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ORIGINAL PAPER

The influence of street environments on fuel efficiency: insights from naturalistic driving

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Abstract Fuel consumption and greenhouse gas emissions in the transportation sector are a result of a "three-legged stool": fuel types, vehicle fuel efficiency, and vehicle miles travelled (VMT). While there is a substantial body of literature that examines the connection between the built environment and total VMT, few studies have focused on the impacts of the street environment on fuel consumption rate. Our research applied structural equation modeling to examine how driving behaviors and fuel efficiency respond to different street environments. We used a rich naturalistic driving dataset that recorded detailed driving patterns of 108 drivers randomly selected from the Southeast Michigan region. The results show that, some features of compact streets such as lower speed limit, higher intersection density, and higher employment density are associated with lower driving speed, more speed changes, and lower fuel efficiency; however, other features such as higher population density and higher density of pedestrian-scale retails improve fuel efficiency. The aim of our study is to gain further understanding of energy and environmental outcomes of the urban areas and the roadway infrastructure we plan, design, and build and to better inform policy decisions concerned with sustainable transportation.

Keywords Street environments · Fuel efficiency · Structural equation modeling · Naturalistic driving

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Introduction

In 2012, a total of 32,113 million metric tons of carbon dioxide were emitted into the Earth's atmosphere, 36 % of which came from oil use. The USA accounted for 17.5 % of the world's carbon dioxide emissions in the same year. Transportation sector, the biggest carbon dioxide generator, generated over 30 % of total carbon dioxide in the USA (followed by industrial sector and residential sector) (U.S. Department of Energy 2013; U.S. Environmental Protection Agency 2013). The environmental impact of automobile travel is well-known and has drawn significant attention in recent years as intensive automobile travel in many places across the world has exacerbated oil dependency and increased greenhouse gas (GHG) emissions that contribute to global warming.

Fuel consumption and emissions from the transportation sector are a result of a "three-legged stool": fuel types, vehicle fuel efficiency, and vehicle miles travelled (VMT) (Ewing et al. 2008). While policies and strategies such as alternative fuels (Rassafi et al. 2006) and fuel-efficient vehicles aim to improve the first two "legs of the stool," many studies show evidence that land use and urban design solutions, such as compact development, smart growth, and new urbanism (Duany et al. 2001; Congress for the New Urbanism 2013), could induce fewer automobile trips, reduce vehicle miles of travel, and decrease transportation-related fuel consumption and emissions (Banister et al. 1997; Newman and Kenworthy 1989; Frank et al. 2006; Cervero and Kockelman 1997; Cervero and Murakami 2010). According to a recent US Department of Transportation Report to the Congress, land use strategies could reduce GHG emissions by 28–84 million metric tons carbon dioxide equivalent per year in the US and this benefit would grow over time to a substantial amount by 2050 (U.S. DOT 2010). Recognizing the benefits of compact land use patterns, the US Environmental Protection Agency (EPA) now encourages state and local government to account for air quality benefits of compact land use strategies in state air quality plans (EPA 2001).

Our understanding about energy and environmental outcomes of the built environment is not complete. While there is a substantial body of literature that examines the potential of reducing VMT and GHG emissions through changes in land use patterns and roadway design (Ewing and Cervero 2001; 2010), few studies have focused on the impacts of the street environment on fuel efficiency (Liu and Shen 2011). Ewing et al. (2008), in research that estimates CO_2 emissions (a product of fuel consumption) for future urban development, suggested that we might need to apply an emission "penalty" for compact development when estimating emission outcomes of such development, as such development could have secondary effects on emission rates by lowering average vehicle speeds (Ewing et al. 2008). However, whether and how much penalty should be imposed on compact development is not known, partially because few existing studies have empirically examined the influence of street environments on fuel efficiency and emission rates. The primary goal of this paper is to fill this gap by examining the relationship between street environments and fuel efficiency. Our study aims to contribute to discussions on the trade-offs between the amount of vehicle travel and the fuel efficiency of vehicle travel.

For a given vehicle type/technology, fuel efficiency is primarily determined by driving styles, such as average speed, acceleration/deceleration, idling, and cruising, which are, in turn, influenced by the built environment along streets. Studies showed that low-speed driving, frequent stop-and-go behaviors, and excessive idling, which is the state of a vehicle when its engine is running but the vehicle is not moving, decrease vehicle fuel efficiency (Brundell-Freij and Ericsson 2005; Ericsson 2001). Compact streets that are characterized by narrow travel lanes, low posted speed limits, pedestrian-oriented retail stores, and ample sidewalks provide promising design solutions for promoting walking and public transit use that induce fewer automobile trips and fewer vehicle miles of travel (Duany et al. 2009; McCann and Rynne 2010). However, the impacts of compact streets on fuel efficiency are not clear. Drivers who travel along compact streets may drive at slow speeds, make frequent stops at traffic lights, wait at stop signs, and yield for pedestrians. Such driving behaviors may contribute to higher vehicle fuel consumption on a per-mile basis. On the contrary, if compact streets promote smooth traffic with modest driving speed and with minimum interruption, driving on such streets could mean higher fuel efficiency.

In order to empirically test the connections between street environments and fuel efficiency, researchers need to overcome two major challenges: (1) quantifying the street environment, and (2) measuring fuel efficiency of vehicle driving. The first challenge stems from the multifaceted nature of the street environment, which includes not only features of the roadway itself but also those of the roadside. Features of the road such as its width, the number of lanes, speed limit, and traffic signals influence the way drivers behave on the road, and subsequently affect the fuel efficiency of their driving. In addition to buildings near the road, businesses, setbacks, driveway, land uses, and other features along roads are part of the overall street environment and also affect how drivers behave. Existing research has focused on the influence of individual on-road features such as intersection (Pandian et al. 2009; Malakootian and Yaghmaeian 2004), roundabout (Várhelyi 2002), and traffic calming devices (Ahn and Rakha 2009) on driving behaviors, fuel efficiency, and emission rates (Fitzpatrick et al. 2001; Malakootian and Yaghmaeian 2004), while studies that examined the relationships between fuel efficiency and multi-dimensional road features have been rare (Nesamani et al. 2011).

The second challenge of studying the influence of street environment on fuel efficiency is to measure street-level fuel efficiency so that it can be related to street environment. Fuel efficiency data are difficult to collect; fuel efficiency measured for every driver traveling on each street is even harder to obtain. Since the 1950s, some on-road studies have used vehicles instrumented with multiple sensors to collect driving information and study the effects of different driving patterns on fuel consumption and emissions. Advanced techniques such as portable emissions measurement system (PEMS) made second-by-second emission data collection possible (Coelho et al. 2009; Frey et al. 2010; Wang et al. 2013). Although instrumented vehicles and PEMS provided the necessary tools for studying the connections between driving behaviors and fuel use, using instrumented vehicles to study the effects of street environments on fuel consumption is challenging. In past studies, a sample of drivers usually drove instrumented vehicles on a set of pre-defined routes on a variety of road types at different times of days (Ericsson 2000; Kenworthy et al. 1992). However, driving patterns and emissions were typically measured for broadly defined road types, such as freeways and arterials, and were not sensitive to land use patterns and other roadside features which may vary for a given type of road. Another limitation is that the monitored driving of the sample drivers may not reflect their natural driving behaviors and, as a result, the fuel use data collected might be biased.

In this study, we addressed the first challenge by measuring the street environment from several dimensions. We measured on-road features such as number of lanes, speed limit, and number of intersections, and roadside features such as pedestrian-scale retail businesses, population density, and employment density. To estimate street-level fuel efficiency, our study used a rich naturalistic driving dataset that recorded detailed driving behaviors of 108 randomly selected drivers from Southeast Michigan. Drivers were recruited with the assistance of the Office of the Secretary of State, the driver licensing authority in Michigan. Each driver was given an instrumented vehicle for 40 days and was asked to use it the same way as he/she would use their own personal vehicles (hence, the term "naturalistic" driving). The vehicle was equipped with multiple sensors that collected, among other measures, information on fuel use, vehicle speed, positions (in latitude and longitude), and time. Using this dataset, we derived a fuel efficiency measure that quantified fuel efficiency for each street segment traversed during each vehicle trip. We also derived driving measures such as average speed and speed variation, which would allow us to test the intermediate effects of driving behavior on fuel efficiency. We then used structural equation modeling (SEM) to test the direct and indirect effects of street environments on fuel efficiency by controlling for trip characteristics, drivers' attributes, and weather conditions. The study was carried out in Mount Pleasant, MI, between 2013 and 2014, while the naturalistic driving dataset used in this study was collected between April 2009 and April 2010.

Materials and methods

Study area and research data

The study area in our research covers six counties in Southeast Michigan region (as shown in Fig. 1). The region includes the city of Detroit, which is one of the most sprawling regions in the USA (Galster et al. 2001). Most of the residents in the region rely on automobiles to meet their daily travel needs. Based on the 2001 National Household Travel Survey, 90 % of all trips made in the Detroit metropolitan area were by private vehicles (NHTS 2004). Although sprawling as a whole, the region hosts a few employment sub-centers, which have relative high job density and employment accessibility (Grengs 2010). The region offers a variety of roads that vary in size and functions and that run through different types of environments ranging from low-density subdivisions, strip malls, to compact and diverse communities.

The naturalistic driving data used in this study were part of the integrated vehicle-based safety systems (IVBSS) program data collected by the University of Michigan Transportation Research Institute's (UMTRI) between April 2009 and April 2010. Sixteen 2006–07 Honda Accord LX sedans instrumented with IVBSS sensors were driven by 108 volunteer drivers, who were randomly selected and recruited from licensed drivers in Southeast Michigan area. The sample of drivers was equally divided by age groups (20–30, 40–50, and 60–70 years) and by gender. Each driver was asked to use the vehicle as his/her own personal vehicle for a period of 40 days. The IVBSS program collected information, among others, on fuel use, vehicle speed, positions (in latitude and longitude), heading, and time, at the frequency of 10 Hz. To obtain a desirable resolution and to maintain a reasonable work load, we used data extracted at 1 Hz from the original dataset. The resulting data captured a total of 213,309 miles, 22,657 trips, equaling to 6,164 hours of driving.

Road and built environment data came from several sources. Road information in 2011 was obtained from the Southeast Michigan Council of Governments (SEMCOG) and was structured by road segments. The road dataset provided information such as segment length, road functional classification, number of lanes, and posted speed limit. But the dataset only contains information for roads which are eligible for receiving federal funds. Information related to local roads which are maintained by local communities was not included in the dataset. Due to data availability, we only considered federal-aid roads in our study. Intersection information was extracted from the TIGER road file from the US Census 2010. Business establishment data were purchased from the private vendor InfoUSA that contains information such as location, the number of employees, and sale records for more than 76,000 business establishments in the study area in 2006. The data categorized business establishments based on a six-digit Standard Industrial Classification (SIC) code. We also obtained population data from US Census 2010.

We excluded road segments of all interstates and other freeways because the road and roadsides interaction on these limited access roads is different than on other types of roads and the mechanism through which road environments

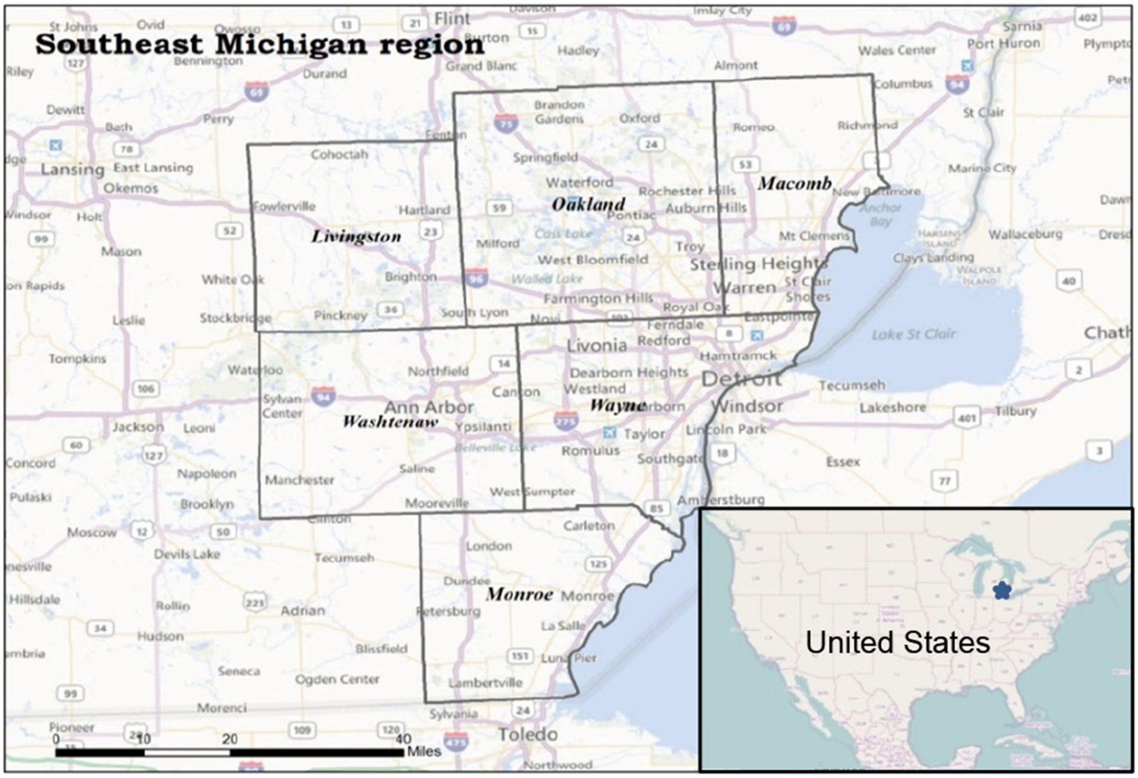


Fig. 1 Study area: Southeast Michigan Region

influence fuel efficiency is likely to be different. To ensure the accuracy of the fuel efficiency estimation, we only selected road segments that were traversed by at least five different drivers in the study period.

Structural equation modeling approach

There are four major categories of influential factors that affect fuel efficiency, which include the built environment (both roadway and roadside environment), driver characteristics, weather, and vehicle/fuel types. Possible variables under each category are summarized in Fig. 2. While factors such as speed and speed change directly influence fuel efficiency, other factors including street environments affect fuel efficiency indirectly through driving behaviors. In order to disentangle the relationships among different variables, we applied the SEM technique to measure the direct and indirect effects between street environments and fuel efficiency while testing the intermediate effects of driving behavior on fuel efficiency.

A SEM comprises endogenous variables and exogenous variables in one linear structural modeling framework and represents multiple regressions among these variables (Hayduk 1988). Exogenous and endogenous variables in a SEM are equivalent to independent and dependent variables in regular regression models, respectively. Different from other statistical models, a SEM estimates inter-relationships between endogenous variables as well as between endogenous and exogenous variables in a simultaneous equation system. It can be applied to confirm the directional influences among these variables. SEM also allows for the decomposition of total effects into direct and indirect effects. While direct effects represent the direct links between exogenous variables and endogenous variables, an indirect effect accounts for an effect which an exogenous variable has on an endogenous variable through the mediation of at least one additional variable. While there are many advanced SEM models, our current SEM structure applies a parsimonious approach to investigate the most important relationships between the built environment and fuel efficiency.

The mathematic equations of the endogenous and exogenous variables and the disturbance terms are specified as the form below:

$$\mathbf{Y} = \mathbf{BY} + \Gamma\mathbf{X} + \zeta \qquad (1)$$

where $\mathbf{Y} = (\mathrm{N_Y} \times 1)$ column vector of endogenous variables ($\mathrm{N_Y}$ is the number of endogenous variables including fuel efficiency and driving behavior measures), $\mathbf{X} = (\mathrm{N_X} \times 1)$ column vector of exogenous variables ($\mathrm{N_X}$ is the number of exogenous variables including street environment measures, traffic conditions, drivers' demographic features, and

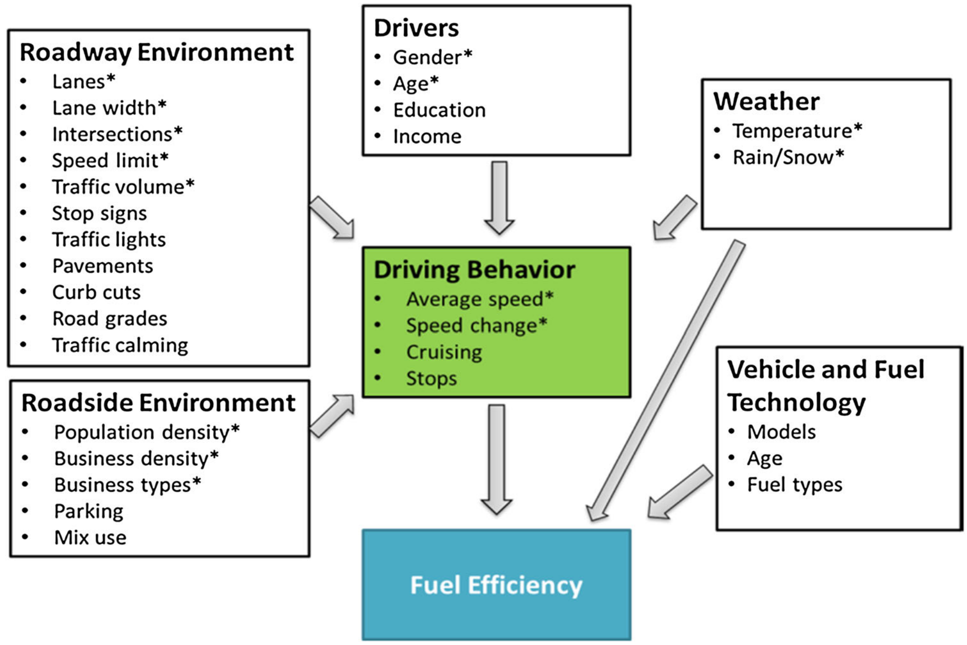


Fig. 2 Research framework: factors that affect fuel efficiency

weather condition), $\mathbf{B} = (N_Y \times N_Y)$ coefficient matrix relating endogenous variables (represents the direct effects from endogenous variables on other endogenous variables), $\boldsymbol{\Gamma} = (N_Y \times N_X)$ coefficient matrix relating exogenous and endogenous variables (represents the direct effects from exogenous variables on endogenous variables), $\boldsymbol{\zeta} = (N_Y \times 1)$ column vector of disturbance terms.

The $\mathbf{B}$ and $\boldsymbol{\Gamma}$ are the structural matrices that represent the relationships between the variables. The patterns of the elements in these matrices are predefined by the hypothesized statements. The SEM is estimated using maximum likelihood estimation with variance–covariance analysis. Let variance–covariance matrix $\mathbf{Var(X)} = \boldsymbol{\Phi}$ for exogenous variables $\mathbf{X}$ and variance–covariance matrix $\mathbf{Var}(\zeta) = \boldsymbol{\Psi}$ for disturbance terms ζ. The model-implied variance–covariance matrix $\hat{\Sigma}$ of observed variables $\mathbf{X}$ and $\mathbf{Y}$ is obtained in terms of the $\mathbf{B}$, $\boldsymbol{\Gamma}$, $\boldsymbol{\Phi}$ and $\boldsymbol{\Psi}$. The goal of model estimation is to minimize the discrepancy between the estimated variance–covariance matrix $\hat{\Sigma}$ and the sample observed variance–covariance matrix $\mathbf{S}$. The estimation equation is specified as below:

$$\begin{pmatrix} s_1^2 & s_{12} \\ s_{21} & s_2^2 \end{pmatrix} - \begin{pmatrix} \hat{\sigma}_1^2 & \hat{\sigma}_{12} \\ \hat{\sigma}_{21} & \hat{\sigma}_2^2 \end{pmatrix} = \begin{pmatrix} s_1^2 - \hat{\sigma}_1^2 & s_{12} - \hat{\sigma}_{12} \\ s_{21} - \hat{\sigma}_{21} & s_2^2 - \hat{\sigma}_2^2 \end{pmatrix}$$
$$\mathrm{S} - \hat{\Sigma} = (\mathrm{S} - \hat{\Sigma})$$

Some of the variables shown in Fig. 2 were more heavily studied than others: for instance, intersection (Pandian et al. 2009; Malakootian and Yaghmaeian 2004), roundabout (Várhelyi 2002), and traffic calming devices (Ahn and Rakha 2009). Although we believe the variables listed in Fig. 2 are comprehensive, they are not exhaustive. Information on other road and road side characteristics that may influence fuel efficiency such as grades, road surface, and mixed-use development were not available in our data and are not included in the current study. However, it should be added that the area is relatively flat without major vertical curvature or large grades and all the road surfaces are paved. The instrumented vehicles used by the study subjects were almost identical (2006–07 Honda Accord LX sedans) and thus preclude any analyses of different vehicle types or alternative fuels. To reduce the complexity of the model, we characterized driving behaviors using two most important driving behavior variables: average speed and speed change. Driving behaviors can be characterized by other variables such as detailed measures of sudden stops and cruising, which can be incorporated in future studies. Variables included in our study were highlighted with stars in Fig. 2.

Dependent variable: fuel efficiency

Fuel efficiency was defined as the ratio of VMT per unit of fuel consumed. The IVBSS dataset provided vehicle fuel use and vehicle position in latitude and longitude. The trips were spatially joined to a network of road segments. Fig. 3 shows an illustration of second-by-second IVBSS data points of five trips from two drivers, which were matched to three road segments. We then used Eq. (2) to obtain fuel efficiency for every road segment for every vehicle trip.

Based on Eq. (2), we calculated the fuel efficiency for each road segment (*i*) traversed by a vehicle trip (*j*), by summing the distance travelled for every second (*m*) of travel on the segment (represented by d_{ijm} in Eq. (2)) and dividing it by total fuel consumption on the same segment from vehicle trip *j* (represented by Σf_{ijm}).

$$E_{ij} = \frac{\sum d_{ijm}}{\sum f_{ijm}} \quad (2)$$

where E_{ij} represents the fuel efficiency calculated for the *i*th road segment during the *j*th trip; f_{ijm} represents fuel consumption for the *m*th second moving on the *i*th road segment during the *j*th trip; d_{ijm} represents distance travelled during the *m*th second moving on the *i*th road segment during the *j*th trip.

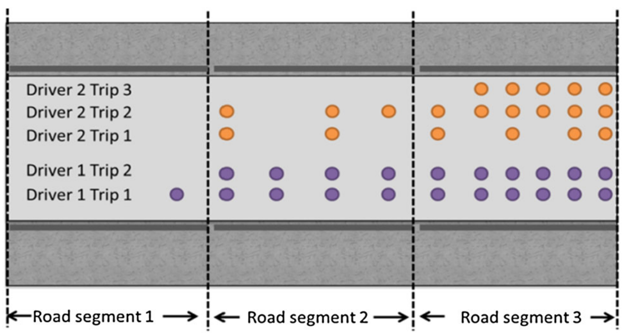


Fig. 3 Illustrations of IVBSS data points

Our study subjects travelled on 8,978 segments from 18,371 trips, resulting in a total of 125,054 observations for fuel efficiency. Each road segment in our sample has been travelled, on average, by 11 drivers during 71 trips. Each trip contains about seven unique road segments. The mean fuel efficiency for all observations is 20.81 miles per gallon, which is comparable to the 21 mpg fuel economy standard released by EPA for the instrumented vehicles used in our study (2006 Honda Accord, six cylinder, auto transmission).

A graph demonstration of spatial distribution of mean fuel efficiency averaged over all trips travelled on each segment in the city of Ann Arbor, MI is shown in Fig. 4. In general, streets in downtown Ann Arbor have relatively low fuel efficiency (highlighted in red and orange color) compared with other streets.

Exogenous variables

Street environment variables

The street environment was measured from several dimensions. Based on past studies, we tried to balance several factors when selecting street environment measures. On-road features including road function, speed limit, number of lanes, intersection density, and traffic characteristics were shown to influence driving behaviors and fuel economy (Ericsson 2000; Brundell-Freij and Ericsson 2005; Nesamani et al. 2011), and hence were

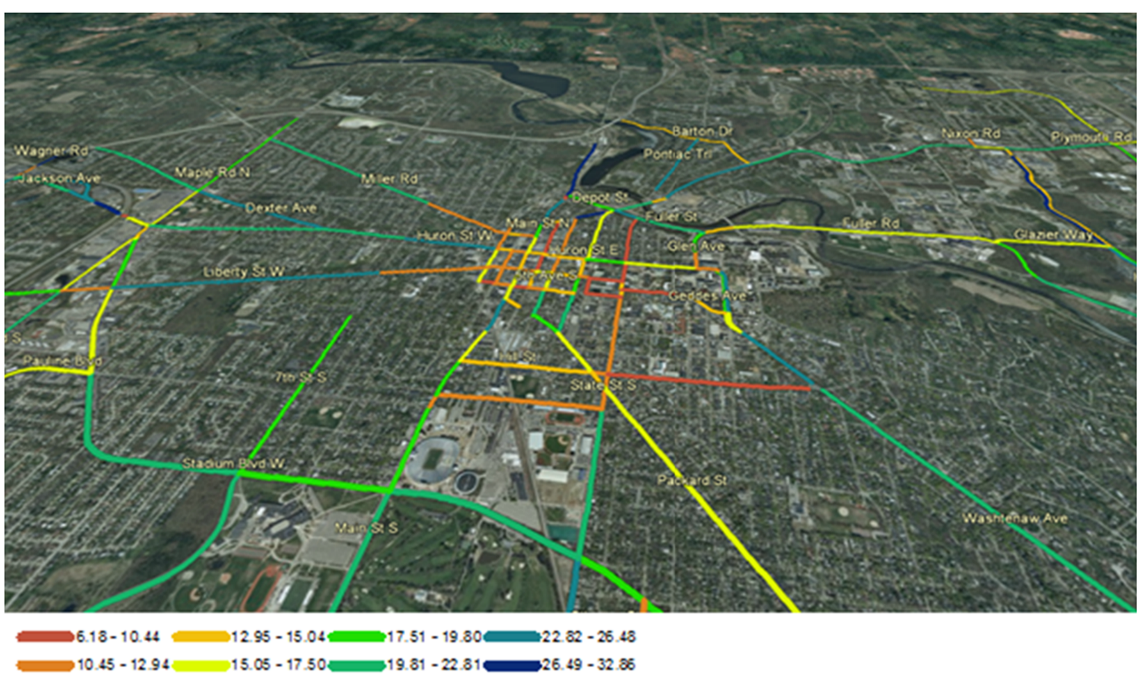


Fig. 4 Spatial distribution of fuel efficiency (mpg), the city of Ann Arbor, MI

included in the current study. As our goal in this study is to contribute to explorations of trade-offs between VMT and fuel efficiency, we also included street features that have close relationships with VMT; although these features might not have been tested in previous fuel efficiency studies. Roadside features including population density, employment density, and pedestrian-scale retails were included in the study, serving as indicators of compact development and pedestrian-oriented design which were shown to promote non-motorized transportation means and reduce vehicle miles of travel. Roadside street environment variables used in this study were measured from features within a quarter-mile buffer of a road segment. We tested various buffer sizes, and street environments within a quarter-mile buffer of road segments produced the-best-fitted SEM models. Each street environment variable is defined and summarized as follows:

Road function: Road function classification is based on the classification code of the Highway Performance Monitoring System (HPMS). Roads in our database were classified as three types: principal arterial (NFC3), minor arterial (NFC4) and major collector (NFC5). All the road segments were categorized into two dummy variables in the model (using major collector as the reference group). We hypothesized that lower-level roads such as major collector roads are related to lower fuel efficiency due to lower driving speed and more intersections with traffic lights or stop signs.

Posted speed limit: Speed limit is incorporated as one of the exogenous street environment variables. Posted speed is closely related to driving speed, although in reality drivers may not drive according to the speed limit.

Number of lanes: The number of lanes is also a determinant of driving patterns and fuel efficiency. Generally, a multi-lane road implies higher speed, less heavy braking, and higher fuel efficiency. However, there are periods of time when the traffic volumes on these roads approaches or exceeds capacity resulting in congestion, which could reduce fuel efficiency.

Intersection density: Intersection density was calculated by dividing the number of intersections along a segment by the length of the segment. Higher intersection density leads to more stop-and-go driving and is likely to reduce fuel efficiency.

Traffic count: Busy streets with heavy traffic may decrease fuel efficiency, as drivers may drive at low speeds and make more stop-and-go activities. We utilized the traffic count information included in the IVBSS dataset. The number of cars in front of a subject vehicle was detected by the vehicle's frontal radar on a second-by-second basis. We derived the traffic count variable by averaging the number of cars in front of a subject vehicle for every second of travel on a road segment. It should be noted that, this variable is not the traditional traffic volume measure which reflects the total number of vehicles passing a point for some period of time.

Population density: Population density was calculated for every segment by dividing total number of population within the quarter-mile buffer by the buffer area. Block-level census population data were merged to our road buffers based on the assumption that population is evenly distributed and that total population is proportionate to land area. We applied log transformation to the derived population density to account for non-normality. Streets in denser neighborhoods may be associated with more stop-and-go traffic and lower fuel efficiency.

Employment density: Employment density was calculated for every segment by dividing total number of business employees per segment by the buffer area. Point-level business data were joined to the segment only if the business was located within the quarter-mile buffer of the segment. We also applied a log transformation to employment density. We hypothesized that streets with a lot of businesses would likely have lower fuel efficiency due to busy traffic induced by employees or business customers.

Pedestrian-scale retails: Pedestrian-scale retail commercial land use is generally found on small size lots with on-street parking and small store setbacks that encourage walking. This type of land use may decrease fuel efficiency, as drivers may need to watch for pedestrians and may have to make frequent stops. In this study, pedestrian-scale retail is defined as a commercial use of 9,999 square feet or less. The resulting variable, pedestrian-scale retails, measures the logarithm of the number of pedestrian-scale retails per segment length.

Control variables

Our study included three control variables: gender, age, and weather. Gender is a dummy variable, which differentiates male (1) and female drivers (0). We created three dummy variables to represent three age groups: younger group (20–30 years), middle-aged group (40–50 years), and older group (60–70 years). Detailed weather information is not provided in the IVBSS dataset. We used temperature and the usage of wipers as proxies for weather conditions. Temperature variable measures the average temperature outside the subject vehicle. Wiper usage variable measures the number of seconds that wipers were used when traveling through a road segment. Higher

Table 1 Descriptive statistics of exogenous and endogenous variables ($N = 125{,}054$)

Variable Name	Descriptive statistics				
	Minimum	Maximum	Mean	SD	Variance
Young	0	1	0.38	0.48	0.24
Middle-aged	0	1	0.35	0.47	0.23
Gender	0	1	0.55	0.49	0.24
Temperature (°C)	−16.54	44.81	14.18	10.89	118.55
Wiper usage (seconds)	0	754	4.25	22.53	507.77
Posted speed (miles per hour)	25	70	39.78	9.97	95.15
Number of lanes	1	8	3.42	1.45	2.1
NFC3	0	1	0.54	0.49	0.25
NFC4	0	1	0.33	0.47	0.22
NFC5	0	1	0.13	0.33	0.11
Traffic count	0	3	1.34	0.5	0.25
Intersection density (intersections per mile)	0	150.9	3.93	6.18	38.14
Employment density (ln employees per acres)	−1.21	11.66	6.22	1.62	2.63
Population density (ln persons per acres)	−1.25	9.59	6.81	1.38	1.92
Pedestrian-scale retail (number of businesses per segment)	0.00	5.19	2.62	1.10	1.20
Average speed (ln meters per second)	−0.31	3.61	2.56	0.47	0.22
Absolute speed change (ln meters per second)	−4.40	1.41	-0.83	0.71	0.51
Fuel efficiency (miles per gallon)	0.20	139.64	20.81	9.38	87.98

numbers indicate it is more likely to be adverse weather condition such as raining or snowing.

Intermediate variables

In order to fully understand how the influence of street environments on fuel efficiency is channeled through driving behaviors, we constructed two intermediate variables, average speed, and average speed change, to characterize driving behaviors.

Average speed

Speed has been shown in existing literature to be one of the most important determinants of fuel efficiency. The relationship between speed and fuel efficiency is not linear. As speed increases, fuel efficiency increases until it reaches an optimum, and then, fuel efficiency starts to decrease (Ericsson 2001). The optimal speed varies with vehicle types, but it is in general in the range of 50–55 mph (EPA 2010). Since our study excluded interstates and other freeways, most of the driving included in our sample (90 % of total driving) was below the optimal range. We explored our data and made the assumption that the log-transformed average speed is linearly related with fuel efficiency and that an increase in average speed is associated with an increase in fuel efficiency. We calculated average speed by taking the mean of the second-by-second speed for all data records on a road segment during a trip.

Average speed change

Speed variation is another important factor that influences fuel efficiency. A higher degree of speed change (e.g., sudden stops) could decrease fuel efficiency significantly (Ericsson 2001). We averaged the second-by-second speed change for all driving on each road segment for each trip. We also applied the log transformation to the average speed change.

Descriptive statistics for all variables are provided in Table 1.

Results and discussion

Our model results are summarized in Table 2 (direct effects) and Table 3 (total effects). Direct effect shows the initial response of the "effect" variable (e.g., driving speed or fuel efficiency) to the change of a "cause" variable (e.g., environment variables such as intersection density) (Hayduk 1988). The indirect effect shows the effect that a variable exerts on another variable through one or more endogenous variables. The total effect of one variable is the sum of direct effect and indirect effect. Although the total effects are our focus, direct effects (summarized in Table 2 and illustrated in Fig. 5) help to understand the paths through which important variables influence driving behavior and fuel efficiency. We tested the performance of different variable combinations to lessen the multi-colin-

Table 2 Direct effect standardized coefficients

Endogenous variables	Average speed ($R^2 = 0.22$)	Absolute speed change ($R^2 = 0.37$)	Fuel efficiency ($R^2 = 0.61$)
Exogenous variables			
Socio-demographics			
Young	0.028 (0.003)	0.025 (0.004)	
Middle-aged	0.017 (0.003)	−0.006 (0.004)	
Gender	0.032 (0.003)	−0.026 (0.004)	
Weather related			
Temperature			0.03 (0.002)
Wiper usage	0.00001 (0.00001)	−0.001 (0.0001)	
On-road street environment			
Posted Speed (miles per hour)	0.015 (0.00001)	0.004 (0.000001)	
Number of lanes	−0.018 (0.001)	0.032 (0.001)	
NFC3	0.154 (0.034)	−0.428 (0.047)	
NFC4	0.109 (0.034)	−0.413 (0.046)	
Traffic conditions	0.121 (0.003)	−0.181 (0.004)	
Intersection density	−0.009 (0.000001)	NS (NS)	
Roadside street environment			
Employment density	−0.029 (0.001)	0.017 (0.001)	
Population density	0.003 (0.000001)	−0.006 (0.001)	
Pedestrian-scale retail	−0.001 (0.000001)	−0.002 (0.001)	
Driving behavior			
Average speed (meter per second)		−0.865 (0.004)	5.045 (0.047)
Absolute speed change (meter per second)			−7.908 (0.031)

All coefficients except ones indicated with "NS" are statistically significant at the 0.05 level. "NS" indicates that the variable is not statistically significant. Model fit indices are in Appendix 1. Standard Errors are included in the parentheses

earity issue. The model fit indexes (as shown in Appendix "1") indicate that our final model has a good model fit. We have also tested the sensitivity of the model by separating our samples into two random groups and conducted SEM analysis for each group. Our model results for these samples are not significantly different from those reported in this paper. The correlation matrix between all exogenous and endogenous variables and the VIF index (an indicator for the severity of multi-collinearity) are listed in Appendix "2".

Among all the variables, both speed and speed change as intermediate variables, have the strongest direct effects on fuel efficiency. The coefficient of direct effect of average speed on fuel efficiency is 5.045 while the coefficient of the total effect is 11.884. It indicates that average speed is a strong predictor of fuel efficiency and that an increase in speed significantly increases fuel efficiency. The direct effect of speed change on fuel efficiency is −7.908, which is the same as the total effect. Lower level of speed change is associated with higher fuel efficiency. The result is consistent with the finding in Ericsson's study (2001), which showed that aggressive driving (defined as sudden and high acceleration and heavy breaking, i.e., higher speed oscillation) was found to cause more power demand of the vehicle and lower fuel efficiency than calm driving. The interaction between two intermediate variables (average speed and speed change) has expected signs for both direct effect and total effect (both coefficients are −0.865 in the model). The result suggests that when driving at relatively high speeds, driving behavior is usually stable and speed variation decreases.

The effect of street environments on driving behaviors and fuel efficiency

Our results showed that both on-road and roadside street environment variables have significant direct and total effects on driving speed and speed variations. The coefficients of road functional type dummies are positive for average speed, and negative for speed change, for both direct and total effects. The results show that, major collectors (the reference group) have the lowest driving speed and the highest speed variation. The total effects of road type dummies on fuel efficiency are all positive, indicating

Table 3 Total effect standardized coefficients

Endogenous variables	Average speed ($R^2 = 0.22$)	Absolute speed change ($R^2 = 0.37$)	Fuel efficiency ($R^2 = 0.61$)
Exogenous variables			
Socio-demographics			
Young	0.028 (0.003)	0.003 (0.005)	0.157 (0.051)
Middle-aged	0.017 (0.003)	−0.021 (0.005)	0.253 (0.052)
Gender	0.034 (0.002)	−0.054 (0.004)	0.586 (0.041)
Weather related			
Temperature			0.037 (0.002)
Wiper usage	0.00001 (0.0000001)	−0.001 (0.00001)	
On-road street environment			
Posted speed (miles per hour)	0.015 (0.00000001)	−0.009 (0.000001)	0.144 (0.002)
Number of lanes	−0.016 (0.001)	0.047 (0.002)	−0.445 (0.016)
NFC3	0.154 (0.004)	−0.197 (0.007)	2.331 (0.547)
NFC4	0.109 (0.004)	−0.139 (0.006)	1.65 (0.546)
Traffic count	0.121 (0.003)	−0.285 (0.004)	NS (NS)
Intersection density	−0.009 (0.000001)	0.007 (0.000001)	−0.099 (0.003)
Roadside street environment			
Employment density	−0.029 (0.001)	0.042 (0.001)	−0.481 (0.01)
Population density	0.003 (0.000001)	−0.009 (0.001)	0.084 (0.006)
Pedestrian-scale retail	−0.001 (0.00000001)	NS (NS)	0.004 (0.007)
Driving behavior			
Average speed (meter per second)		−0.865 (0.004)	11.884 (0.05)
Absolute speed change (meter per second)			−7.908 (0.031)

All coefficients except ones indicated with “NS” are statistically significant at the 0.05 level. “NS” indicates that the variable is not statistically significant. Model fit indices are in Appendix “1”. Standard errors are included in the parentheses

that major collectors also have the lowest fuel efficiency due to low-speed driving and high speed changes.

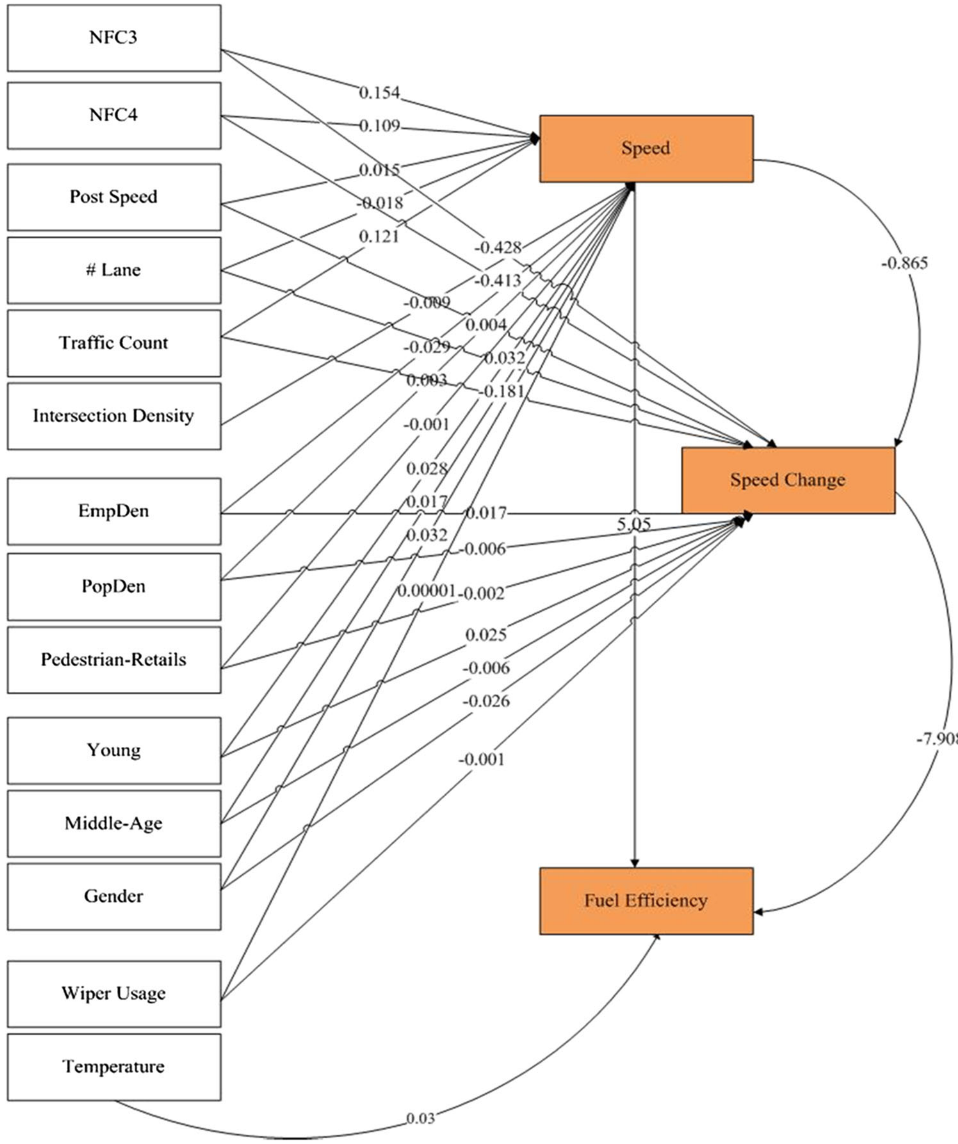
Higher intersection density is associated with lower driving speed and higher speed change, although the total effect coefficients are rather modest (−0.009 and 0.007, respectively). The total effect of intersection density on fuel efficiency is −0.099, indicating that an increase in intersection density leads to a reduction in fuel efficiency.

Posted speed limits have a positive direct effect on average driving speed (the coefficient is 0.015), which is intuitive. The effects of posted speed limits on speed change are interesting: while posted speed limit has a positive direct effect on speed change (0.004), the indirect effect is negative. The indirect effect of posted speed on speed change is primarily channeled through driving speed. Higher speed limit increases driving speed which is associated with more stable driving patterns (fewer speed changes). The intermediating effect of driving speed on speed change is stronger than the direct effect of posted limit on speed change, which makes the combined effect on speed change negative (−0.009). The positive effect on driving speed and the negative effect on speed change both lead to higher fuel efficient, generating a total positive effect (0.144).

Roadside street environment variables all have significant effects on driving behaviors and fuel efficiency. Higher employment density is associated with lower driving speed, higher speed change, and subsequently, lower fuel efficiency. The total effect of employment density on driving speed, speed change, and fuel efficiency is −0.029, 0.042, and −0.481, respectively. Drivers traveling on roads with high business/employment concentration are likely to encounter traffic signals, stop signs, and also congestion, so driving in such areas entails lower speed and more speed variations (i.e., decelerations, accelerations, stops and starts).

Compared with employment density, population density has completely different effects on driving behaviors and fuel efficiency. Controlling for the effects of other roadside variables, especially employment density, higher population density leads to higher driving speed, lower speed variations, and higher fuel efficiency. The total effect of population density on driving speed, speed change, and fuel efficiency is 0.003, −0.009, and 0.084, respectively. Different from busy commercial streets, streets with higher number of residents may have less complicated traffic flow

Fig. 5 Direct effects



which allows for faster but more stable driving which leads to higher fuel efficiency.

The total effect of pedestrian-scale retail on speed is negative (−0.001) which is consistent with that of employment density, indicating that higher number of pedestrian-scale retails might decrease driving speed, possibly due to narrower lanes, more traffic signals, or other traffic calming measures. Different from that of employment density, the direct effect of pedestrian-scale retails on speed change is negative meaning that drivers have lower speed variations when driving on such streets. Streets with more pedestrian-scale retail commercial use might attract more pedestrians. Anticipating and watching for pedestrians, drivers might drive more cautiously, and hence make less sudden acceleration and heavy braking. The reduced speed change further improves fuel efficiency and makes the coefficient of pedestrian-scale retails on fuel efficiency positive (0.004).

Higher number of lanes is shown to have a negative direct effect on speed (−0.018) and a positive direct effect on speed change (0.032). In general, roads with multiple lanes imply higher driving speed and less heavy braking. However, our results showed the opposite: a multi-lane road is associated with lower-speed driving and more speed variations. Our results might reflect congestion conditions on multi-lane roads. When traffic volumes exceed road capacity, the resulting congestion could reduce driving speed, induce more stop-and-go driving behavior, and hence reduce fuel efficiency. The total effect of number of lanes on fuel efficiency is negative (−0.445).

Traffic count has a negative direct effect on speed change (−0.181) and a positive direct effect on speed (0.121). It shows that drivers maintain relatively higher driving speeds with fewer driving variations when there is a lot of traffic, which is counterintuitive. One explanation of this result may be that our traffic count variable does not measure traffic volume but is a proxy of local traffic density. The traffic count data used in this study were collected from the front radar of the subject vehicle, which can only detect the number of vehicles in the front. More vehicles in the front do not necessarily mean a heavy traffic condition such as congestion. It simply indicates that there are several vehicles surrounding the subject vehicle which is moving with the traffic. A different traffic measure based on this variable could be developed in the future research.

The effect of control variables on fuel efficiency

Social-demographic and environmental control variables are also the significant determinants of driving speed, speed change, and fuel efficiency. Relative to older drivers, both young and middle-aged drivers have positive total effects on average speed, meaning that they drive faster than older drivers. As discussed early, higher speed generally increase fuel efficiency. Because of their higher driving speed, young and middle-aged drivers have higher fuel efficiency (their total effects are 0.157, and 0.253, respectively). Younger drivers have lower fuel efficiency compared with middle-aged drivers, due to more aggressive accelerations and frequent stops: the total effect of young drivers on speed change is much higher than middle-aged. Gender also has significant and positive direct and total effect on fuel efficiency. The results show that female drivers are less fuel efficient than male drivers, which is due to lower driving speed and more speed changes.

Among the environmental control variables, wiper usage was used to indicate the weather condition of the day. Either rainy or snowy conditions lead to higher speed and fewer speed variations, which is possibly due to more cautious but hastily driving behaviors under weather. Outside temperature has a positive relationship to fuel efficiency. When controlling other factors, fuel economy drops when the outside temperature decreases.

Conclusion

Our research used SEM to examine how driving behaviors and fuel efficiency respond to different street environments. We capitalized upon a rich naturalistic driving dataset that recorded detailed driving patterns of 108 randomly selected drivers from the Southeast Michigan region. Results indicate that both on-road and roadside street environment variables have statistically significant total effects on fuel efficiency. Significant indirect effects of street environment variables indicate that effects of street environment on fuel efficiency are channeled through driving speed and speed variation. Driving behavior variables, speed and speed change, were found to be strongly related to fuel efficiency: higher speed and lower speed change lead to better fuel efficiency. Street environment features that decrease driving speed and increase speed variations will most likely reduce fuel efficiency. The results show that roads that have lower functional classification, lower speed limit, higher intersection density, and higher employment density are associated with lower driving speed, more speed change, and lower fuel efficiency. Our results suggest that, when estimating fuel consumption and emission for urban development, there is a reason to apply for a “penalty” for streets that have aforementioned features. While compact streets generally encourage shorter trips and greater shares of non-motorized modes, they may also result in higher fuel consumption per unit of driving distance.

In addition, we found some features of the compact streets that might be exempted from the “penalty.” For instance, higher density of pedestrian-oriented retail commercial use might be associated with lower level of speed change and hence increased fuel efficiency. Streets with higher population density are similarly associated with better fuel efficiency when controlling for the effects of other roadside variables. There might be other street features that can improve fuel efficiency and that are not captured in our study. Nonetheless, our study illustrates how to find these features and how to gauge their effects.

Since fuel efficiency is primarily determined by driving behaviors such as speed and speed change, policy makers and transportation planners need to focus on changing the built environment in a way that does not promote extreme low-speed driving and sudden speed changes. For example, roundabouts in a compact area might increase fuel efficiency due to the fact that it promotes constant traffic flow at a reasonable speed. Pedestrian malls, business streets designed for pedestrians and closed off to vehicle traffic, could improve fuel efficiency in that the separation between pedestrian and vehicles could reduce the pedestrian-vehicle conflict and ensure a smooth travel for all road users. Identifying strategies that can lessen the fuel efficiency “penalty” for compact streets might be a potential research topic.

Our findings show that while there is clear potential for further research using the naturalistic driving dataset, there are also some data and methodology challenges that need to be addressed for modeling relationships among street environment, driving patterns and fuel efficiency. We characterized driving behaviors using average speed and speed change. Although these two variables are the most important variables influencing fuel efficiency, driving behaviors can be characterized by other variables such as detailed measures of sudden stops and cruising. Future studies could incorporate a more comprehensive set of driving behavior measures. Moreover, it would be beneficial to develop and incorporate more on-road and roadside street environment variables such as road grades, pavement condition, traffic calming devices, traffic lights, stop signs, and traffic volume. Categorization of street environments using factor analysis and cluster analysis could provide insights on how different environmental features are mixed and combined and how such mixtures influence fuel efficiency. It might also be informative to include detailed activity-related trip information in the analysis. For example, the purpose of the trip, time of the day, trip origin, and destinations may influence where people drive and how they behave while driving. Future research directions should also consider the changes in fuel-efficient vehicles. As these vehicles (such as plug-in hybrid electric vehicles) become more prevalent, it is important to conduct similar analysis that examines the interconnections between the vehicle technology, land use, and fuel efficiency.

The current study applied a parsimonious SEM modeling technique. It might be also useful to analyze these data with more advanced modeling techniques. Recent developments in advanced statistical methods have improved the SEM modeling capacity in various aspects. For instance, multilevel structural equation modeling (ML-SEM) allows for a full-integration of SEM and multilevel modeling (MLM) (Kline 2011). Application of this modeling technique would allow us to model the built environment nested at different geographies and to better capture the role that built forms play in travel behavior analysis. Recent developments in data mining techniques for "big data" provide researchers with unprecedented opportunities to extract important patterns and trends from vast amounts of data (Hastie et al. 2009). The naturalistic driving data together with the road and roadside information certainly can be considered as "big data". Thus, data mining could offer an innovative way of further exploring to the relationships between the on-road, roadside, driving, and fuel efficiency in data from naturalistic driving.

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Appendix 1

See Table 4.

Table 4 Model fit indices

Model fit indices	Formula	Description	Recommended cutoff value	Model value
$\chi^2(df)$	$(N-1)F_{\min}$	Measuring the discrepancy between the observed and model-implied covariance matrices. χ^2 depends on sample size. Smaller the values indicate better model fit.	$P < 0.05$	$\chi^2 = 372.197$ df = 13 p = 0.000
RMSEA (root mean square error of approximation)	$\mathrm{RMSEA} = \sqrt{\max[\frac{(\chi^2/df)-1}{n-1}, 0]}$	Measuring the amount of error of approximation per model degree of freedom, while controlling for sample size. Smaller values indicate better model fit.	<0.05	0.015
SRMR (standardized root mean square residual)	$\sqrt{\sum_1^{\mu} (\varepsilon_{m-\varepsilon b})^2}$ where $\mu = p(p+1)/2$ is the number of unique variances/covariances among the p variables in the model	Measuring the overall discrepancy between observed and model-implied covariances	<0.05	0.003
CFI(comparative fit index)	$\mathrm{CFI} = 1 - \frac{\max[(\chi^2_{\mathrm{model}} - \mathrm{df}_{\mathrm{model}}),0]}{\max[(\chi^2_{\mathrm{model}} - df_{\mathrm{null}}),(\chi^2_{\mathrm{model}} - df_{\mathrm{model}}),0]}$	Assessing the improvement of the hypothesized model M compared with the base model with unrelated variables	>0.9	0.99
TFL (Tucker-Lewis index)	$\frac{\frac{\chi^2_b}{df_b} - \frac{\chi^2_m}{df_m}}{\frac{\chi^2_b}{df_b} - 1}$			

Appendix 2

See Table 5.

Table 5 Correlation Coefficient and VIF

	Young	Middle-aged	Gender	Temp	Wiper	Posted speed	N_Lanes	NFC3	NFC4	Traffic count	Intersection Den	EmpDen	PopDen	PedRetail	Speed	Speed chg	VIF
Young	1	−0.559**	0.016**	−0.033**	−0.072**	−0.065**	0.004	0.032**	−0.044**	−0.039**	0.046**	0.047**	0.057**	0.038**	−0.017**	0.032**	1.48
Middle-aged	−0.559**	1	−0.004	0.010**	0.219**	0.077**	−0.027**	−0.022**	0.019**	0.023**	0.009**	−0.056**	−0.095**	−0.036**	0.034**	−0.033**	1.54
Gender	0.016**	−0.004	1	0.023**	0.008**	0.092**	−0.093**	−0.073**	0.062**	−0.045**	0.010**	−0.112**	−0.124**	−0.103**	0.074**	−0.056**	1.03
Temp	−0.033**	0.010**	0.023**	1	−0.037**	0.041**	−0.023**	−0.028**	0.027**	−0.025**	−0.018**	−0.022**	−0.009**	−0.022**	0.033**	−0.048**	1.06
Wiper	−0.072**	0.219**	0.008**	−0.037**	1	0.001	−0.016**	−0.029**	0.026**	0.038**	0.015**	0.006*	−0.014**	0.021**	−0.053**	0.063**	1.05
Posted speed	−0.065**	0.077**	0.092**	0.041**	0.001	1	−0.013**	0.059**	0.060**	0.108**	−0.109**	−0.256**	−0.178**	−0.243**	0.399**	−0.201**	1.31
N_Lanes	0.004	−0.027**	−0.093**	−0.023**	−0.016**	−0.013**	1	0.442**	−0.249**	0.251**	0.006*	0.293**	0.105**	0.302**	−0.033**	0.055**	1.38
NFC3	0.032**	−0.022**	−0.073**	−0.028**	−0.029**	0.059**	0.442**	1	−0.765**	0.344**	0.034**	0.217**	0.048**	0.230**	0.074**	−0.062**	3.1
NFC4	−0.044**	0.019**	0.062**	0.027**	0.026**	0.060**	−0.249**	−0.765**	1	−0.226**	−0.031**	−0.138**	−0.040**	−0.148**	0.016**	0.002	2.57
Traffic Count	−0.039**	0.023**	−0.045**	−0.025**	0.038**	0.108**	0.251**	0.344**	−0.226**	1	−0.004	0.149**	0.048**	0.145**	0.151**	−0.192**	1.23
Intersection Den	0.046**	0.009**	0.010**	−0.018**	0.015**	−0.109**	0.006*	0.034**	−0.031**	−0.004	1	0.071**	0.109**	0.102**	−0.154**	0.080**	1.05
EmpDen	0.047**	−0.056**	−0.112**	−0.022**	0.006*	−0.256**	0.293**	0.217**	−0.138**	0.149**	0.071**	1	0.365**	0.663**	−0.242**	0.171**	1.99
PopDen	0.057**	−0.095**	−0.124**	−0.009**	−0.014**	−0.178**	0.105**	0.048**	−0.040**	0.048**	0.109**	0.365**	1	0.330**	−0.113**	0.045**	1.21
PedRetail	0.038**	−0.036**	−0.103**	−0.022**	0.021**	−0.243**	0.302**	0.230**	−0.148**	0.145**	0.102**	0.663**	0.330**	1	−0.184**	0.113**	1.9
Speed	−0.017**	0.034**	0.074**	0.033**	−0.053**	0.399**	−0.033**	0.074**	0.016**	0.151**	−0.154**	−0.242**	−0.113**	−0.184**	1	−0.588**	1.81
Speed chg	0.032**	−0.033**	−0.056**	−0.048**	0.063**	−0.201**	0.055**	−0.062**	0.002	−0.192**	0.080**	0.171**	0.045**	0.113**	−0.588**	1	1.58

** Correlation is significant at the 0.01 level (2-tailed)

* Correlation is significant at the 0.05 level (2-tailed)

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