	β	Null in unadjusted models (NR). Excluded from final analysis.	NR
Clark-Reyna et al., 2016	GPA	Modelled, total diesel PM risk	β	Negative −0.023	$p = 0.008$
	GPA	Modelled, on-road mobile diesel PM risk	β	Negative −0.018	$p = 0.022$
Donovan et al., 2020	Math scores	Road density at 100 m around home	β	Negative −0.155	$p = 0.050$
	Math scores	Road density at 100 m around school	β	Null NR	NR
	Reading scores	Road density at 100 m around home	β	Negative −0.656	$p = 0.002$
	Reading scores	Road density at 100 m around school	β	Null NR	NR
	Math/reading scores	Road density at 200/500 m around home/ school	β	All Null NR	NR
Gaffron & Niemeier 2015	School API score	Modelled load of traffic associated PM2.5 in land use parcel for all schools	*r*	Negative −0.209	$p = 0.000$
Grineski et al., 2016	GPA	Modelled, total diesel PM risk	β	Negative −0.128	$p = 0.005$
	GPA	Modelled on-road mobile diesel PM risk	β	Negative −0.093	$p = 0.012$
Kweon et al. 2018	Failing to meet Math standards	Distance to nearest highway	β	Negative −0.03	$p < 0.10$
	Failing to meet English standards	Distance to nearest highway	β	Negative −0.06	$p < 0.001$
Mizen et al., 2020	CPS scores	Short term NO_2 exposure (single pollutant model)	β	Negative −0.044	(-0.079, −0.008)
	CPS scores	Short term NO_2 exposure (adjusted for $PM_{2.5}$ & pollen)	β	NR figure suggests Negative	NR
	CPS scores	Short term $PM_{2.5}$ exposure (single-pollutant model)	β	Positive 0.074	(0.002, 0.146)
	CPS scores	Short term $PM_{2.5}$ exposure (adjusted for NO_2 & pollen)	β	NR figure suggests null	NR
	CPS scores	Short term Ozone exposure (single-pollutant model)	β	Null 0.004	(-0.017, 0.024)
Shier et al., 2019	3rd grade math scores	Annual measures of ozone in cross sectional regressions	β	Negative −0.03, −5.23, −2.92	$p < 0.05$, $p < 0.01$, $p < 0.01$
	3rd grade math scores	Annual measure of ozone in child fixed effects model	β	Negative −0.90	$p < 0.01$
	3rd grade math scores	All measures of cumulative exposure to ozone	β	Negative −1.00, −1.03, −2.45	$p < 0.01$, $p < 0.05$, $p < 0.05$
	3rd grade math scores	Exposure to ozone on the day of testing	β	Null 0.00	NR
	3rd grade math scores	Maximum value of ozone in the week before testing	β	Null 0.14	NR
	3rd grade reading scores	All annual measures of ozone in cross sectional regressions	β	Null −0.02, −1.05, −0.87	NR
	3rd grade reading scores	Annual measure of ozone in child fixed effects model	β	Null −0.24	NR
	3rd grade reading scores	Cumulative exposure to ozone: Indicator for whether 2- years above standard	β	Negative −2.14	$p < 0.05$
	3rd grade reading scores	Other cumulative measures of exposure to ozone	β	Null −0.03, 0.32	NR
	3rd grade reading scores	Exposure to ozone on the day of testing	β	Null 0.01	NR
	3rd grade reading scores	Maximum value of ozone in the week before testing	β	Null 0.05	NR
	5th grade math scores	All annual measures of ozone in cross sectional regressions	β	Null 0.02, −0.21, −0.40	NR
	5th grade math scores	Annual measure of ozone in child fixed effects model	β	Null 0.35	NR
	5th grade math scores	All measures of cumulative exposure to ozone	β	Null −0.49, −0.21, −1.88	NR
	5th grade reading scores	All annual measures of ozone in cross sectional regressions	β	Null −0.00, −0.23, −0.45	NR
	5th grade reading scores	Annual measure of ozone in child fixed effects model	β	Null −0.21	NR
	5th grade reading scores	Cumulative exposure to ozone: Indicator for whether 2-years above standard	β	Negative −1.99	$p < 0.05$
	5th grade reading scores	Other cumulative measures of exposure to ozone	β	Null −0.15, 0.57	NR
	3rd grade math scores	Maximum annual value of $PM_{2.5}$ in cross sectional regressions	β	Negative −0.03	$p < 0.05$
	3rd grade math scores	Other annual measures of $PM_{2.5}$ in cross sectional regressions	β	Null −0.05, −0.16	NR

(*continued on next page*)

Table 6 (*continued*)

Citation	Outcome measure	TRAP measure	Type of Estimate	Association & effect estimate	95% CI/ p value
	3rd grade math scores	Annual measure of $PM_{2.5}$ in child fixed effects model	β	Negative −0.25	$p < 0.01$
	3rd grade math scores	Cumulative exposure to $PM_{2.5}$: Number of years above standard	β	Negative −0.26	$p < 0.05$
	3rd grade math scores	Other measure of cumulative exposure to $PM_{2.5}$	β	Null −0.05, −0.52	NR
	3rd grade reading scores	Maximum annual value of $PM_{2.5}$ in cross sectional regressions	β	Negative −0.03	$p < 0.05$
	3rd grade reading scores	Other annual values of $PM_{2.5}$ in cross sectional regressions	β	Null 0.00, −0.26	NR
	3rd grade reading scores	Annual measure of $PM_{2.5}$ in child fixed effects model	β	Null 0.13	NR
	3rd grade reading scores	Cumulative exposure to $PM_{2.5}$: Number of years above standard and indicator for whether 2- years above standard	β	Negative −0.44, −1.25	$p < 0.01$, $p < 0.01$
	3rd grade reading scores	Other cumulative measure of exposure to $PM_{2.5}$	β	Null −0.43	NR
	5th grade math scores	All annual measures of $PM_{2.5}$ in cross sectional regressions	β	Negative −0.06, −0.16, −1.10	$p < 0.01$, $p < 0.01$, $p < 0.01$
	5th grade math scores	Annual measure of $PM_{2.5}$ in child fixed effects model	β	Null −0.09	NR
	5th grade math scores	Cumulative exposure to $PM_{2.5}$: Number of years above standard and indicator for whether 2- years above standard	β	Negative −0.36, −1.37	$p < 0.01$, $p < 0.05$
	5th grade math scores	Other measure of cumulative exposure to $PM_{2.5}$	β	Null −0.39	NR
	5th grade reading scores	Maximum annual value of $PM_{2.5}$ in cross sectional regressions	β	Negative −0.04	$p < 0.05$
	5th grade reading scores	Other annual values of $PM_{2.5}$ in cross sectional regressions	β	Null −0.08, −0.57	NR
	5th grade reading scores	Annual measure of $PM_{2.5}$ in child fixed effects model	β	Positive 0.18	$p < 0.05$
	5th grade reading scores	Cumulative exposure to $PM_{2.5}$: Number of years above standard and indicator for whether 2- years above standard	β	Negative −0.40, −1.94	$p < 0.01$, $p < 0.01$
	5th grade reading scores	Other measure of cumulative exposure to $PM_{2.5}$	β	Null −1.33	NR
	3rd grade reading scores	Annual percentage of days above standard for PM_{10}	β	Positive 0.18	$p < 0.05$
	3rd/5th grade reading/math scores	All other annual PM_{10} measures	β	Null ranging from 0.43 to −0.34	NR
Stingone et al., 2016	Math scores	High exposure to diesel PM only	β	NR figure suggests null	NR
	ELA scores	High exposure to diesel PM only	β	NR figure suggests null	NR
	Failing to meet math standards	High exposure to diesel PM only	RR	Null 1.03	(0.99, 1.06)
	Failing to meet ELA standards	High exposure to diesel PM only	RR	Negative 1.03 (Positive association between exposure and failing to meet standards represents a negative association between TRAP and academic performance)	(1.00, 1.05)
Marcotte, 2017	Reading scores	Exposure to PM2.5 at time of testing	β	Negative −0.020	p < 0.05
	Reading scores	Exposure to PM2.5 2 weeks before testing	β	Null 0.008	NR
	Reading scores	Lifetime exposure to PM2.5	β	Null 0.050	NR
	Reading scores	Exposure to Ozone at time of testing	β	Null 0.006	NR
	Reading scores	Exposure to Ozone 2 weeks before testing	β	Null 0.01	NR
	Reading scores	Lifetime exposure to Ozone	β	Null −0.044	NR
	Math scores	Exposure to PM2.5 at time of testing	β	Null 0.001	NR
	Math scores	Exposure to PM2.5 2 weeks before testing	β	Null −0.001	NR
	Math scores	Lifetime exposure to PM2.5	β	Null 0.064	NR
	Math scores	Exposure to Ozone at time of testing	β	Null 0.007	NR
	Math scores	Exposure to Ozone 2 weeks before testing	β	Null −0.027	NR
	Math scores	Lifetime exposure to Ozone	β	Null −0.073	NR

β = Beta coefficient; NR = Not reported; *r* = Pearson's correlation r; RR = Risk Ratio

performance extracted in this SR are summarised in Table 6. Analyses containing full study samples were extracted while stratified analyses, presented by some authors to explore potential mechanisms or compare sub-groups, were not extracted. Only fully adjusted models were extracted if multiple models existed with different covariates included, excepting Mizenet al. (2020), who reported models controlling for multiple pollutants alongside single pollutant models. Most studies did not control for other pollutants due to collinearity, therefore, both single- and multi-pollutant models were extracted from Mizen et al (2020) to allow accurate comparison. A total of 138 analyses were extracted. The most analyses extracted from a single paper were 72 (Shier et al., 2019), and the least was two (Clark-Reyna et al. 2016; Grineski et al. 2016). Out of the 10 studies reviewed, 9 found some significant association between TRAP and academic performance. However, out of 138 extracted associations there were 38 negative associations, three positive (specifically between measures of $PM_{2.5}$

exposure and academic performance in all three cases), and 97 null associations.

The study designs were highly heterogeneous, making it impossible to identify consistent patterns of association for specific combinations of individual pollutants, age groups, learning domains, exposure windows, and exposure locations. Across the papers, exposure was assessed at both homes and schools. $PM_{2.5}$, PM_{10}, nitrogen dioxide, and ozone were the TRAP most included in single-pollutant analyses. Individual learning domains assessed were literacy and numeracy. Finally, effect sizes for significant associations were small in most papers.

3.5. Confidence in the body of evidence

Overall confidence in the body of evidence was low. The evidence profile is reported in Supplementary Table S12. The studies were all observational which, per the OHAT tool, automatically grades a low initial confidence in the body of evidence (Rooney et al. 2014). Factors lowering confidence in the body of evidence included the serious RoB within individual studies, imprecision of effects due to wide confidence intervals (CI) or a lack of reporting of CI, and the potential for publication bias. Nine papers either explicitly stated an absence of conflict of interest (COI) or reported funding sources which did not raise concerns over COI, and declared the independence of the viewpoints presented. One paper failed to report on sources of funding or potential COI (Marcotte, 2017).

4. Discussion

4.1. Summary of evidence

Of the 10 articles identified, 9 found some evidence that children and adolescents exposed to higher levels of TRAP pollutants show poorer academic performance than those exposed to lower levels of TRAP pollutants. This is consistent with other research finding evidence for associations between academic performance and indoor air quality or non-traffic sources of ambient pollution (Mohai et al. 2011; Stafford 2015). Therefore, TRAP may be another environmental factor affecting school children from which they should be protected. However, the majority of analyses extracted in this review found null associations. Furthermore, the study designs were highly heterogeneous, making it impossible to conduct any *meta*-analyses or to identify consistent patterns of association between individual pollutants, age groups, learning domains, exposure windows, and exposure locations. Finally, the size and emergent nature of the body of evidence raised concerns for potential publication bias (OHAT, 2015). The predominance of null associations, followed by associations with declines in academic performance, indicates that it is not only papers with significant findings in one direction which are being published in this field. However, some exposure metrics are used in single studies only and these findings need to be replicated in other settings to strengthen the validity of these methods.

Important foundations have been laid for future research. In particular, the suggestion in some papers that low SES and ethnic minority groups experience a higher risk of exposure and possibly more adverse effects should be further investigated (Gaffron and Niemeier 2015; Kweon et al., 2018). These findings are in accordance with other studies exploring racial gaps in exposure to harmful pollutants at school, highlighting the issue of environmental injustice in school-based exposures (Chakraborty, 2009; Korenstein & Piazza, 2002; Wu & Batterman, 2006). Policy makers should be aware that failing to protect children from TRAP at school could also exacerbate social inequalities.

4.2. Limitations and recommendations for future research

The current body of literature on TRAP and academic performance is small with vast room for improvement and further exploration. All studies reviewed were observational. Although it is possible to make causal inferences from observational studies where there is plausibly exogenous variation in exposure, the studies in this SR do not present robust strategies for identifying causality. Rather they rely on the inclusion of many control variables in the analysis. Experimental studies would contribute greatly to the body of evidence, however, allocating children to different levels of TRAP exposure is impracticable. One alternative is exploring interventions, for example a study by Austin et al (2019) found a positive association between the retrofitting of school buses to reduce toxic exposures and student health and academic performance (Austin et al., 2019). Such observational research could also be adapted into studies with random allocation to intervention or control groups.

It should be noted that throughout the COVID-19 pandemic, short-term reductions in air pollution and disruptions to education practices and school attendance have been observed (He et al., 2020; Menut et al. 2020; Radha et al., 2020). Therefore, the pandemic represents an additional challenge to the identification of plausibly exogenous variation missing from the current body of observational research. This strengthens the case for focussing on intervention studies, at least in the short term.

The majority of studies in this review were cross-sectional ($n = 7$) and, therefore, unable to estimate changes in the strength or direction of the TRAP-academic performance relationship over time. Although five studies assumed that their TRAP measures represented cumulative exposure, longitudinal research with repeated measures would be more appropriate. Such methodology has been used to find a negative association between TRAP exposure at school and cognitive development in children from the ages of 7–10 years (Sunyer et al., 2015)

The overall risk of bias in individual studies was graded to be serious. In particular, the exposure assessments selected by most studies were proxy measures which were subject to exposure misclassification and were limited in their accuracy in terms of estimated concentrations of TRAP. While the validity of the exposure metrics used is of concern, it should be noted that such proxy measures are likely to underestimate effects and bias results towards the null. Nevertheless, future studies must use valid and reliable exposure metrics and avoid using the USEPA's NATA modelled estimates. Personal/ on-site monitors measuring individual pollutants would provide the most accurate assessment of TRAP exposure. However, these methods are more resource intensive and would not be feasible when measuring large samples. Such trade-offs in research design mean that different studies with different strengths are needed to create a strong body of research. Therefore, personal/ on site monitoring is not the only acceptable option. Other systematic reviews exploring associations between health outcomes and TRAP exposure report heterogeneity in exposure assessments used (Clark et al. 2020; Khreis et al. 2017; Lau et al., 2018). However, the quality of the exposure assessments identified in these reviews is higher than those found in this investigation with a greater application of LUR modelling along with air quality monitoring data and the assessment of specific pollutants. Assessing the effect of individual pollutants is important because the composition of TRAP may vary within and between different geographic areas. Multi-country research using harmonised methodologies to compare concentrations PM of varying aerodynamic diameter and assessing the ratios between PM compositions and NO_2, report significant variations between different areas in Europe (Eeftens et al. 2012). Research based in China has also found that the concentrations and associated health effects of PM and ozone vary between regions (Xie et al. 2019). In addition, the potential confounding or co-exposure role of indoor (home and school) air pollution exposure has not been examined in this review and these factors may contribute to residual confounding effects and the inconsistent results observed between the papers in this review.

Future research should also make use of individual level outcome data, ensure consistency across studies in the use of confounders controlled for in analyses, and report and justify methods of sampling

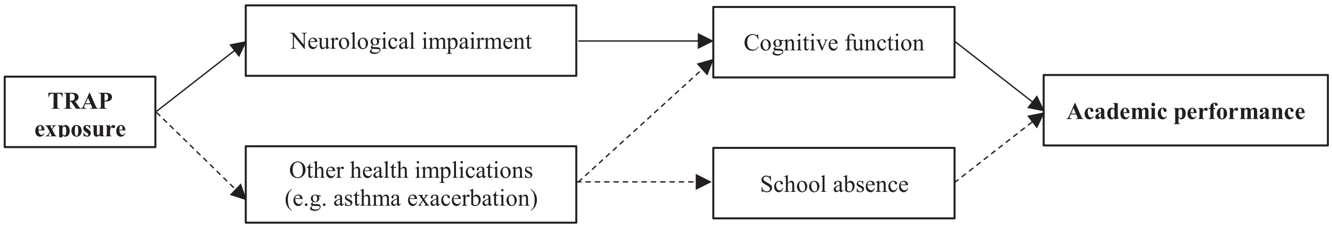

Fig. 3. Proposed conceptual framework for understanding the mechanisms through which TRAP affects academic performance. Solid lines = direct effect on academic performance, dashed lines = indirect effect on academic performance.

and statistical analysis.

To expand the scope of the present body of evidence, mechanisms and interactions of the TRAP-academic performance relationship can be explored. The predominant mechanisms of the TRAP-academic performance relationship proposed in the literature are displayed in Fig. 3. Firstly, a direct impact of TRAP on academic performance due to impaired cognitive function is proposed. UFP and $PM_{2.5}$ reaches brain regions associated with learning and memory directly via the olfactory bulb and indirectly by penetrating the lungs and entering the bloodstream, causing neuro-inflammation (Allenet al. 2017; Calderón-Garcidueñas et al. 2007; Elder et al. 2006; Jayaraj et al., 2017; Sunyer, 2008). Further cognitive impairments include white matter damage, disruption to the dopamine and glutamine neurotransmitter systems, changes in synaptic plasticity and the presence of amyloid plaques resembling those occurring in Alzheimer's disease (Allen et al. 2017; Calderón-Garcidueñas et al. 2007; Calderón-Garcidueñas et al. 2008). Psychological distress, headaches, disturbed sleep due to asthma exacerbation and adverse respiratory symptoms are also proposed to impair cognitive function indirectly (Basch 2011; Chen, 2019). Alternatively, an indirect pathway between TRAP and academic-performance is presented based on the increase in school absences due to ill-health associated with TRAP exposure (Currie et al., 2009; Pastor et al., 2004). Relationships between asthma exacerbation, school absence and academic performance have been particularly explored, although this pathway has not been firmly established (Goldizen et al., 2016; Moonie et al., 2008; Sullivan et al., 2018).

It is likely that both pathways influence the relationship between TRAP and academic performance, with the importance of each depending on the context of exposure. The current body of evidence includes a mix of home vs. school and short vs. long term exposure assessments. It could be hypothesised that school exposures represent more acute effects of TRAP, with health impairments such as asthma exacerbation and headaches playing a more important role. Meanwhile, home exposures may represent more chronic effects, including cognitive impairment. For example, previous literature argues that cumulative exposure to air pollution is the greatest threat to cognitive function (Allenet al. 2017; Zhang et al., 2018). As the body of evidence on TRAP and academic performance grows it will become possible to compare the effects of different exposure contexts.

The relationship between TRAP, green space and academic performance should also be further explored. Green space has been recommended as an intervention to improve academic performance based on proposed restorative effects (Browning and Rigolon 2019). It has also been proposed as an intervention to reduce TRAP exposure by reducing space available for cars around schools (Rivas et al., 2018) based on the finding that schools with more greenness within and surrounding the site were found to have lower ambient levels of TRAP pollutants (Dadvand et al. 2015). Future research should explore whether green space shows a positive interaction with TRAP exposure, based on restorative effects, or merely acts as an effect modifier (He et al., 2020; Menut et al. 2020; Radha et al., 2020).

4.3. *Strengths and limitations of the systematic review*

This is the first SR assessing the relationship between TRAP and academic performance in children and adolescents. The small number and high heterogeneity between included papers, precluded a formal *meta*-analysis. Extensive recommendations for future research are made to facilitate future development of this literature.

Although the processes of assessing risk of bias in individual studies and rating confidence in the body of evidence are inherently subjective, the use of the OHAT framework involved extensive documentation and justification of decisions, maximising transparency and consistency (Rooney et al. 2014). The selection of search terms for a SR also involves a degree of subjectivity. However, an extensive combination of terms based on similar research and key words identified in relevant papers was used. Retrieval of evidence was partially incomplete as some papers did not report numerical effect estimates for all analyses (Donovan et al. 2020; Stingone et al. 2016). Although authors were contacted, the data could not be retrieved.

5. Conclusion

In conclusion, this review found some evidence that children and adolescents exposed to higher levels of TRAP pollutants show poorer academic performance than those exposed to lower levels of TRAP pollutants. However, this evidence was judged to be weak because the existing body of literature is small, lacks the inclusion of high-quality exposure measures, and presents limitations in reporting. Further research is required to strengthen the body of evidence and to determine the precise mechanisms through which the TRAP-academic performance relationship may operate.

CRediT authorship contribution statement

Chloe Stenson: Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing. **Amanda J. Wheeler:** Conceptualization, Methodology, Investigation, Formal analysis, Writing - original draft, Writing - review & editing, Supervision. **Alison Carver:** Conceptualization, Methodology, Writing - review & editing. **David Donaire-Gonzalez:** Formal analysis, Writing - review & editing. **Miguel Alvarado-Molina:** Formal analysis, Writing - review & editing. **Mark Nieuwenhuijsen:** Conceptualization, Supervision, Writing - review & editing. **Rachel Tham:** Methodology, Investigation, Formal analysis, Writing - review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary material

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