ECONOMIC AND HEALTH METRICS OF ACTIVE SCHOOL TRAVEL: A PRACTICAL TOOL FOR TRANSPORTATION PLANNERS AND EDUCATORS

FINAL PROJECT REPORT

by

Professor Anne Vernez Moudon, Principal Investigator
Dr. Xiao Shi, Research Assistant
University of Washington

Sponsorship
PacTrans and WSDOT as matching external sponsors
Charlotte Claybrooke

for

Pacific Northwest Transportation Consortium (PacTrans)
USDOT University Transportation Center for Federal Region 10
University of Washington
More Hall 112, Box 352700
Seattle, WA 98195-2700

In cooperation with U.S. Department of Transportation,
Office of the Assistant Secretary for Research and Technology (OST-R)

DISCLAIMER

TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No.	2. Government Accession No. 01764503	3. Recipient's Catalog No.
4. Title and Subtitle ECONOMIC AND HEALTH METRICS OF ACTIVE SCHOOL TRAVEL: A PRACTICAL TOOL FOR TRANSPORTATION PLANNERS AND EDUCATORS		5. Report Date November 2022 6. Performing Organization Code
7. Author(s) and Affiliations Prof. Anne Vernez Moudon, 0000-0001-8485-4799 ; Dr. Xiao Shi, Research Assistant University of Washington		8. Performing Organization Report No. 2020-S-UW-2
9. Performing Organization Name and Address PacTrans Pacific Northwest Transportation Consortium University Transportation Center for Federal Region 10 University of Washington More Hall 112 Seattle, WA 98195-2700		10. Work Unit No. (TRAIS) 11. Contract or Grant No. 69A3551747110
12. Sponsoring Organization Name and Address United States Department of Transportation Research and Innovative Technology Administration 1200 New Jersey Avenue, SE Washington, DC 20590		13. Type of Report and Period Covered 14. Sponsoring Agency Code
15. Supplementary Notes Report uploaded to: www.pactrans.org		

16. Abstract

The objective of this project was to complement school walkability measures with measures of health as outcomes related to rates of Active School Travel (AST). We carried out a meta-analysis of 11 studies measuring moderate to vigorous physical activity (MVPA) related to school travel We found that daily AST could contribute between 3 and 9 minutes of MVPA per child per day or 5 to 16 percent of a child's daily MVPA as recommended by the Centers for Disease Control and Prevention. Future research can add this health outcome metric to the Washington School Walk Score (WS*2), the individual school-level walk score that has been validated with data from the state's Youth Travel Surveys. This work will create a tool, the *Children Walking to School Tool*, that treats the predictors of walking contained in the current WS*2 as inputs and health outcomes as outputs. Other health metrics related to the MVPA assigned to AST can be estimated, such as Disability Adjusted Life Years (DALYs) or health care costs savings, which would enrich the tool. A Children Walking to Health Tool will provide policy makers with evidence of the health outcomes of transportation investments. It will also include an interactive function, allowing policy makers and stakeholders to assess the health effects of interventions by changing the values of predictors of AST, such exposure to highly trafficked streets in the school neighborhood or the size of school enrollment.

17. Key Words Refer to and utilize keywords found in the Transportation Research Thesaurus http://trt.trb.org/trt.asp?		18. Distribution Statement	
19. Security Classification (of this report) Unclassified.	20. Security Classification (of this page) Unclassified.	21. No. of Pages	22. Price N/A

Form DOT F 1700.7 (8-72) **Reproduction of completed page authorize**

Table of Contents

List of Figures

List of Tables

LIST OF ABBREVIATIONS

ADA	Americans with Disabilities Act
AST	Active School Travel
BMI	Body Mass Index
DALY	Disability Adjusted Life Years
DOH	Department of health
DOT	Department of transportation
MVPA	Moderate to vigorous physical activity
PacTrans	Pacific Northwest Transportation Consortium
SRTS	Safe Routes to School
USDOT	United States Department of Transportation
VMT	Vehicle miles traveled
WS*2	Washington School Walk Score
WSDOH	Washington State Department of Health
WSDOT	Washington State Department of Transportation

EXECUTIVE SUMMARY

The objective of this project was to complement commonly used school walkability measures with measures of health. The benefits of Active School Travel (AST) are well understood. They range from reducing traffic congestion and environmental pollution near schools to providing children with opportunities to be physically active and to explore their neighborhood environment. Tools have been developed that allow transportation professionals and policy makers to assess the effect of school neighborhood environmental characteristics and school policies on rates of ATS. However, these rates in turn have an effect on children's health, which should be included in the formula used to calculate walkability. This project was to provide measures of health outcomes related to rates of AST.

We carried out a meta-analysis of 11 studies measuring the moderate to vigorous physical activity (MVPA) related to school travel. We found that daily AST could contribute between 3 and 9 minutes of MVPA per child per day, which corresponded to a significant 5 to 16 percent of a child's daily MVPA recommended by the Centers for Disease Control and Prevention. This finding indicates that AST can contribute significantly to a child's health. Further, promoting AST could be a strategy to reverse the unhealthy trend of growing physical inactivity in children and youth.

This MVPA health outcome metric can be added to the recently developed Washington School Walk Score tool (WS*2). WS*2 is a school-level walk score tool that has been validated with mobility data from the state's Youth Travel Surveys (Moudon, Shi, and Chen 2020). The tool estimates rates of AST for each K-8 school in Washington state. Its interactive function uses predictors of walking to estimate AST rates. Adding the MVPA health outcome to WS*2 will yield a new tool, the *Children Walking to School Tool*, where the predictors of walking contained in the current WS*2 are treated as inputs and health outcomes as outputs. A Children Walking to Health tool will provide evidence documenting the health outcomes of transportation investments. The tool's interactive function will allow transportation professionals, stakeholders, and policy makers to assess the health effects of different types of interventions by changing the values of predictors of AST, such exposure to highly trafficked streets in the school neighborhood or the size of school enrollment.

Other health metrics related to the MVPA can be estimated and assigned to AST. Future research can explore such measures of health as Disability Adjusted Life Years (DALYs) or health care costs savings, which would further enrich the tool.

CHAPTER 1. BACKGROUND AND PURPOSE

Active School Travel (AST) and **Safe Routes to School (SRTS)** programs present a challenge to the transportation sector with a contradictory situation: on the one hand, they hold great promise for reducing the negative effects of traffic congestion and environmental degradation and, on the positive side, for improving human health. Yet at the same time, AST programs have a low profile in the transportation policy arena and suffer from low funding levels. Strategies and tools are needed to empower SRTS administrators and educators to better compete for transportation funding.

1.1. Emphasis on the Benefits: How Children Travel to and from School Has Impacts on Their Health, on the Efficiency of Transportation Systems, and on the Quality of Neighborhood Environments

As of 2019, there were 35.5 million K-8 students in the nation and 1.1 million in Washington state. Of those, 76 percent were not physically active enough, and nearly 20 percent were obese. A decade of research has established that AST can provide 10 percent of the physical activity that a child needs to be fit and healthy (Faulkner et al. 2009; Janssen and LeBlanc 2010; Poitras et al. 2016; Steinbeck 2001). Children walking or bicycling to and from school also positively address transportation woes by reducing vehicle miles traveled (VMT), which in turn reduces traffic congestion and associated greenhouse gas emissions and other pollutants generated by motor vehicles. Finally, AST has long-term effects on children's social skills because it affords them the opportunity to learn to be independent from adults and, specifically, to navigate using their senses (Baslington 2008).

After a long hiatus, transportation policies have changed to recognize the multiple benefits of AST. Our research has shown that where SRTS programs have been implemented, they have been successful at increasing the number of children walking and bicycling to school (Stewart, Moudon, and Claybrooke 2014).

1.2. Addressing the Challenge: Safe Route to School Programs Must Compete for Resources in an Already Financially Stressed Transportation Sector

Washington state is one of the nation's top three states running a Safe Routes to School program. Since 2005, Washington SRTS has awarded funds for projects at 306 schools. Uniquely, the Washington State Department of Transportation (WSDOT) has collaborated with the Washington State Department of Health (WSDOH) to monitor and evaluate the effects of SRTS programs. The two departments have conducted bi-yearly Student Travel Surveys since

2014. With 9,656 respondents from 178 schools in 2014, and 11,421 respondents from 228 schools in 2016, the surveys have included about 10 percent of the state's students. Survey results have been encouraging. They have shown significant increases in the percentage of children walking (a 16.4 percent increase between 2014 and 2016) and biking (a 56 percent increase). Importantly, SRTS has an equity dimension: 17.4 percent of students using AST have been at lower-income schools in comparison to 14.9 percent at higher-income schools (Washington State Department of Health 2017).

1.3. Project Objective: Contribute to Producing a Data-Analytic Tool That Quantifies the Economic and Health Benefits of Active School Travel

Evidence-based tools are needed to help generate policies focused on effectively increasing rates of AST. By increasing children's physical activity levels, AST leads to improved health, which in turn leads to lower morbidities as well as to cost savings for health care. Staff in departments of transportation (DOTs) and of departments of health (DOHs) need simple and clear metrics of the health benefits of AST, which will help them better communicate with policy makers. This project was intended to generate such metrics and thus to directly contribute to a fair and effective approach to allocating funds for AST and SRTS.

CHAPTER 2. ADDING TO PREVIOUS RESEARCH

In an increasingly data-driven world, indices have become quasi-universal metrics to assess a phenomenon and to evaluate change. For example, the Transportation Services Index was created by the USDOT Bureau of Transportation Statistics to measure and track the movement of freight and passengers. Since 2018, The Transportation Public Health Link, the International Professional Association for Transport & Health, and the Institute of Transportation Engineers have been collaborating to create a Transport and Health Performance Metric Guidebook (https://www.ipathinc.org/transport--health-performance-metric-guidebook.htmlhttps://www.ipathinc.org/transport--health-performance-metric-guidebook.html). In the area of non-motorized, active travel, *walkability indices* have proliferated to help policy makers promote walking and to guide consumers in their selection of healthy environments in which to live, work, and play. Building on the popularity of the commercially available Walk Score, the U.S. Environmental Protection Agency developed an open source Walkability Index (https://edg.epa.gov/metadata/catalog/search/resource/details.page?uuid=%7B251AFDD9-23A7-4068-9B27-A3048A7E6012%7D).

There were no children- and youth-focused walkability indices until recently (Giles-Corti et al. 2011). Existing walkability indices were applicable to able-bodied adults but could not be generalized to youth populations, not only for such obvious reasons as the limited navigational ability of children and youth but also because youth travel purposes are different from those of adults. Yet the trip to and from school is an important routine event in the life of a child, taking place 175 to 180 days per year. It is the child's equivalent of the adult's work commute. Our team recently produced novel child- and youth-focused walkability indices, which were applied to the 1,728 K-8 schools in Washington state (Moudon, Shi, and Chen 2020). Specifically, we developed **WS*2** (for Washington School Walk Score), which estimates the school-level *rate of AST*, measured as the expected number of children walking to school divided by the number of students in the school, for each school in the state. A detailed summary description of the WS*2 is provided in Appendix A.

At this time, WS*2 provides an estimate of the likely rate of AST for each school in Washington state. In the present project, we aimed to add a health dimension to the WS*2 by quantifying *how rates of AST correspond to actual health benefits*. The objective was to complement WS*2 with estimates of the health and monetary benefits of AST at the school level. This will help create what we call a *Children Walking to Health Tool* that combines predictors of walkability with health outcomes.

Obtaining metrics of health and monetary benefits of AST consisted of "translating" rates of AST into expected health and economic outcomes. For this translation, we carried out meta-analyses of the results of previous studies that correlated school-based active travel or physical activity with health outcomes and health care cost savings.(Moher et al. 2009)

CHAPTER 3. METHODS

We followed well-established meta-analysis methods, which included steps to identify, screen, select, and include relevant studies for analyses (Moher et al. 2009).

3.1. Study Selection and Inclusion in Meta-Analyses

To identify studies for inclusion in the meta-analyses, we could use a variety of databases, including PubMed, Web of Science, Google, and Google Scholar (plus Academic Search Premier, MEDLINE, TRIS Online, and Web of Knowledge). We proposed to select studies published in English after 2010 in order to focus on newer studies that is more relevant to current school context. We also restricted the search to studies of children agr 14 and below because adolescents, defined as aged between 15-17 according to the Centers for Disease Control and Prevention, have physical strength, behaviors, and needs in walking environment that differ significantly from children of younger age. Focusing on a more narrowly defined age group will increase the accuracy of the tool and reduce potential biases and errors. In addition, the tool aimed to serve AST programs targeting K-8th schools, which usually enrolls children age up to 14 years old. Using such keywords as "active school travel," "walking," and "physical activity" coupled with "children" and "health benefit," a preliminary scan of the literature showed that 20 to 30 studies could be included in our analyses of health outcomes. For assessing the cost benefits of reduced morbidity, we could use such key words as "active school travel," "walking," "physical activity," and "obesity" coupled with "children" and "economic benefit." A preliminary search identified five to ten studies that could be included in the analyses of economic metrics.

Meta-analyses combine the results of different studies. To calculate the effect size of health outcomes related to rates of walking, we could use such simple and direct measures as physical activity (moderate or vigorous), as well as downstream outcomes such as the prevalence of obesogenic and/or cardiovascular diseases, which are among the most common agents of mortality and morbidity (Cunningham, Walton, and Carter 2018).

3.2. Analyses for Weighted Average Effect Size

In any meta-analysis, the heterogeneity of the selected publications first needs to be assessed. We used the Inconsistency Index I^2 (Haby et al. 2006), which describes the percentage of total variation across studies that is due to heterogeneity rather than chance. If the studies vary greatly (I^2>75%) in terms of participants, outcomes, study design, and/or limitations, then the studies can be divided into subgroups that share similar characteristics or be excluded if they are significantly different from others, until the Index I^2 of each subgroup reaches below 75 percent. In addition, if low heterogeneity (I^2<25%) is observed, then a Fixed Effects Model can be used to estimate the effect size and its confidence interval. If moderate to high heterogeneity (I^2>25%) is observed, then a Random Effects Model can be used instead.

In the Fixed Effects Model, the weighted average effect size (E) is the sum of effect sizes reported in the individual study (e_i) while weighted by the inverse of their variance (σ_i) (formula 1). The confidence interval of the effect size is also calculated by using the variance of individual study (formula 2).

$$E = \frac{\sum_{i=1}^{N} \frac{1}{\sigma_i^2} e_i}{\sum_{i=1}^{N} \frac{1}{\sigma_i^2}} \qquad \mathbf{(1)}$$

where E is the weighted average effect size, e_i is the effect size reported in individual study i, σ_i^2 is the variance of the reported effect size in individual study i, and N is the total number of studies included in the analysis.

$$(Lower\ Limit, Upper\ Limit) = (E - 1.96 * \sum_{i=1}^{N} \frac{1}{\sigma_i^2}, E + 1.96 * \sum_{i=1}^{N} \frac{1}{\sigma_i^2}) \qquad \mathbf{(2)}$$

where E is the weighted average effect size and σ_i^2 is the variance of the reported effect size in individual study i.

In the Random Effects Model, the formulas for weighted average effect size and its confidence interval are similar to those in the Fixed Effects Model, except that instead of using the variance of the individual study, the sum of within-study variance and the between-studies variance is used (formulas 3 and 4).

$$E = \frac{\sum_{i=1}^{N} \frac{1}{\tau_i^2} e_i}{\sum_{i=1}^{N} \frac{1}{\tau_i^2}} \quad , \qquad \tau_i^2 = v_i^2 + u^2 \ \mathbf{(3)}$$

where E is the weighted average effect size, e_i is the effect size reported in individual study i, v_i^2 is the variance of the reported effect size in individual study i, u^2 is the in between variance of all studies, and N is the total number of studies included in the analysis.

$$(Lower\ Limit, Upper\ Limit) = (E - 1.96 * \sum_{i=1}^{N} \frac{1}{\tau_i^2}, E + 1.96 * \sum_{i=1}^{N} \frac{1}{\tau_i^2}), \qquad \tau_i^2 = v_i^2 + u^2 \qquad (\mathbf{4})$$

where E is the weighted average effect size, v_i^2 is the variance of the reported effect size in individual study i, and $u^2$is the in between variance of all studies.

Of note, there is a still ongoing debate, with no clear consensus, as to when exactly the heterogeneity assumption holds and which model fits which context. Whereas some recommend using the Random Effects Model only in clinical psychology and the health sciences (Cuijpers 2016), others argue that the Fixed Effects Model should always be preferred for putting less weight on smaller studies with biases (Furukawa, McGuire, and Barbui 2003).

Finally, an <u>assessment of bias</u> must be carried out. The most common bias threatening the validity of meta-analysis is publication bias, which refers to the bias caused by studies that might have been left out of the analysis, especially the ones that are difficult to publish because they do not have positive results. We used a funnel plot, a scatterplot of effect size against study size, to assess the existence of biases. If publication bias is not present, then the plot is expected to have a symmetric inverted funnel shape (figure 3.1a). Larger studies tend to cluster closely to the point estimate whereas smaller studies are scattered to both sides of the point estimate of effect.

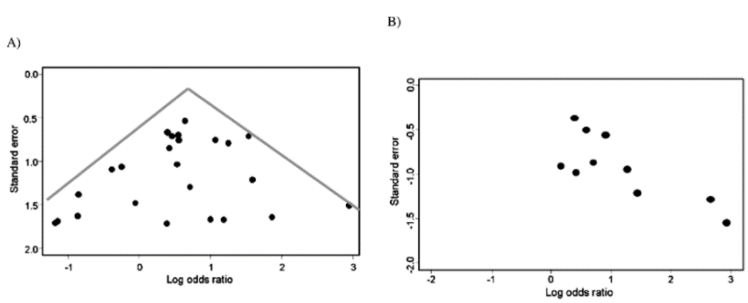

Figure 3.1. An example of a funnel plot in meta-analysis (Haidich 2010). a) Symmetrical funnel plot. b) Asymmetrical funnel plot in which small negative studies in the bottom left corner are missing.

CHAPTER 4. RESULTS

4.1. The Literature

The literature search procedure and inclusion criteria followed the standards recommended for public health studies (Brown 2016; Cunningham, Walton and Carter 2018; Faulkner et al. 2009; Giles-Corti et al. 2011). The inclusion criteria for the targeted literature are listed in table 4.1. The main population of interest was children attending K-8 schools, namely those ages 4 to 14. We included studies that covered populations beyond this age range but excluded those focused entirely on teenagers older than 14. Only studies conducted after 2010 were considered to obtain estimations that were most relevant to current conditions. Health outcome measures were

(1) physical activity, and specifically moderate to vigorous physical activity (MVPA) achieved through walking to school or AST, which included walking and cycling; comparison measures included being driven to school or other forms of passive travel (e.g., driving or riding transit)

(2) body weight or Body Mass Index (BMI).

Finally, we focused on studies conducted in North American and European countries, which have cultural and environmental contexts similar to those of Washington state.

Table 4.1. Targeted literature

Participant	Children attending K-8 schools (age 4-14)
Outcome (measurement)	• physical activity (MVPA), • weight (BMI)
Intervention	• walking to school, • active travel mode (walking + cycling)
Comparison	• driven to school • passive travel mode (driven + bus)
Study Type	Peer-reviewed journal articles, exclude systematic reviews
Time	Published within 10 years (after 2010)
Location	North America, Europe
Language	English

The databases searched were the Web of Science and PubMed, last accessed April 9, 2021. The searching code was as follows:

> (((((physical activity[Title/Abstract]) OR (BMI[Title/Abstract])) OR (weight[Title/Abstract])) **AND** (children[Title/Abstract])) **AND** ((active travel to school[Title/Abstract]) OR (active school transport[Title/Abstract]))) **AND** (English[Language]) AND (Year[2010-2021])

Figure 4.1 shows the literature selection procedure and the number of studies included and excluded at each step of the process. Eleven studies were included in the final analyses. In comparison to previously published systematic reviews, the number of studies included in this analysis was on the smaller side, mostly because of the stricter inclusion criteria that were required for meta-analysis.

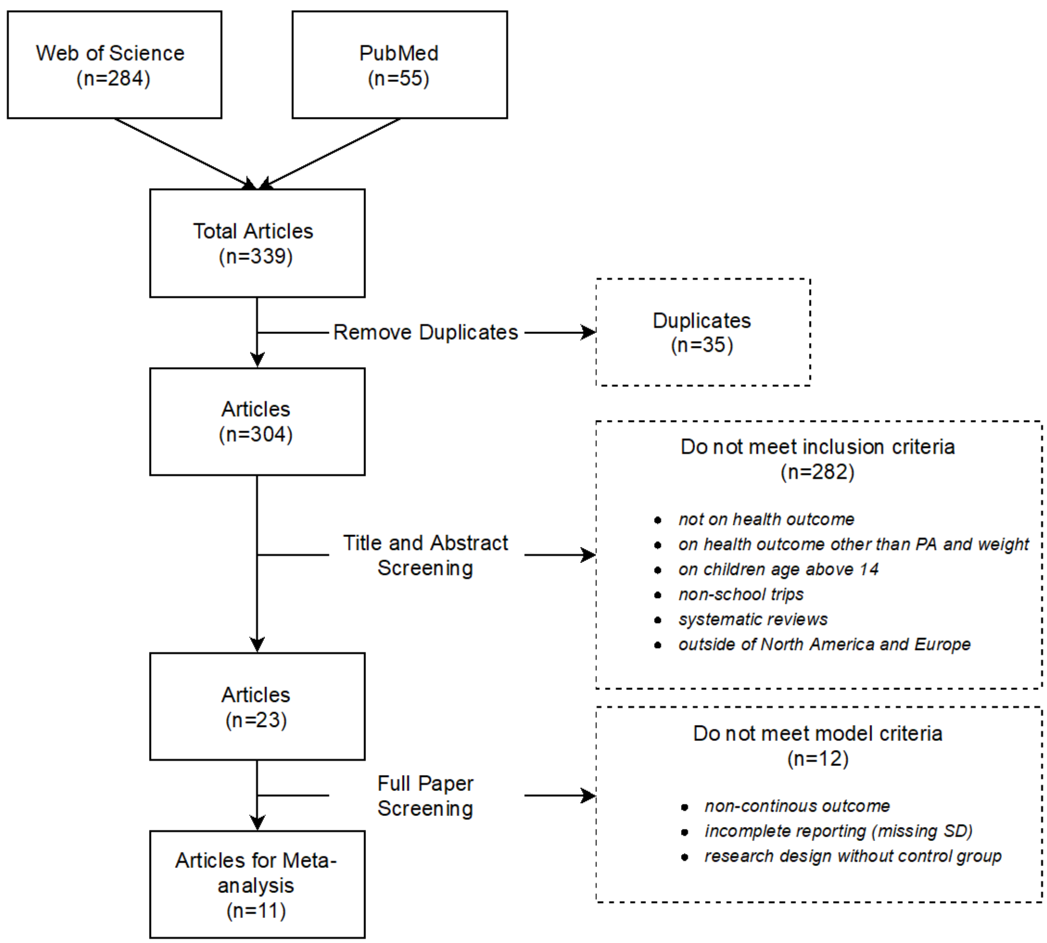

Figure 4.1. Flow diagram of study screening and selection

Table 4.2 summarizes the characteristics of the studies included in the analyses. The complete list of studies is shown in table B.1 in Appendix B.

Table 4.2. Summary characteristics of included studies (n=11)

Characteristics	**Descriptive statistics**
Participant age coverage	7-12 years
Outcome	Physical activity (n=6) BMI (n = 5)
Year of publication	2011-2021
Location	North America (n=2)
	Europe (n = 9)

4.2. Estimated Effect Size

Of the two approaches to estimating the pooling effect sizes in meta-analysis, the Fixed Effects Model assumes that all studies, along with their effect sizes, are drawn from a single homogeneous population. To calculate the overall effect, all effect sizes are averaged, where studies with greater precision (i.e., with a larger sample size or smaller standard error) are given higher weights. In contrast, the Random Effects Model is recommended when studies have more variance than when drawn from a single population.

The test of heterogeneity, which was used to statistically test the level of difference among studies (table 4.3) showed that the studies that were included presented heterogeneity, namely, their samples came from populations with different characteristics. As a result, the Random Effects Model was used to obtain unbiased estimations. One random effect model was estimated for each of the three physical activity and body weight outcome measures (1-trip MVPA, 2-daily MVPA, 3-BMI and BMI z-score). Results estimated with Fixed Effects Model were reported as a sensitive test.

For the BMI outcome measure, some studies reported BMI while others reported a BMI z-score. To obtain consistent estimation, the outcomes were first transformed to a standardized effect size before the model was run, and the final estimation was transformed back to the scale of the targeted outcome afterwards. The details of this step are documented elsewhere (Lipsey and Wilson 2001).

Table 4.3. Heterogeneity test and analysis selected

Outcomes	Measurements	N (studies)	N (Sample)*	N (Participants)	Heterogeneity Test	Selected model
Physical Activity	1-MVPA (trip)	3	3	2,370	P<0.01	Random Effects
	2-MVPA (day)	3	5	3,330	P<0.01	Random Effects
Weight	3-BMI and BMI z-score	5	7	10,171	P<0.01	Random Effects

*A study may report results on multiple samples (i.e., different study site, gender group, or age group).

4.3. Model Results

Model results showed that for children between ages 7 and 12, AST was associated with 7.7 minutes more MVPA during school trips and 9.17 minutes more daily MVPA (table 4.4). The estimated effect size of MVPA during school trips was not significant based on the Random Effects Model, likely because of the heterogeneity of the included studies. The reduction in BMI associated with AST was 0.81. The relationship was not significant, likely because of the more complex and indirect relationship between AST and BMI.

Table 4.4. Random Effects Model results

Outcomes	Measurements	Unit	Fixed Effects Model Estimate	Random Effects Model Estimate
Physical activity	MVPA (trip)	min/trip	3.05*	7.67
	MVPA (daily)	min/day	6.07*	9.17*
Weight	BMI	kg/m^2	-2.6*	-0.81

*Significant at p<0.05 level

CHAPTER 5. DISCUSSION

We estimated that increases in MVPA associated with AST corresponded to between 3 and 9 additional minutes of MVPA per day in comparison to being driven or taking transit to and from school. This is between 5 and 16 percent of the recommended 60 minutes of daily MVPA for children (ACSM 2018). Thus the effect of AST is considerable at the individual child level. And given that more than two thirds of the child and youth population does not meet the recommended levels of MVPA in the U.S., the results suggest that AST has an even greater potential to make the entire population of children and youth active enough to contribute to their good health.

Locally, the currently low figures of children and youth "practicing" AST also suggest that there is room for improvement. For Washington state, we estimated that 21.78 percent of students used AST (SD 16.43 percent, ranging from 0 to 78 percent) (Moudon, Shi, and Chen 2020). These figures are in line with available statistics for the U.S. as a whole, where 76.8 percent (95 percent CI 75.4–78.1) of high school students are not physically active at least 60 minutes per day on all seven days of the week, and for Seattle, where the percentage is 80.8 (95 percent CI 77.9–83.4) (CDC 2019). Facilitation and encouragement of AST will help increase participation.

It is important to consider the physical activity benefits of AST because sufficient levels of physical activity have positive effects not only on physical health but also on the physiological and mental health of children and youth, protecting them from many non-communicable diseases such as cancers and being overweight. It follows that public health officials seeking to make children more active should work more closely with transportation officials to make AST more readily accessible to the school age population. The combined benefits of AST on the health of youth and on reducing traffic congestion and environmental pollution should further motivate and convince both sectors to work together.

On the method side, the analyses were promising, as results from both the Fixed Effects and the Random Effects models were consistent for daily MVPA. For BMI, associations were in the right direction but not significant.

CHAPTER 6. FURTHER RESEARCH

The substantial health benefits of AST documented in this study strongly suggest the need to work to increase the number of children walking to and from school. Several known and tested strategies and interventions exist that can help increase the rates of AST. As mentioned, the WS*2 is a walkability index instrument that is based on an algorithm that combines indicators that predict the rate of AST for individual schools. The MVPA outcomes of AST, which were calculated in the present study, can be integrated with the WS*2 to create an instrument that we call the *Children Walking to Health Tool*. The tool can directly relate levels of walkability to health. Such an instrument can also help assess the health impacts of changes in walkability and thus help policy makers assess the health impacts of improvements in walkability.

6.1. Framework for Tool Development

Figure 6.1 describes the structure of a *Children Walking to Health Tool* that can be developed to gauge the health benefits of different levels of walkability. At the center of the figure is the previously developed **WS*2,** whose algorithm has been described in Appendix **A** and in Moudon, Shi, and Chen, 2020. The left-hand side of the figure summarizes the INPUT variables used to calculate WS*2, while the right-hand side of the figure lists the new economic and health benefits of AST, as OUTPUTS of the tool.

The *Children Walking to Health Tool* can be used interactively. Input data for the tool will be the WS*2 values (percentage of children in each school expected to use AST) available for Washington state K-8 schools, while output data will be the estimated health and economic benefits of AST values. The tool can also serve to examine the impacts of various scenarios by changing the value of any of the input cells of the matrix. Thus changes in WS*2 can be input to obtain their effects on health and economic benefits. Or alternatively, changes in the built environment around a school or in the school population can be put into the matrix to examine the new WS*2 value and related new benefits.

	DATA INPUT into the Tool FROM PREVIOUS RESEARCH							DATA OUTPUT		
Individual school	Variables used to estimate WS*2						WALK SCORE WS*2	NEW METRICS		
	Built environment		School population					Health benefits		Economic benefits
	Street connectivity	Traffic exposure	Grade	School bus	Free lunch	School enroll-ment		Increase in MVPA	Reduction in DALYs	Health care cost savings
School 1							proportion of children walking to school	Additional minutes of MVPA	Disability-adjusted life years saved	Life cost savings
School 2										
School N										

Figure 6.1: Structure of the proposed *Children Walking to Health Tool*

6.2. Method for Building the Children Walking to Health Tool

The *Children Walking to Health Tool*, which integrates the WS*2 algorithm and the health and economic effect size estimated from the meta-analyses, can be developed as an automated Excel model using the formula builder function of Excel. This data-analytic tool uses open-source data and software; it is Americans with Disabilities Act (ADA) compliant and user-friendly. Excel has been used widely for building data analysis models in the transportation and health sectors. Transparency and versatility are its important qualities. Some of the frequently used tools include the Transportation Health Tool developed by the USDOT (https://www.transportation.gov/mission/health/transportation-and-health-tool-data-Excel) (WSDOT 2015) and the Urban Transport Data Analysis Tool used by the World Bank (https://www.worldbank.org/en/topic/transport/publication/urban-transport-data-analysis-tool-ut-dat1) (World Bank). Both tools allow users to compare key health and transportation indicators in their regions. However, they differ from our proposed tool in that they do not interactively link travel behavior to health outcomes. Rather, they itemize factors related to both transportation and health, such as road traffic fatalities, and percentage of trips made by foot or bicycle. As such, these tools only compile datasets.

6.3. Functionality and Usability of the Tool

Generally, the *Children Walking to Health Tool* will make it possible to examine how changes in walkability (using WS*2) might affect health and economic benefits at the state, county, and the school district levels. For example, tool users can estimate how SRTS projects in given locations will increase rates of AST. They can follow up with an examination and calculation of the health and economic benefits related to different types and magnitudes of SRTS investments. Such assessments could be used to convince policy makers who may be internal or external (e.g., state legislators) to WSDOT to invest in SRTS projects.

Second, scenarios can be designed to focus on changes in specific aspects of the built environment around schools to promote more walking (e.g., building more sidewalks, installing crosswalk markings or traffic lights). Scenarios can also aim to investigate the impact of changing school policies (e.g., changing the school assignment to increase the number of children living within walking distance of the school, changing the school lunch program, etc.) on rates of ATS and related health and economic metrics. Scenario building should be done in collaboration with stakeholders and policy makers in both transportation and education. Children should be involved as well.

Of note, the *Children Walking to Health Tool* is disaggregated at the school level, which can provide flexibility for SRTS coordinators assigning SRTS projects to individual schools. Also, as a school-level tool, it allows for convenient updates of the data related to school enrollment, children in the free lunch program, and other variables considered in WS*2.

The data and methods used to calculate the benefits will be fully documented so that other states or jurisdictions can replicate the approach.

6.4. Optional Health Metrics

Other metrics related to obesogenic or cardiovascular diseases can be used, such as the commonly used disability-adjusted life years (DALYs). Also, morbidity outcomes can be used by transforming obesogenic outcomes such as BMI or cardiometabolic measurements into changes in morbidity by using the potential impact fraction method (Haby et al. 2006).

For economic benefits, *life-long health-care cost savings* can be used and transformed into corresponding reduced morbidity. These can be expressed in U.S. dollars by applying a 5 percent discount rate per year (Brown 2016)

CHAPTER 7. CONCLUSIONS

7.1. Outcomes and Achievements

This work champions the quantification of the health and economic benefits of Active School Travel (AST) for use in transportation policy and budget allocation. Establishing actual health and economic values of AST will help demonstrate the importance of accommodating AST as a sustainable travel mode. The algorithms used to measure expected rates of AST and its associated benefits have been validated thanks to the availability of unique data on AST from Washington state. The data and methods used to calculate the benefits are open source and can be fully replicated by other states or jurisdictions.

7.2. Outputs

The study represents a first step toward the development of an interactive Excel tool. The tool first estimates the number (or proportion) of children that are expected to walk to and from school based on the built environment and school population characteristics. Second, the tool quantifies the health benefits of AST in the form of increased MVPA. Other more general health outcome measures could be used, such as reduced DALYs, reduced health care costs, or reduced morbidity. Importantly, the data required to calculate expected AST are available nationally, meaning that there will be no barriers for other jurisdictions interested in using the tool.

7.3. Impacts

When developed as an open data and software instrument, the *Children Walking to Health Tool* can have a national impact. It will help pave the way for transportation policies that support a sustainable and healthy travel mode, thus addressing timely issues related to mobility, accessibility, and environmental quality.

LIST OF REFERENCES

ACSM (American College of Sports Medicine). 2018. US Physical activity guidelines. Physical Activity in School-Aged Children 2018. https://americanfitnessindex.org/tag/u-s-physical-activity-guidelines/

Baslington, Hazel. 2008. "Travel Socialization: A Social Theory of Travel Mode Behavior: International Journal of Sustainable Transportation: Vol 2, No 2." 2008. https://www.tandfonline.com/doi/abs/10.1080/15568310601187193.

Brown, Vicki. 2016. "A Systematic Review of Economic Analyses of Active Transport Interventions That Include Physical Activity Benefits." *Transport Policy*, 19.

Centers for Disease Control and Prevention. 2019. Youth Risk Behavior Surveillance System. High School YRBS Survey Seattle, WA 2019 and United States 2019 Results. https://nccd.cdc.gov/Youthonline/App/Default.aspx

Cuijpers, P. 2016. Meta-analyses in mental health research. A practical guide. *Amsterdam, the Netherlands: Pim Cuijpers Uitgeverij*

Cunningham, Rebecca M., Maureen A. Walton, and Patrick M. Carter. 2018. "The Major Causes of Death in Children and Adolescents in the United States." *New England Journal of Medicine* 379 (25): 2468–75. https://doi.org/10.1056/NEJMsr1804754.

Faulkner, Guy E J, Ron N Buliung, Parminder K Flora, and Caroline Fusco. 2009. "Active School Transport, Physical Activity Levels and Body Weight of Children and Youth: A Systematic Review." *Preventive Medicine*, 6.

Furukawa, T. A., McGuire, H. & Barbui, C. Low dosage tricyclic antidepressants for depression. *Cochrane database of systematic reviews* (2003)

Giles-Corti, Billie, Gina Wood, Terri Pikora, Vincent Learnihan, Max Bulsara, Kimberly Van Niel, Anna Timperio, Gavin McCormack, and Karen Villanueva. 2011. "School Site and the Potential to Walk to School: The Impact of Street Connectivity and Traffic Exposure in School Neighborhoods." *Health & Place*, Geographies of Care, 17 (2): 545–50. https://doi.org/10.1016/j.healthplace.2010.12.011.

Lipsey, M. W. & Wilson, D. B. *Practical meta-analysis.* (SAGE publications, Inc, 2001).

Haby, M. M., T. Vos, R. Carter, M. Moodie, A. Markwick, A. Magnus, K.-S. Tay-Teo, and B. Swinburn. 2006. "A New Approach to Assessing the Health Benefit from Obesity Interventions in Children and Adolescents: The Assessing Cost-Effectiveness in Obesity Project." *International Journal of Obesity* 30 (10): 1463–75. https://doi.org/10.1038/sj.ijo.0803469.

Haidich, A B. 2010. "Meta-Analysis in Medical Research." *Hippokratia* 14 (Suppl 1): 29–37.

Janssen, Ian, and Allana G LeBlanc. 2010. "SReyvieswtematic Review of the Health Benefits of Physical Activity and Fitness in School-Aged Children and Youth," 16.

Moher, David, Alessandro Liberati, Jennifer Tetzlaff, and Douglas G. Altman. 2009. "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement." *BMJ* 339 (July). https://doi.org/10.1136/bmj.b2535.

Moudon, A. V., X. Shi, Y. Chen. "Washington State School Walk Score." Pacific Northwest Transportation Consortium. 2020. http://hdl.handle.net/1773/45599

Poitras, Veronica Joan, Casey Ellen Gray, Michael M Borghese, Valerie Carson, Jean-Philippe Chaput, Ian Janssen, Peter T Katzmarzyk, et al. 2016. "Systematic Review of the Relationships between Objectively Measured Physical Activity and Health Indicators in School-Aged Children and Youth" 41: 43.

Steinbeck, K. S. 2001. "The Importance of Physical Activity in the Prevention of Overweight and Obesity in Childhood: A Review and an Opinion." *Obesity Reviews* 2 (2): 117–30. https://doi.org/10.1046/j.1467-789x.2001.00033.x.

Stewart, Orion, Anne Vernez Moudon, and Charlotte Claybrooke. 2014. "Multistate Evaluation of Safe Routes to School Programs." *American Journal of Health Promotion* 28 (3_suppl): S89–96. https://doi.org/10.4278/ajhp.130430-QUAN-210.

United States Department of Transportation. 2015. Transportation and Health Tool Data in Excel." US Department of Transportation. October 26. Accessed January 31, 2020 https://www.transportation.gov/mission/health/transportation-and-health-tool-data-excel

Washington State Department of Health Office of Healthy Communities, Washington State Department of Transportation Local Programs Division. 2017 "Washington State 2016 Student Travel Survey State Report." Accessed January 15, 2020. https://wsdot.wa.gov/sites/default/files/2009/01/09/ATP_WA-2016-Student-Travel-Survey-Report.pdf

World Bank. Urban Transport Data Analysis Tool (UT-DAT). Accessed January 31, 2020. https://www.worldbank.org/en/topic/transport/publication/urban-transport-data-analysis-tool-ut-dat1.

APPENDIX A

Washington School Walkability Score (WS*2) as the Data-Analytic Index for School-Level Rate of AST

WS*2 models two aspects of walkability (Moudon, Shi, and Chen, 2020). The first aspect captures the characteristics of the built environment element around schools, and the second adds the characteristics of the school student population, which has been documented to affect rates of AST. WS*2 was validated by using 2016 Washington State Student Travel Survey data, which are unique in the nation. WS*2 was created by using a three-phase process to address the issue of limited data availability at the state level:

1. We first ran the models using the very detailed built environment data and large number of observations available from King County (and with 66 out of the 284 schools having travel data).
2. Next models were run for Washington state in which built environment data were limited (and with 225 out of 1,728 schools having travel data).
3. Then we applied the Washington state model to the King County sample and compared the results with the first set of King County models for which we had data.

Results of the Spearman's Rank Correlation Coefficient test were fair, if not robust, at 0.44 ($p<0.001$).

The final WS*2 was calculated with the following formula:

$$\boxed{\text{School Walkability Index} = 2.22 + 0.20*z(\text{connectivity}) - 0.20*z(\text{traffic}) + 0.00*z(\text{grade}) -0.16*z(\text{bus}) + 0.07*z(\text{lunch})}$$

where connectivity = area in network buffer/area in Euclidian buffer (2 km buffer);

Traffic=length of main roads/length of local roads;

Grade = percentage of children below grade 4;

Bus = number of school bus riders at each school;

Lunch = percentage of free and reduced lunch enrollment.

The index was used to rank the schools, and the number of children walking at each school was normalized by school enrollment and generated on the basis of the distribution of schools for which AST data were available. WS*2 values ranged from 0 to 78 percent of students at each school using AST, with a mean of 21.78 percent (SD 16.43 percent) (figure A.1). Variations in WS*2 were noted at both the state and the local levels, but no clusters of either high or low WS*2 were detected (figure A.2). This meant that school districts and WSDOT SRTS both have choices as to the selection of schools needing to improve their rate of AST.

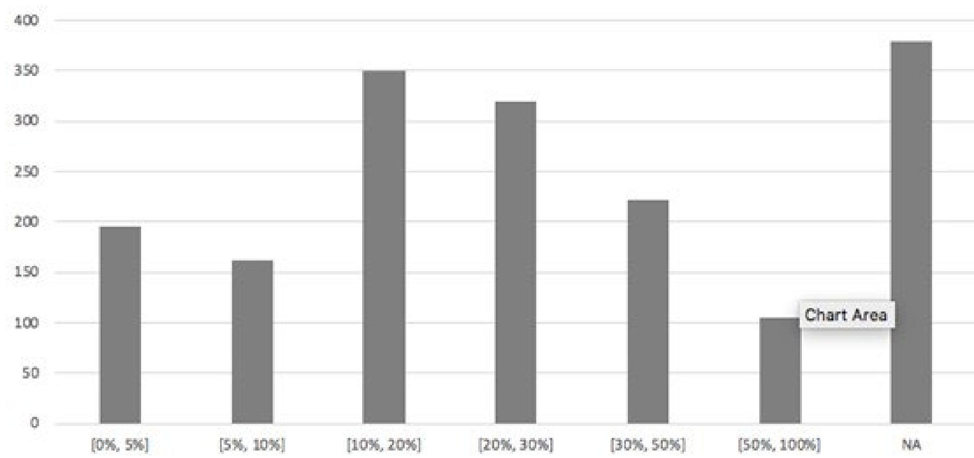

Figure A.1. Distribution of schools by walking potential score WS*2 (percentage of students using AST at the school level; n=1,352 schools)

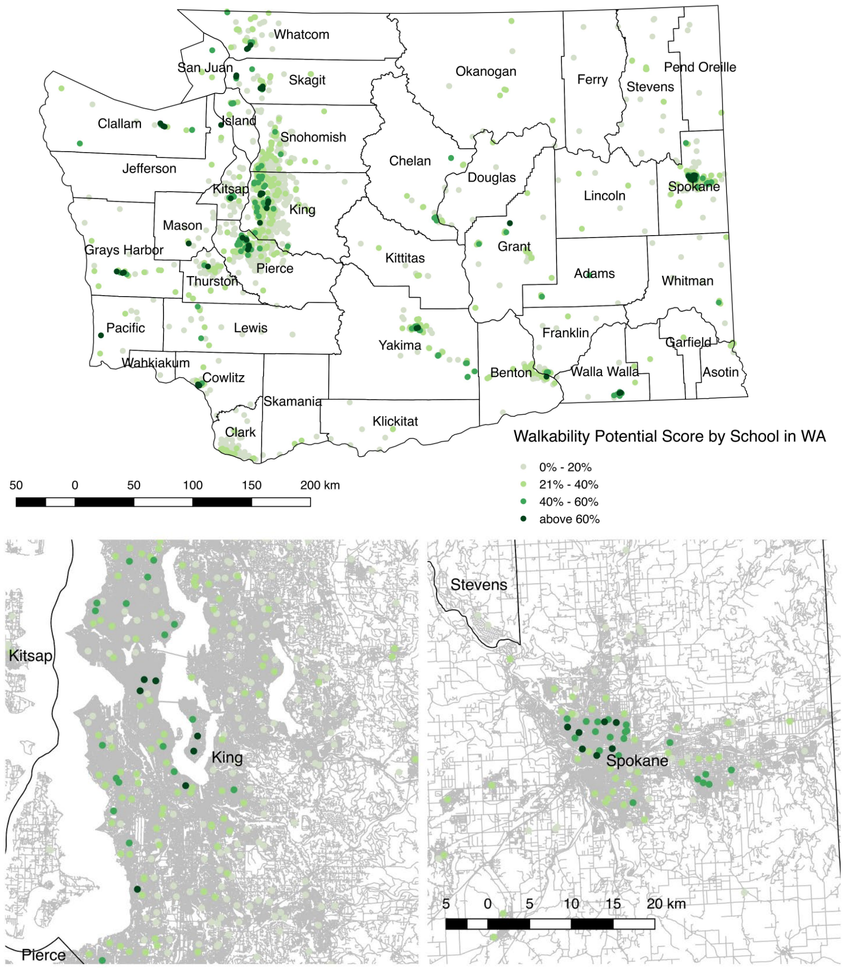

Figure A.2. Geographic distribution of WS*2: Top Washington state; bottom left Seattle area; bottom right Spokane area.

APPENDIX B

Table B.1. List of studies included in the meta-analyses

Author (Year)	Location	Age	Research Design	Outcome	N	Treatment
Larouche (2011)[1]	Canada	9-11	Cross-sectional	BMI	315	Active commuting vs Passive Commuting
Cooper (2012)[2]	UK	10-11	Prospect Cohort	MVPA (daily)	1307	Walk vs Car
Owen (2012)[3]	UK	9-10	Cross-sectional	MVPA (trip)	2035	Active commuting vs Passive Commuting
Ostergaard (2013)[4]	Norway	9	Cross-sectional	BMI	1684	Walk vs Car
Machado-Rodrigues (2014)[5]	Portugal	7-9	Cross-sectional	BMI	665	Active commuting vs Passive Commuting
Mendoza (2014)[6]	US	10-11	Prospect Cohort	BMI	7938	Active commuting vs Passive Commuting
Lee (2014)[7]	US	7-12	Cross-sectional	MVPA (trip)	112	Walk vs Car
Jago (2014)[8]	UK	9-10	Cross-sectional	MVPA (daily)	469	Active commuting vs Passive Commuting
Dalene (2018)[9]	Norway	9	Cross-sectional	MVPA (daily)	2366	Active commuting (>16min) vs Active commuting (>6min) vs Active commuting (<5 min)
Martienz (2019)[10]	Spain	8	Cross-sectional	MVPA (trip)	455	Walk vs Car
Zhang (2020)[11]	UK	10-12	Cross-sectional	BMI	432	Active commuting (<5 min)

1. Larouche, R., Lloyd, M., Knight, E. & Tremblay, M. S. Relationship between active school transport and body mass index in Grades-4-to-6 children. *Pediatric exercise science* **23**, 322–330 (2011).
2. Cooper, A. R., Jago, R., Southward, E. F. & Page, A. S. Active travel and physical activity across the school transition: The PEACH Project. *Medicine and science in sports and exercise* **44**, 1890–1897 (2012).
3. Owen, C. G. *et al.* Travel to school and physical activity levels in 9–10 year-old UK children of different ethnic origin; child heart and health study in England (CHASE). *PloS one* **7**, e30932 (2012).
4. Østergaard, L., Kolle, E., Steene-Johannessen, J., Anderssen, S. A. & Andersen, L. B. Cross sectional analysis of the association between mode of school transportation and physical fitness in children and adolescents. *International journal of behavioral nutrition and physical activity* **10**, 1–7 (2013).
5. Machado-Rodrigues, A. M. *et al.* Active commuting and its associations with blood pressure and adiposity markers in children. *Preventive medicine* **69**, 132–134 (2014).
6. Mendoza, J. A. & Liu, Y. Active commuting to elementary school and adiposity: an observational study. *Childhood Obesity* **10**, 34–41 (2014).

7. Lee, C. & Li, L. Demographic, physical activity, and route characteristics related to school transportation: an exploratory study. *American journal of health promotion* **28**, S77–S88 (2014).

8. Jago, R. *et al.* School travel mode, parenting practices and physical activity among UK year 5 and 6 children. *BMC Public Health* **14**, 1–10 (2014).

9. Dalene, K. E. *et al.* Cross-sectional and prospective associations between sleep, screen time, active school travel, sports/exercise participation and physical activity in children and adolescents. *BMC public health* **18**, 1–10 (2018).

10. Martinez-Martinez, J., Aznar, S., Gonzalez-Villora, S. & López-Sánchez, G. F. Physical activity and commuting to school in Spanish nine-year-old children: Differences by gender and by geographical environment. *Sustainability* **11**, 7104 (2019).

11. Zhang, X. *et al.* Active travelling to school is not associated with increased total daily physical activity levels, or reduced obesity and cardiovascular/pulmonary health parameters in 10–12-year olds: a cross-sectional cohort study. (2020)