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What drives urban transportation safety? Exploring the role of modal composition and travel exposure

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Abstract

Purpose – Past urban transportation safety efforts have largely focused on controlling road user behavior through tactics such as speed management and separating users in space and time. This research moves beyond roadway behavior to examine associations between kinetic energy exposure and safety via travel behavior factors such as vehicle miles traveled (VMT) and mode share.

Design/methodology/approach – After analyzing 227 USA urban areas and controlling for state-level heterogeneity via linear mixed-effects models, we found that kinetic energy exposure is more strongly associated with transportation safety outcomes than variables focused on roadway behavior such as vehicle speeds, education requirements, enforcement efforts, alcohol involvement or seat belt use.

Findings – Urban areas with lower commute mode share by car and, to a lesser extent, lower VMT are most strongly associated with lower per capita transportation fatality rates.

Originality/value – These results add new knowledge by suggesting that, in addition to focusing on trying to get people to behave better on the roads – as many current safety frameworks do – reducing driving exposure by facilitating shorter driving distances and providing viable multimodal options is also strongly associated with improved safety outcomes. The findings suggest that prevailing transportation safety paradigms, such as the Safe System Approach, may benefit from greater consideration of driving exposure.

Keywords Roadway hazard, Transportation safety, Driving exposure, Hazard elimination, Land use, Multimodal, Travel behavior

Paper type Research article

1. Introduction

Per capita fatality rates in the United States of America (USA) declined steadily from the mid-1970s until 2010 (Figure 1). However, these rates have increased over the past decade – especially in USA cities – diverging from the downward trends observed in most other high-income countries (Schneider *et al.*, 2026). Why have USA fatality rates worsened relative to other high-income countries, and which factors are most strongly associated with safe transportation outcomes within the US context? Addressing these questions is essential for informing evidence-based policy interventions aimed at reducing road fatalities and ensuring that all people have access to safe transportation options.

The above research question is intentionally broad because while there are strong bodies of transportation safety research focused on infrastructure, land use, socioeconomic conditions

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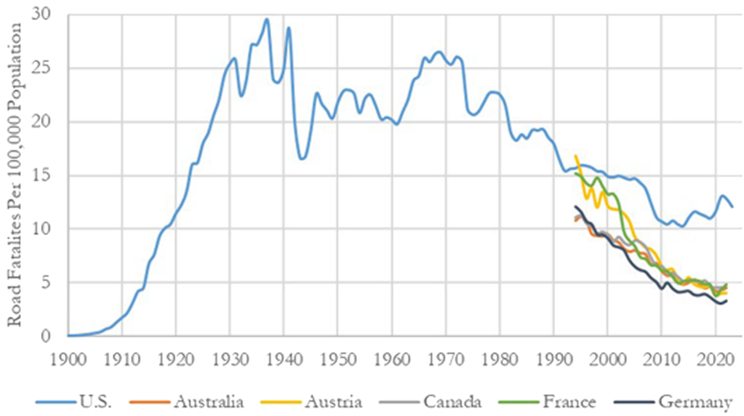

Figure 1. Road fatalities per 100,000 population Data Sources: National Highway Traffic Safety Administration (NHTSA) for USA (NHTSA, 2024a); Organisation for Economic Co-operation and Development (OECD) for international (OECD, 2025)

and demographic characteristics, this study seeks to build upon that foundation by also incorporating transportation behavior variables such as driver education requirements, enforcement efforts, indicators of unsafe driving behavior (e.g. vehicle speeds, alcohol involvement and lack of seat belt use) and travel exposure metrics such as vehicle miles traveled (VMT) and mode share, which have not been comprehensively analyzed and compared in prior work.

Given the broad scope of variables under investigation, this study focuses on urban areas as defined by the US Census Bureau, which encompass both urban and suburban contexts. This focus is justified for two primary reasons. First, a majority – approximately 59% – of USA road fatalities occur in urban areas, a proportion that has steadily increased for more than two decades (Schneider *et al.*, 2026). Second, urban environments can utilize a broader range of potential safety countermeasures, whereas rural areas are more spatially dispersed and often rely on high-speed automobile travel, limiting the feasibility of many interventions.

This study examines per capita road fatality rates across 227 USA urban areas nested within 45 states for the year 2022. Linear mixed-effects models allowed us to estimate fixed effects for the independent variables while simultaneously accounting for random effects introduced by state-level heterogeneity. The results are subsequently interpreted in relation to prevailing transportation safety paradigms, contributing new insights to frameworks such as the Safe System Approach and Vision Zero.

2. Background

Urban sprawl has been linked to elevated overall and pedestrian crash rates, outcomes that are often attributed to higher traffic speeds and greater VMT in sprawling contexts (Ewing *et al.*, 2003, 2016). Other research similarly suggests that denser development patterns – such as those promoted by the 15-minute city concept (Carvalho *et al.*, 2025; Papas *et al.*, 2023; Wang *et al.*, 2025) – may yield improved traffic safety due to lower levels of motor vehicle activity and reduced travel speeds (Chen, 2015; Chen and Shen, 2016; Dumbaugh and Rae, 2009).

Since travel in sprawling areas often occurs at higher speeds, these environments tend to rely on high-speed arterials characterized by lower network connectivity (Barrington-Leigh and Millard-Ball, 2020). Less dense and less connected road networks have been associated with higher vehicle speeds and VMT due to longer trips and decreased multimodal travel

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(Ewing *et al.*, 2020). In turn, lower intersection density has been found to be associated with more collisions across all severities, even after controlling for exposure (Marshall and Garrick, 2010, 2011a). Similarly, lower intersection density per roadway length has been associated with higher pedestrian fatality rates (Mohan *et al.*, 2017) and more pedestrian and bicyclist crashes (Zhang *et al.*, 2015). Given the links with transportation safety identified by prior research, we included vehicle speeds and VMT as variables in our analysis. In addition to VMT, we also included commute time as another measure of exposure to the transportation system. In addition to vehicle speeds, we also included other measures of unsafe roadway behavior – namely, the proportion of road fatalities that were unrestrained, the proportion of motorcycle fatalities that were unhelmeted and the proportion of road fatalities that were alcohol impaired – to more comprehensively account for unsafe roadway behavior.

Other safety research has examined travel behavior beyond VMT by studying mode choice, finding that cities with higher levels of public transit use tend to experience better traffic safety outcomes (Litman, 2014). For instance, increases in per capita mass transit miles traveled over a 29-year period across 100 USA cities were associated with lower traffic fatality rates (Stimpson *et al.*, 2014), likely because fatality rates for automobile occupants are estimated to be roughly 15 times higher than for transit users (Savage, 2013). Numerous studies have also demonstrated that cities with higher rates of bicycling activity exhibit improved safety outcomes, both for bicyclists themselves (Elvik, 2017; Fyhri *et al.*, 2017; Jacobsen *et al.*, 2015) and for other road users (Marshall and Ferenchak, 2019; Marshall and Garrick, 2011b). Considering that much of the aforementioned research on sprawl and street networks cites two potential mechanisms – vehicle speeds and VMT – and that the mode share findings in this paragraph introduce additional nuance, it is important to systematically distinguish between the effects of vehicle speed, VMT and mode share in understanding safety outcomes. We therefore also included mode share in our analysis.

Socioeconomic and demographic characteristics also shape traffic safety risk. A substantial body of research indicates that Black, Hispanic, lower-income and less-educated populations face disproportionately higher risk of traffic-related fatalities and injuries (Braver, 2003; Campos-Outcalt *et al.*, 2003; Harper *et al.*, 2000; Marshall and Ferenchak, 2017; McAndrews *et al.*, 2013; Schiff and Becker, 1996). Past researchers have hypothesized that this may be due to underinvestment in certain neighborhoods (Ferenchak and Marshall, 2021; Sanders and Schneider, 2022), limited access to automobiles leading to increased reliance on vulnerable travel modes (Ferenchak and Abadi, 2021; Schmitt, 2020), some populations being exposed to more aggressive driving behaviors (Goddard *et al.*, 2015) or a combination thereof. We therefore included socioeconomic and demographic variables related to income, educational attainment, age, race/ethnicity and family structure in our analysis.

In addition to the vehicle speed, VMT and mode share factors and the underlying importance of socioeconomics and demographics described above, there are other strategies that seek to promote safe road behavior, which generally fall into the categories of education or enforcement. The link between these education and enforcement strategies and road safety is less well-established and has been largely siloed from the aforementioned factors.

In terms of education, teens who participated in driver education courses were found to experience fewer injury and fatality crashes (Shell *et al.*, 2015), although such benefits may be short-lived (Waring *et al.*, 2024). In contrast, a systematic review found that driver education courses for young drivers may lead to earlier licensing and, consequently, worse safety outcomes (Roberts and Kwan, 1996). Additionally, a meta-analysis of road safety campaigns such as billboards, television and radio campaigns reported a weighted average crash reduction of 9% (Phillips *et al.*, 2011), although other research suggests such campaigns may also potentially distract road users (Decker *et al.*, 2015). Collectively, these findings suggest that educational interventions can have positive effects on safety, but those relationships are complex and difficult to track over the long term. We included variables representing driver education requirements and the earliest legal driving age on the state level in our analysis, which represented the best education proxies we could identify that met the geographic scale of the study.

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In terms of enforcement, more speeding and seat belt citations and increased fine amounts have been linked to crash reductions (Elvik, 2016; Rezapour Mashhadi *et al.*, 2017), with evidence suggesting that enforcement is especially effective at night and for female drivers (Luca, 2015). Policies mandating fines for driving while drunk have been associated with an 8% reduction in fatal crashes involving drivers with a blood alcohol content (BAC) ≥0.08 g/dl, although policies mandating jail time for such offenses were found to have little effect (Wagenaar *et al.*, 2007). We included variables representing the proportion of residents with speeding tickets and the presence of automated enforcement on the state level in our analysis as proxies for enforcement intensity.

While research suggests that both education and enforcement can contribute to improved road safety outcomes, studies on these topics largely remain siloed (Elvik, 2016). To our knowledge, no comprehensive analysis has simultaneously examined education and enforcement alongside other relevant factors related to road user behavior and travel behavior.

In addition, prior research has shown that older and larger vehicles are less safe, particularly for vulnerable road users (Christoforou *et al.*, 2010; Hu and Cicchino, 2022; Hu *et al.*, 2024). We, therefore, included average vehicle age in our analysis.

This study addresses a critical gap in the current knowledge. Past research has established that sprawled land uses, disconnected street networks and larger roadways can lead to poor safety outcomes because of higher vehicle speeds and VMT, cities with increased multimodal mode share have been associated with improved safety outcomes, socioeconomics and demographics are a key determinant of safety outcomes and education and enforcement efforts can improve safety by altering user behavior. However, this study is the first to comprehensively examine the comparative strength of all these factors: the mode of travel, the amount of travel, road user behaviors (e.g. vehicle speed, alcohol use, etc.), efforts to control road user behaviors (e.g. education and enforcement), socioeconomics and demographics. Additionally, this study fills another gap by using per capita road fatality rates as the dependent variable, thereby framing transportation safety from a public health perspective, an approach that has been absent in previous research for some of these areas (Marshall and Ferenchak, 2017).

The remainder of the paper is organized as follows. Section 3 describes the data sources and structure, and Section 4 outlines the data analysis methods. Section 5 presents the results, followed by a discussion in Section 6 and conclusions in Section 7.

3. Data

We compiled data representative of conditions in 2022 for 227 USA urban areas across 45 states. Urban areas are defined by the US Census Bureau as continuously developed areas with populations of at least 5,000 residents, regardless of municipal boundaries. As opposed to metropolitan statistical areas (MSA) that are built from counties and often include rural parts of those counties, urban areas strictly consist of developed areas. Although the Census Bureau has identified 2,637 urban areas, our analysis focuses on the 227 urban areas for which the Federal Highway Administration (FHWA) provides VMT data.

We used per capita road fatality rates as our dependent variable since this is a measure of how safe a transportation system is for all residents as opposed to fatalities per mile driven, which is more a measure of the safety of driving (Marshall and Ferenchak, 2017). We utilized a spatial join in a geographic information system (GIS) to obtain fatality counts from NHTSA's Fatality Analysis Reporting System (FARS) for each urban area using polygon geographies from the US Census Bureau. To address potential edge effects for crashes occurring on boundary roads, a 50-foot buffer was applied to each urban area polygon prior to the spatial join. We then divided each urban area's 2022 road fatality count by its corresponding US Census population figure to determine per capita road fatality rates.

We sought to compile a comprehensive set of potential covariates to thoroughly understand the factors that contribute to urban transportation safety (Table 1). To avoid multicollinearity between the large number of variables, we categorized independent variables into three

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Table 1. List of independent variables and data sources

Variable	Source	Geographic level
Transportation		
Modal composition		
Commute mode share by car	ACS	Urban area
Travel exposure		
Daily VMT	FHWA	Urban area
Commute time per capita	ACS	Urban area
Roadway behavior		
% Fatalities unrestrained	NHTSA	State
% Motorcycle fatalities unhelmeted	NHTSA	State
% Fatalities alcohol impaired	NHTSA	State
Motor vehicle speed	OSM	Urban area
Behavior control		
Driver education required	NHTSA	State
Earliest driving age	NHTSA	State
Automated traffic enforcement present	NHTSA	State
% Residents w/ speed ticket	Insurify	State
Other transportation		
Vehicle age	NHTS	Census division
Gas price	SLD	Block group
People		
Socioeconomics		
% Bachelor’s degree or higher	ACS	Urban area
Median household income	ACS	Urban area
% Zero-car household	SLD	Block group
Gini index	ACS	Urban area
Median gross rent	ACS	Urban area
Demographics		
% Age 70+ years old	ACS	Urban area
% White non-Hispanic	ACS	Urban area
% Families married w/ Kids	ACS	Urban area
Built environment		
Transportation network		
Road network density	SLD	Block group
Intersection density	SLD	Block group
Land use		
Residential density	SLD	Block group
Population density	SLD	Block group
Employment density	SLD	Block group
Employment and household entropy (diversity)	SLD	Block group
National walking index	SLD	Block group
Median year structure built	ACS	Urban area

primary blocks and ran analysis on these blocks and subblocks before using those results to select our full comprehensive models:

(1) Transportation block (consisting of the subblocks modal composition, travel exposure, roadway behavior, behavior control and other transportation);

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(2) People block (consisting of the subblocks socioeconomics and demographics) and

(3) Built environment block (consisting of the subblocks transportation network and land use).

The Modal Composition subblock consisted of mode share, which directly reflects the mode of travel occurring within a transportation system. The Travel Exposure subblock consisted of variables representing the amount of travel, including VMT and commute time. The Roadway Behavior subblock consisted of variables directly representing road user behavior, such as motor vehicle speed and seat belt use. The Behavior Control subblock included variables that did not directly capture road user behavior but instead intended to influence it, such as enforcement and education. The Other Transportation subblock included variables that did not align with any other subblock, such as vehicle age and gas price.

The primary data source was 2022 five-year estimates from the American Community Survey (ACS), which provided data at the urban-area level on most socioeconomic and demographic variables, the median year of construction for housing structures, average commute time per capita and commute mode share by car, truck or van (hereafter referred to as “commute mode share by car” for clarity). While detailed descriptions of each variable are available from their respective data sources, we refrain from providing exhaustive definitions here due to the large number of variables. Instead, we provide an in-depth discussion of the most pertinent variables in the discussion section.

The second primary data source was the US Environmental Protection Agency’s Smart Location Database (SLD). Because SLD data are reported at the census block group level, we calculated urban-area values by averaging all block groups entirely contained within each urban-area boundary. Future research could explore population-weighted aggregation of block-group variables to represent the built environment experienced by the average resident, which may better reflect exposure to transportation conditions. The SLD provided data on most of the built environment variables, the proportion of zero-car households and gasoline prices. We were unable to obtain data on infrastructure characteristics such as traffic control devices, roadway geometry or pedestrian and bicycle facilities due to the scale of the study.

Several safety-related proxies were obtained from NHTSA on the state level, including the proportion of fatalities in which occupants were unrestrained, the proportion of motorcyclist fatalities in which the rider was not wearing a helmet and the proportion of fatalities involving alcohol (NHTSA, 2024b). NHTSA also provided data on state-level driver education requirements – specifically, whether driver education is mandated and the minimum legal driving age – reflecting conditions in 2011 from the most up-to-date comprehensive dataset that we could identify (Chaudhary *et al.*, 2011). In addition, NHTSA supplied 2020 data on automated enforcement, indicating whether such enforcement was permitted and operational within a given jurisdiction (NHTSA, 2025). This measure was meant to serve as a general proxy for the extent to which traffic enforcement is prioritized.

A more direct indicator of traffic enforcement intensity was the proportion of residents with a recorded speeding violation. These data were obtained at the state level from Insurify, an automobile insurance marketplace that compiles driver records from across all 50 states and maintains information on more than ten million drivers.

We obtained daily VMT for 2022 from FHWA’s *Highway Statistics Series* at the urban-area level (FHWA, 2024). Average vehicle age, measured in years, was sourced from the 2022 National Household Travel Survey’s online data query system and reported at the census-division level.

To estimate motor vehicle speeds, we generated 15 origin–destination (OD) points within each urban area using the “Create Spatial Sampling Locations” tool in ArcGIS Pro. We then connected each unique set of OD points, yielding 105 OD pairs per urban area. We wrote a Python script to derive routes between each OD pair using the OpenStreetMap (OSM) application programming interface (API), producing 105 routes for each of the 227 urban areas

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or 23,835 routes in total. The routing process did not account for live traffic conditions, which we considered advantageous as it provided an unbiased representation of the road network under free-flow conditions. For each route, we extracted total distance and estimated travel time, from which we calculated a speed estimate. The OSM API estimated travel times were based on speed limits and standard OSM turn penalties. Spot checks against Google Maps routing indicated strong alignment between the two platforms for non-congested periods. Average speeds were then computed across all routes within each urban area. The route set included a mix of short and long trips, some traversing central business districts and others on the urban periphery, providing a broad representation of travel conditions within each urban area. Although these estimates do not include any observed vehicle speed data, they are intended to serve as a proxy for average system-level operating speeds. Also, the measure reflects average network speed and may not capture upper-end speeding behavior (e.g. 85th percentile speeds).

4. Methods

Our data processing and statistical analysis methods are summarized in the data flow chart in Figure 2. After data collection, we converted all independent variables to Z-scores to allow for direct comparison between each variable's estimate. To more fully understand the relationship between the driving exposure variables, we also derived an interaction variable for mode share and VMT.

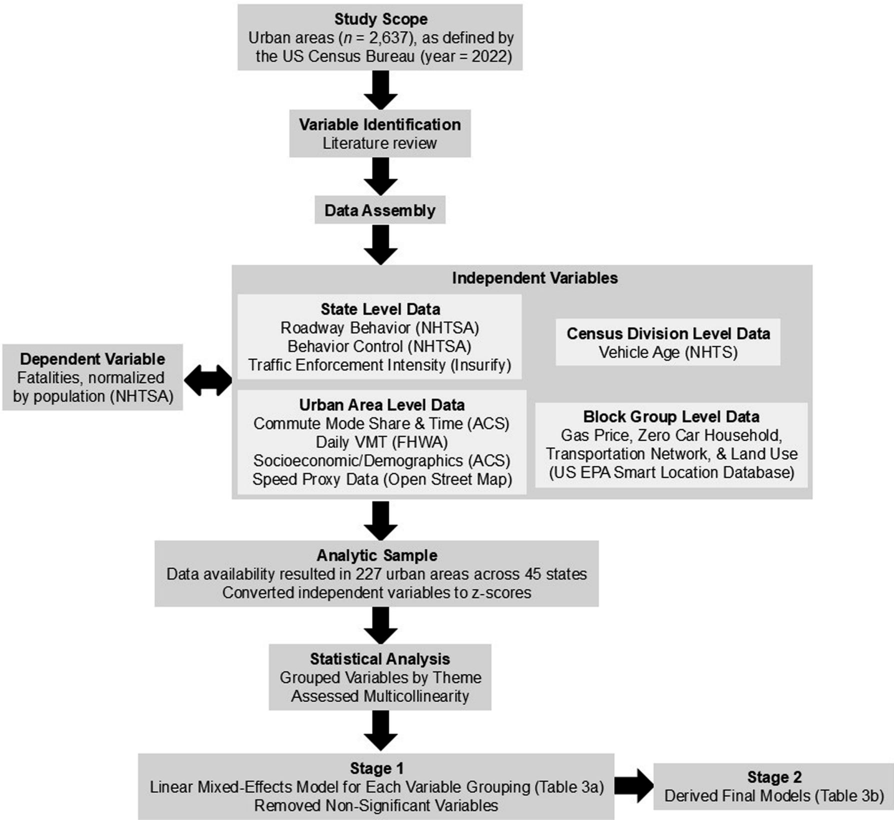

Figure 2. Data flow chart

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Given that the dependent variable – per capita fatality rate – was continuous and the data structure consisted of 227 urban areas nested within 45 states, we employed linear mixed-effects models (LMEMs) as our analytical approach. LMEMs account for geographic clustering by incorporating random intercepts, thereby allowing us to control for unobserved heterogeneity at the state level. The form of the LMEM (Equation 1) used for statistical analysis in this paper was:

$$Y_{ij} = \beta_0 + \sum_{k=1}^{p} \beta_k X_{k,ij} + u_j + \varepsilon_{ij} \tag{1}$$

Where:

Y_{ij} = per capita fatality rate for urban area *i* in state *j;*

β_0 = fixed intercept;

β_k = fixed effect coefficient for covariate *k;*

$X_{k,ij}$ = value of covariate *k* for urban area *i* in state *j;*

$u_j \sim N(0, \sigma_u^2)$ = random intercept for state *j and*

$\varepsilon_{ij} \sim N(0, \sigma^2)$ = residual error.

We generated the LMEMs in R (version 4.1.3) using the “lmer” function from the “lme4” package (version 1.1–32). We obtained *p*-values for our independent variables using Satterthwaite’s degrees of freedom method via the “lmerTest” package (version 3.1–3) and obtained marginal (i.e. fixed effects alone) and residual (i.e. both fixed and random effects) R^2 values using the “r.squaredGLMM” command in the “MuMIn” package (version 1.43.17).

Given the large number of independent variables and the presence of multicollinearity, we adopted a two-stage modeling approach. First, we estimated separate LMEMs for thematic variable blocks and subblocks, removing any variables that exhibited multicollinearity within their respective blocks or subblocks. We derived LMEMs for the Transportation subblocks and People block but not the Built Environment block because of high multicollinearity with other blocks (e.g. between road network density and vehicle speed and between population density and mode share). In the People block (Model 6 in Table 3), we removed educational attainment, median gross rent and proportion of families married with kids due to multicollinearity with median household income. Median household income was retained in the People block analysis because it resulted in the strongest model.

Second, we combined the statistically significant variables from the block- and subblock-level analyses into a full model, eliminating variables with high correlation or multicollinearity based on Pearson correlation coefficients, variance inflation factors (VIFs) and conceptual redundancy. The models’ residuals indicated approximate normality, supporting the suitability of the LMEM approach.

5. Results

We provide descriptive statistics for the dependent and independent variables in Table 2. We then briefly summarize the findings from each block and subblock model (Models 1–6 in Table 3) and provide a more detailed discussion dedicated to the comprehensive models (Models 7–9 in Table 4).

5.1 Block and subblock model results

Commute mode share by car, daily VMT and motor vehicle speed were significant positive predictors of per capita fatality rates within the subblock models (Models 1–3 in Table 3) and

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Table 2. Descriptive statistics on the urban area level

Variable	Mean	Std. Dev	Min	Max
Population	930,538	1,854,000	66,065	18,908,608
Road fatality rate per capita	8.21	3.74	0.00	24.14
Transportation				
Modal composition				
Commute mode share by car	92.4%	5.0%	60.0%	98.0%
Travel exposure				
Daily VMT	25.5	7.6	2.2	64.6
Commute time per capita (daily minutes)	23.7	4.8	14.1	45.0
Roadway behavior				
% Fatalities unrestrained	43.1%	7.3%	28.0%	59.0%
% Motorcycle fatalities Unhelmeted	35.1%	24.5%	0.0%	78.0%
% Fatalities alcohol impaired	31.9%	5.1%	22.0%	43.0%
Motor vehicle speed (mph)	32.9	3.7	23.6	42.3
Behavior control				
Driver education required (0 = *n*; 1 = y)	0.73	0.44	0.00	1.00
Earliest driving age (years)	15.2	0.5	14.0	16.0
Automated traffic enforcement present (0 = *n*; 1 = y)	0.67	0.47	0.00	1.00
% Residents w/ speed ticket	9.4%	2.4%	8.5%	11.7%
Other transportation				
Vehicle age (years)	10.4	1.0	8.5	11.7
Gas price (cents per gallon)	251.9	40.4	210.0	342.0
People				
Socioeconomics				
% Bachelor's degree or higher	36.8%	10.1%	16.0%	75.0%
Median household income ($)	76,033	18,523	50,072	171,448
% Zero-car household	7.6%	3.1%	2.5%	28.2%
Gini Index	0.46	0.03	0.37	0.55
Median gross rent ($)	1,341	383	721	2,677
Demographics				
% Age 70+ years old	10.6%	3.2%	4.4%	28.6%
% White non-hispanic	58.9%	17.8%	3.0%	88.0%
% Families married w/ kids	27.9%	5.4%	12.7%	45.8%
Built environment				
Transportation network				
Road network density (miles per sq. mile)	16.9	3.4	8.1	26.8
Intersection density (int. per sq. mile)	83.4	24.7	23.9	164.5
Land use				
Residential density (housing units per acre)	3.2	2.2	0.7	23.6
Population density (people per acre)	7.5	5.2	1.8	54.7
Employment density (jobs per acre)	2.9	2.5	0.7	27.5
Employment and household entropy (diversity)	0.51	0.04	0.39	0.69
National walking index	10.2	2.0	6.2	13.8
Median year structure built	1982	11.4	1953	2010

were therefore retained in the comprehensive model. Notably, VMT demonstrated statistical significance while commute time did not, suggesting that the amount of driving was a more critical factor than the amount of time spent within the transportation system.

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Table 3. Linear mixed-effects models for per capita fatality rates in USA urban areas accounting for state-level random effects: Analysis of individual blocks and subblocks

	Model 1 Modal composition		Model 2 Travel exposure		Model 3 Roadway behavior		Model 4 Behavior control		Model 5 Other transport		Model 6 People	
Variable	Est	S.E.	Est	S.E.	Est	S.E.	Est	S.E.	Est	S.E.	Est	S.E.
Intercept	8.233	0.432***	8.152	0.420***	8.109	0.472***	8.184	0.440***	7.779	0.481***	8.253	0.390***
Commute mode share by car	1.073	0.202***										
Daily VMT			0.767	0.255***								
Commute time per capita			0.156	0.225								
% Fatalities unrestrained					0.408	0.413						
% Motorcycle fatalities unhelmeted					−0.308	0.451						
% Fatalities alcohol impaired					−0.388	0.467						
Motor vehicle speed					0.621	0.208***						
Driver education required							−0.887	0.373**				
Earliest driving age							−0.973	0.398**				
Automated traffic enf. present							0.670	0.390*				
% Residents w/ speed ticket							−1.347	0.468***				
Gas price									−1.605	0.609**		
Vehicle age									0.087	0.450		
% Bachelor's degree or higher											–	
Median household income											−1.206	0.238***
% Zero-car household											−0.238	0.282
Gini index											−0.150	0.239
Median gross rent											–	
% Age 70+ years old											0.562	0.250**
% White non-hispanic											−0.854	0.284***
% Families married w/ kids											–	
Marginal R^2	0.079		0.044		0.051		0.172		0.142		0.123	
Residual R^2	0.495		0.415		0.479		0.489		0.534		0.435	
REML	1161.3		1179.8		1176.3		1170.7		1178.7		1160.1	
No. of observations	227		227		227		227		227		227	
No. of groups	45		45		45		45		45		45	

Note(s): $*p < 0.10$; $**p < 0.05$; $***p < 0.01$

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Table 4. Linear mixed-effects models for per capita fatality rates in USA urban areas accounting for state-level random effects: Comprehensive models

Variable	Model 7 Mode share and VMT Est	S.E.	Model 8 Mode share Est	S.E.	Model 9 VMT Est	S.E.
Intercept	8.092	0.287***	8.111	0.335***	8.061	0.282***
Commute mode share by car	0.668	0.306**	0.848	0.198***	–	
Daily VMT	0.768	0.264***	–		1.023	0.225***
Mode share × VMT interaction	0.019	0.282	–		–	
Commute time per capita	–		–		–	
% Fatalities unrestrained	–		–		–	
% Motorcycle fatalities unhelmeted	–		–		–	
% Fatalities alcohol impaired	–		–		–	
Motor vehicle speed	0.465	0.201**	0.583	0.199***	0.519	0.204**
Driver education required	−0.626	0.259**	−0.726	0.295**	−0.590	0.255**
Earliest driving age	–		–		–	
Automated traffic enf. present	–		–		–	
% Residents w/ speed ticket	−0.528	0.292*	−0.611	0.337*	−0.442	0.286
Gas price	–		–		–	
Vehicle age	–		–		–	
% Bachelor's degree or higher	–		–		–	
Median household income	−1.197	0.218***	−1.049	0.216***	−1.381	0.212***
% Zero-car household	–		–		–	
Gini index	–		–		–	
Median gross rent	–		–		–	
% Age 70+ years old	0.366	0.228	0.346	0.232	0.420	0.230*
% White non-Hispanic	−0.728	0.261***	−0.477	0.269*	−0.836	0.261***
% Families married w/ kids	–		–		–	
Marginal R^2	0.381		0.302		0.368	
Residual R^2	0.491		0.493		0.466	
REML	1117.7		1125.5		1125.5	
No. of observations	227		227		227	
No. of groups	45		45		45	

Note(s): *$p < 0.10$; **$p < 0.05$; ***$p < 0.01$

Within the Behavior Control subblock (Model 4 in Table 3), since two education proxies and two enforcement proxies were statistically significant, we retained the one proxy for each category that had the strongest association with fatality rates in the comprehensive model: whether driver education is required for the education proxy and the proportion of residents with a speeding ticket for the enforcement proxy, both of which had negative associations with fatality rates.

Although gas price had a significant negative relationship with fatality rates in its subblock model (Model 5 in Table 3), it was strongly correlated with median household income and was therefore excluded from the comprehensive model to avoid multicollinearity.

In the People block (Model 6 in Table 3), median household income (negative association), the proportion or residents aged 70 years or older (positive association) and the proportion of residents identifying as White non-Hispanic (negative association) were statistically significant and were therefore retained in the comprehensive model.

The highest residual R^2 values emerged in the Other Transportation, Modal Composition, Behavior Control and Roadway Behavior subblocks, indicating that variations in fatality rates were predominantly explained by transportation-related factors, while also being strongly influenced by the socioeconomic and demographic characteristics of residents.

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5.2 Comprehensive model results

The strongest transportation predictors of per capita fatality rates in the initial comprehensive model were daily VMT and commute mode share by car (Model 7 in Table 4). The positive estimates indicate that increased VMT and higher proportions of car commuters were most strongly associated with elevated fatality rates. The interaction term between VMT and mode share was not statistically significant, indicating no meaningful effect modification between the variables. This finding underscores that the amount of driving is a primary determinant of urban transportation fatality rates.

The next strongest transportation variables were related to driver education and enforcement (Model 7 in Table 4). The negative estimates suggest that driver education requirements and more driver enforcement were both associated with lower fatality rates. Motor vehicle speed was also significant and positively associated with fatality rates, though its effect was less pronounced than that of other transportation variables. This finding may suggest that controlling excessive speeding via strategies such as enforcement is more critical for improving safety outcomes than reducing average speeds.

In terms of the People variables in the initial comprehensive model (Model 7 in Table 4), lower median household income and a lower proportion of White non-Hispanic residents were significantly associated with higher fatality rates. Age was not significant in the comprehensive model. Median household income was the strongest factor in the comprehensive models, highlighting the importance of addressing not only transportation-specific factors but also the underlying socioeconomic conditions that shape people's transportation options and choices.

Given the moderate correlation between car mode share and VMT, we derived separate comprehensive models for each of these variables (Models 8 and 9 in Table 4). Doing so strengthened the individual estimates of mode share and VMT and widened the gap between them and the other transportation variables, further emphasizing the importance of driving exposure as a determinant of transportation fatality rates. Among the comprehensive models, Model 8 – which focused exclusively on car mode share – exhibited the highest residual R^2, indicating the best overall fit. This highlights the particular importance of modal composition in determining transportation safety outcomes and suggests that cities with more multimodal options are safest (Table 4).

6. Discussion

Results suggest that in addition to traditional transportation safety strategies focused on controlling the behaviors of drivers and other road users while they are on the street, greater emphasis on reducing the overall amount of driving – and therefore exposure to the kinetic energy introduced by motor vehicles – is significantly associated with meaningful safety gains. To continue to explore this concept, we situate our findings within a broader context of current transportation safety frameworks and consider potential strategies and policies for reducing exposure to motor vehicles to achieve transportation safety improvements.

6.1 Novelty in relation to current transportation safety frameworks

To assess the effectiveness of various transportation safety strategies, Ederer *et al.* recently introduced the hierarchy of controls (HoC) – originally developed by the US Occupational Safety and Health Administration (OSHA) – into the field of transportation (Ederer *et al.*, 2023) (Figure 3). To prevent injuries, the HoC first prescribes interventions that eliminate or substitute hazards as most effective, then interventions that safely control hazards and finally interventions that protect users from hazards (OSHA, 2016).

Because Ederer *et al.*'s (2023) exploration of the HoC was strictly theoretical, we seek to advance this concept by examining the alignment of the HoC framework with our statistical results (Ederer *et al.*, 2023). The hazard in transportation safety must first be identified.

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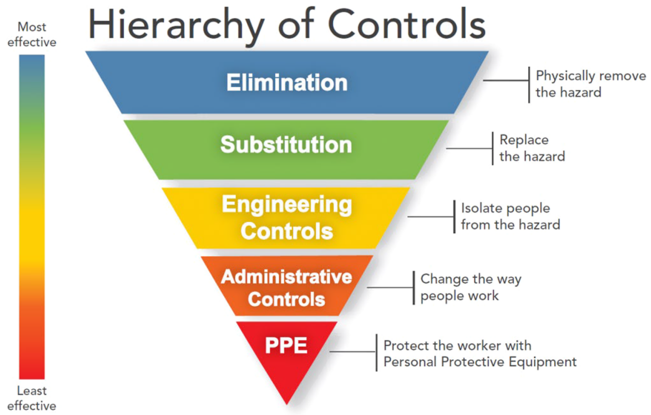

Figure 3. Hierarchy of controls for reducing risk from OSHA (OSHA, 2016)

Because nearly all road fatalities and serious injuries result from motor vehicle crashes, this is the primary hazard of concern. How then to eliminate the hazard of a motor vehicle crash? (Mitman *et al*., 2026). Strategies such as speed management may control the hazard but do not fully eliminate it. Complete elimination of the hazard must logically be accomplished by reducing exposure to motor vehicles, a conclusion reinforced by our statistical modeling that found reduced commute mode share by car to be the most significant transportation determinant of safety outcomes (Figure 4). Elimination of the hazard via reduced exposure to motor vehicles is therefore consistently and strongly associated with improved urban transportation safety outcomes both theoretically through the HoC and empirically in our statistical analyses.

However, these findings should not be interpreted as suggesting that reducing car mode share or VMT alone is sufficient to improve safety outcomes. For example, during the COVID-19 pandemic, substantial reductions in travel were accompanied by worsening traffic safety outcomes, indicating that lower levels of travel do not automatically translate into safer

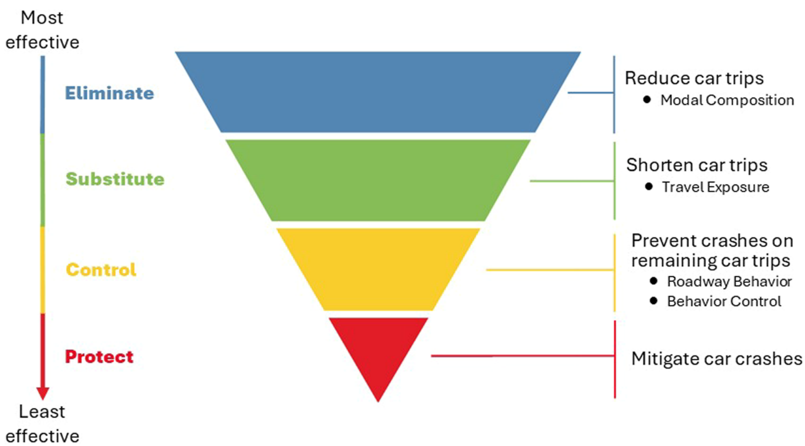

Figure 4. HoC adopted to transportation safety with corresponding transportation variable subblocks

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conditions. Rather, variables such as mode share and VMT are embedded within broader systems that shape both how much people travel and how they travel.

The next strongest predictor from our models was VMT. This aligns with the next level of the HoC which calls for substitution of the hazard (Figure 4). In this case, lowering VMT may represent hazard substitution by replacing longer trips for shorter trips, thereby lowering exposure to motor vehicles without fully eliminating it. The first two layers of the HoC are therefore consistent with our statistical results. In this context, land use patterns may represent a more fundamental upstream determinant, as they directly influence trip distances, mode availability, and reliance on motor vehicles.

If the hazard cannot be eliminated or substituted, the next HoC priority is to control it (Figure 3). Many traditional safety strategies – particularly those emphasizing speed management – fall into this category of hazard control. While reducing vehicle speeds can lower the prevalence and severity of crashes, it would likely not fully eliminate the hazard. In other words, hazard control approaches can be effective, but they likely do not achieve the higher-order objective of hazard elimination and substitution that would likely require reducing exposure to motor vehicle interactions. This was again consistent with our statistical findings, which showed stronger estimates for exposure variables (i.e. mode share and VMT) than for speed, education or enforcement variables.

Future research should better distinguish between engineering and administrative controls in the HoC (Figure 3). Although administrative controls are typically considered less effective, our results suggest that education and enforcement may outperform average vehicle speed measures. However, we do not interpret this as definitive evidence that administrative controls are superior. A likely limitation is that our speed variable reflects average urban speeds rather than high-speed conditions on specific corridors, which engineering controls are designed to address.

Finally, when elimination, substitution or control are not feasible, the remaining option is to mitigate the hazard, which is identified as personal protective equipment in the HoC (Figure 3). This category aligns with the transportation safety principles of vehicle crashworthiness (e.g. seatbelts and airbags) and enhanced emergency response that are not aimed at preventing crashes but rather at reducing their severity and the resulting harm. The placement of this category at the lower end of the effectiveness scale on the HoC was again supported by our statistical analysis as variables such as seatbelt and helmet use did not reach statistical significance during the block/subblock modeling stage. This is not to suggest that these measures are ineffective or unworthy of pursuit but rather that their impact is comparatively limited when considered against the higher-order objective of hazard elimination.

While the HoC does not address socioeconomic factors, Ederer *et al.* (2023) incorporated them as the base of their Safe System pyramid that they adapted from the HoC (Ederer *et al.*, 2023). Our statistical results similarly suggest that socioeconomics remain an important factor that should be considered when developing transportation safety interventions. Though higher income is often associated with greater levels of driving at the individual level, we observed the opposite relationship at the city level. Higher-income cities such as New York City, San Francisco, Boston and Washington, DC, tend to have lower overall levels of driving, which may help explain their lower fatality rates.

The two primary paradigms in contemporary transportation safety are Vision Zero and the Safe System Approach. While our analysis suggests that reducing exposure to motor vehicles through fewer or shorter car trips is significantly associated with improved urban transportation safety, Vision Zero primarily treats this exposure as a given and focuses on creating safer motor vehicle interactions through strategies such as speed management (Belin *et al.*, 1997). For instance, by recommending that pedestrians should not be exposed to motor vehicle speeds exceeding 30 km/h, Vision Zero seeks to lower the speed of motor vehicle interactions but does not typically address the prevalence of such interactions (Johansson, 2009).

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Although the Safe System Approach extends further back in the causal chain than Vision Zero by accounting for human factors, its focus remains similar: making motor vehicle interactions safer as opposed to changing the number of interactions (Larsson and Tingvall, 2013). While Safe System strategies may improve safety outcomes, the framework does not explicitly acknowledge lower exposure to vehicles as a potentially critical strategy for achieving transportation safety goals. The Safe System Approach has a strong focus on lowering the kinetic energy of collisions by controlling driving behavior but no direct focus on the level of exposure to collisions. The US Department of Transportation (USDOT) says as much in a report that provides more detail on their approach to Safe System:

> Speed directly influences the severity of traffic crashes because the laws of physics dictate that energy released in a crash is directly proportional to the velocity of the vehicle(s) involved. Therefore, speed management is one of the most important components of a Safe System Approach to traffic safety, and any effort toward achieving zero fatalities and serious injuries must be centered on keeping speeds at levels that account for human injury tolerance (USDOT, 2023).

While we do not disagree with the above statement, it overlooks a critical consideration – the importance of exposure to collisions and the upstream systems that generate this exposure – as demonstrated in our statistical analyses.

6.2 Policy implications to explore with future research

While outside the scope of this current paper to empirically analyze policy approaches, there are several research strings that may be worth pursuing as possible policy routes to implement our exposure-based findings. For instance, recent adaptations to the Safe System framework by the Transportation Association of Canada (TAC, 2023) and the Washington State Department of Transportation (WSDOT, 2024) begin to hint at the safety benefits of reducing exposure to motor vehicles via land use planning. TAC's "Safe Land Use Planning" and WSDOT's "Safer Land Use" wedges that they have added to their Safe System Approach both emphasize compact development as a means to improve road safety via, among other mechanisms, reduced private vehicle travel. While this is an initial recognition of driving exposure within Safe Systems, the TAC and WSDOT frameworks do not examine exposure reduction strategies beyond land use nor compare their relative effectiveness to other strategies. Our results suggest that exposure reduction merits broader and more systematic integration into safety frameworks.

Variables such as mode share and VMT should not be viewed as independent policy levers but rather as outcomes of underlying land use and transportation systems. Policies that reduce trip lengths may lower VMT without substantially changing mode share, while policies that enable shifts to non-driving modes may alter mode share even if total travel remains similar. Coordinated approaches that address both may therefore be more effective. In addition, changes to mode share and VMT likely need to be accompanied by changes to the built environment that support and enable lower levels of exposure. In much of the USA, the existing land use and transportation system makes reducing driving difficult while also producing environments where walking and bicycling may be unsafe. Efforts to reduce exposure must therefore be paired with changes to these underlying conditions.

Land use is particularly important because it may influence multiple levels of the HoC. Accessible land use planning – which aims to increase the ease of reaching valued destinations by minimizing travel distances – can enable non-driving modes to replace car trips, thereby facilitating the elimination of the roadway hazard (Merlin *et al.*, 2020). Additionally, more accessible destinations may shorten the remaining car trips, further decreasing overall driving activity by substituting longer car trips with shorter car trips. Since existing research has documented higher traffic speeds in sprawling areas, accessible land use planning may also contribute to slower vehicle speeds on the remaining trips, thereby acting as a hazard control (Ewing *et al.*, 2016). By potentially enabling hazard elimination, substitution and control,

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accessible land use planning holds particular promise and warrants further exploration. Despite this potential, it has been largely neglected by previous traffic safety initiatives and the Safe System Approach (Levinson *et al.*, 2017). More broadly, this suggests that transportation safety should be approached as part of a holistic planning process in which land use, transportation systems and travel behavior are jointly considered.

Economic levers have been shown to influence driving levels and may therefore be associated with transportation safety outcomes (Forsyth and Krizek, 2010). The limited prior research on this topic supports this idea, as fuel prices between 2005 and 2015 were found to be significantly and negatively linked with fatal crash trends in Great Britain (Naqvi *et al.*, 2020). Another economic lever aimed at reducing driving, congestion pricing, has also been shown to improve transportation safety, although existing evidence remains relatively limited (Singichetti *et al.*, 2021). For instance, a road pricing scheme in Milan, Italy, was found to coincide with an 18.8% reduction in crashes within the treated area and contributed to a 16% reduction citywide (Percoco, 2016).

The above policy approaches align with the principles of transportation demand management (TDM), which encompass coordinated strategies designed to influence travel behavior and reduce reliance on single-occupancy vehicles. Despite its relevance, TDM has received relatively little attention within the transportation safety literature, suggesting that future research in this area is warranted (Litman and Fitzroy, 2025). Economic strategies may take the form of sticks, such as increased fuel taxes or congestion charges that make driving more costly as mentioned above, or carrots, such as parking cash-out programs that financially reward non-driving modes.

While this current paper empirically established and validated the theory and framework of hazard elimination, future research may assess whether the policy approaches discussed above are effective in advancing hazard elimination and whether specific policies translate to improved transportation safety outcomes.

More work is also needed to understand the scale at which mode shift is associated with improved transportation safety outcomes. For small-scale shifts, mode shifts away from automobiles for a few individual users may expose those travelers to greater risk within transportation systems that are still auto-dominated (Abdollahi *et al.*, 2023). For large-scale shifts, the relationship may not simply reflect the direct safety characteristics of individual modes. Prior research has documented a “safety in numbers” effect, whereby the safety of non-motorized users tends to improve as their numbers increase (Elvik and Bjørnskau, 2017; Jacobsen, 2015). It could therefore be hypothesized that safety benefits would amplify as: (1) mode shift toward non-motorized modes decreases exposure to cars’ kinetic energy; (2) the safety of those non-motorized users improves as their numbers increase and (3) the demand and delivery of safer multimodal infrastructure increases with more participation. It remains unclear at what threshold such broader system-wide safety benefits of mode shift may begin to emerge.

Relatedly, there may also be a point where the safety benefits of kinetic energy exposure reduction diminish. This question may be particularly relevant for international contexts where non-motorized mode shares are already relatively high. While we hypothesize that the theory of hazard elimination applies broadly, an open question remains whether places that have already achieved substantial mode shift would experience only marginal additional safety gains by pursuing further hazard elimination. For example, would a city reducing car mode share from 20% to 10% experience similar safety outcomes as a city reducing from 95% to 85% (still predominantly auto-oriented) or from 75% to 65% (potentially transitioning toward a less auto-dominated system)? Because the USA cities included in our analysis were predominantly auto-oriented, we were unable to examine such nuances. In addition to examining international contexts with varying levels of kinetic energy exposure, we also hope to further examine different geographic scales in future studies, including state and census tract levels.

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We also hope to examine longitudinal changes in driving exposure and transportation safety trends to begin to explore causality. Future research on finer spatial scales could incorporate potentially confounding variables such as detailed street design elements – including numbers of lanes and multimodal infrastructure elements like bike lanes, bus lanes and sidewalks – as well as more nuanced land use measures beyond density proxies.

7. Conclusions

Both the empirical and theoretical findings from this work suggest that, rather than primarily striving to make interactions with motor vehicles safer, efforts to improve urban transportation safety may benefit from greater emphasis on enabling travel by non-driving modes. Doing so likely reduces exposure to motor vehicles, thereby eliminating the primary roadway hazard. Results further suggest that reducing the overall amount of driving is more strongly associated with safety outcomes than reducing the total time spent within the transportation system. Tactics toward this end may include accessible land use planning, multimodal infrastructure and other initiatives that promote non-driving modes. Efforts should secondarily be focused on controlling interactions with the remaining motor vehicle trips through strategies that manage road user behaviors such as speed management. Efforts should lastly be focused on mitigating crashes.

These findings should not be interpreted to suggest that reducing VMT or car mode share alone is sufficient to improve safety outcomes. Rather, these measures reflect broader system-level conditions – particularly land use patterns – that shape both how much people travel and how they travel. In this sense, mode share reflects the composition of travel, while VMT reflects the overall level of exposure and improving safety likely requires addressing both.

This work addresses a fundamental question in road safety research: should the primary objective of road safety research be to improve safety on existing roads and within current transport systems or to instead fundamentally re-envision and design transportation systems that better align with safety goals? Our results suggest that, to meet our transportation safety goals, the field may benefit from moving beyond the former mindset and increasingly engaging with the latter approach.

It may be that the USA has fallen behind its international peers in transportation safety, despite many jurisdictions adopting the Safe System Approach, because it continues to be highly auto-dependent. As the USA strives to close the safety gap, transportation professionals may benefit from pursuing a fundamental shift toward enabling more non-driving trips and shorter driving trips, rather than merely attempting to make interactions with motor vehicles safer.

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