Rethinking traffic safety: the case for reducing kinetic energy exposure, not just speed

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ABSTRACT

Background This study extends beyond traditional speed and conflict management approaches to explore the role of kinetic energy exposure in shaping road safety outcomes.

Methods We examined the associations between exposure-based metrics (ie, mode share, vehicle miles travelled (VMT) and commute time) and fatality rates (ie, overall, vehicle occupant, pedestrian and bicyclist) by analysing 227 urban areas across 45 US states, controlling for other transportation and socioeconomic covariates. We used linear mixed-effects models to account for unobserved heterogeneity at the state level.

Results The results indicate that exposure plays a central role in shaping traffic fatality rates. Overall, measures of auto-dominance – particularly automobile mode share and VMT – are most strongly associated with higher fatality rates. When examining specific road users, time spent in the transport system emerges as a key predictor across modes. However, mode share appears more strongly associated with safety outcomes for vulnerable road users (ie, pedestrians and cyclists) whereas VMT is more strongly associated with motor vehicle occupant fatality rates. Notably, exposure-related factors remain strong and significant even for individuals travelling in cars, underscoring that increased system exposure elevates risk across all user types.

Discussion and conclusions Our findings also reinforce the association between socioeconomic and demographic conditions and safety outcomes. However, in addition to longstanding strategies focused on kinetic energy severity (eg, speed management) and kinetic energy likelihood (eg, conflict management), our results suggest that reducing fatality rates requires reducing overall kinetic energy exposure. Providing viable modal alternatives and designing communities that enable shorter travel distances and less time spent in the transportation system may be critical components of a comprehensive road safety strategy.

BACKGROUND

Many transportation safety efforts focus on making driving safer or interactions between motor vehicles and those outside the vehicle safer via strategies such as speed management, spatial or temporal separation of users and education and enforcement campaigns aimed at influencing driver behaviour. However, far less attention has traditionally been paid to reducing baseline exposure to automobiles by building places that help shorten driving distances, reduce time spent in the transportation system and/or reduce the number of driving trips via mode substitution.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ Speed and conflict management strategies are effective at improving road safety outcomes.

WHAT THIS STUDY ADDS

⇒ Reducing exposure to motor vehicle kinetic energy via reduced car mode share, vehicle miles travelled and time in the system are also strongly associated with safe outcomes for all road users.

HOW MIGHT THIS STUDY AFFECT RESEARCH, PRACTICE OR POLICY

⇒ Tactics that provide modal alternatives and reduce travel distances and time may be essential components of a comprehensive road safety strategy.

Past research has established that there are three components of kinetic energy risk: exposure, likelihood and severity.[1] Severity is primarily associated with vehicle speed, while likelihood reflects the frequency or probability of conflicts.[2] Exposure, in contrast, represents the total amount of kinetic energy present within the system. The role of exposure in safety is increasingly being discussed as public health best practices and injury prevention enter the transportation dialogue[3] and as comparisons are made between the US and peer countries that have superior safety records.[4 5] However, most safety efforts have traditionally focused on managing kinetic energy likelihood (eg, conflict management) and kinetic energy severity (eg, speed management). These approaches tend to be reactive, addressing risk only after it is present. Focusing on kinetic energy exposure allows us to be proactive by reducing risk before it occurs, consistent with public health principles. Traffic safety statistics have implied this exposure relationship for nearly a century.[6 7] Yet, the relative importance of exposure has rarely been compared directly with other risk factors.

To illustrate this concept, consider a signalised intersection that accommodates 10 000 vehicles per day. Suppose that, on average, two drivers per year run a red light. In this case, the likelihood of a kinetic energy transfer event is relatively low, but the potential severity is high. If the intersection is converted to a roundabout, the frequency of crashes may increase, indicating a higher likelihood of kinetic energy transfer. However, these events tend to occur at lower speeds and are therefore less severe, possibly resulting in improved overall safety outcomes.

Both approaches, however, are fundamentally reactive, as they assume a fixed volume of 10 000 vehicles and seek to mitigate risk within that constraint. In contrast, addressing kinetic energy exposure is proactive: it involves reducing the total amount of energy in the system, for example, by decreasing traffic volumes (eg, from 10 000 to 5000 vehicles per day) through the provision of alternative modal options or by enabling shorter trips.

Accordingly, this paper asks: how is kinetic energy exposure – measured through commute time, vehicle miles travelled (VMT), and mode share – associated with overall road safety outcomes, while accounting for kinetic energy likelihood, kinetic energy severity and population factors? How do kinetic energy exposure factors affect safety outcomes for different types of road users, including pedestrians, bicyclists and motor vehicle occupants? This represents a critical research gap, as prior studies have linked exposure to safety outcomes, but few have systematically compared different types of kinetic energy exposure or explored how their effects vary across distinct road user groups.[8]

We address these research questions by examining how the amount of time spent in the transportation system (ie, commute time), the amount of driving (ie, VMT) and the proportion of trips made by car (ie, car commute mode share) are associated on the urban area level with overall transportation fatality rates (ie, road fatalities per 100 k population), motor vehicle occupant fatality rates (ie, motor vehicle occupant fatalities per 10 k car commuters), pedestrian fatality rates (ie, pedestrian fatalities per 10 k pedestrian commuters) and bicyclist fatality rates (bicyclist fatalities per 10 k bicyclist commuters). To better understand how vehicle exposure itself matters, our statistical models also account for other pertinent safety factors, including an average vehicle speed proxy, state-level driver education requirements, driver enforcement (eg, speeding citation rates), unsafe roadway behaviour rates (eg, alcohol impairment) and the study populations' socioeconomic and demographic characteristics.

METHODS

Data collection and preparation

We sought to compile data representative of conditions in 2022 for US urban areas. Urban areas are defined by the US Census Bureau as continuously developed areas, regardless of municipal borders, with populations of at least 5000 residents. While the US Census Bureau has identified 2637 urban areas, we chose to analyse the 227 urban areas – across 45 states – for which the Federal Highway Administration (FHWA) provided VMT data.

Urban areas are an appropriate geographic unit for this analysis because key exposure measures are more meaningfully captured at a broader spatial scale. Residents in smaller geographic units, such as block groups, may have low VMT themselves while still experiencing substantial pass-through traffic from outside their block group. Additionally, residents of smaller geographic areas may generate a substantial share of their VMT outside their area of residence. Using urban areas helps minimise these distortions and better aligns measured travel activity with the population and travel behaviour being studied. Furthermore, strategies aimed at reducing kinetic energy exposure – such as reducing the amount of driving and the proportion of car trips – are generally more feasible in urban areas than in rural contexts.

Our dependent variables were rates of road fatalities per capita, motor vehicle occupant fatalities per car commuter, pedestrian fatalities per pedestrian commuter and bicyclist fatalities per bicyclist commuter. We used overall per capita fatality rates because we wanted to understand how safe it was to live in an urban area, as opposed to controlling for VMT, which would instead represent the safety of driving. Because urban areas differ in their levels of driving, walking and bicycling, and because we sought to assess the safety of engaging in each activity, we used the most appropriate exposure measures available at the urban area scale: the number of car, pedestrian and bicyclist commuters.

Table 1 List of independent variables and data sources

Variable	Source	Geographic level
Transportation		
Kinetic energy exposure		
Commute time per capita (min)	ACS	Urban area
Commute mode share by car (%)	ACS	Urban area
Daily VMT	FHWA	Urban area
Kinetic energy likelihood/severity		
Driver education required	NHTSA	State
Earliest allowable driving age (years)	NHTSA	State
% Residents w/speed ticket	Insurify	State
% Fatalities alcohol impaired	NHTSA	State
Average urban motor vehicle speed (mph)*	OSM	Urban area
Vehicle age (years)	NHTS	Census division
People		
Socioeconomics		
Median household income ($)	ACS	Urban area
Gini index	ACS	Urban area
Demographics		
% Age 70+ years old	ACS	Urban area
% White non-Hispanic	ACS	Urban area
% Families married w/kids	ACS	Urban area

*Average motor vehicle speeds were calculated from a set of origin and destination points in each urban area (see description in section 2.1).
ACS, American Community Survey; FHWA, Federal Highway Administration; NHTS, National Household Travel Survey; NHTSA, National Highway Traffic Safety Administration; OSM, OpenStreetMap; VMT, vehicle miles travelled.

We used a spatial join in a geographic information system (GIS) to obtain fatality counts from the National Highway Traffic Safety Administration's (NHTSA) Fatality Analysis Reporting System for each urban area using polygon geographies from the US Census Bureau. We obtained and averaged fatality counts for 2021, 2022 and 2023 to minimise the effects of annual variability in fatality counts. 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 road fatality count by its corresponding 2022 US Census population and commuting figures to determine the total, motor vehicle occupant, pedestrian and bicyclist fatality rates.

We sought to compile a comprehensive set of potential covariates that we categorised into two primary blocks and associated subblocks (table 1). Within the Transportation block, the Kinetic Energy Exposure subblock consisted of variables representing the amount and type of travel, including commute time and VMT. Five-year estimates from the 2022 American Community Survey (ACS) provided average commute time per capita at the urban-area level. Given that commuting accounts for approximately 30% of total travel, the average commute time likely serves as a reasonable proxy for overall time spent in the transportation system.[9] FHWA's *Highway Statistics Series* provided 2022 daily VMT at the urbanised area level. This geography is based on the urban area definition but is minimally modified by state departments of transportation and metropolitan planning organisations to include or exclude fringe roads, making it more suitable for transportation system analysis.[10] The Kinetic Energy Exposure subblock also included mode share, which reflects the type and relative kinetic energy of travel occurring within a transportation system. Five-year estimates from the 2022 ACS provided data at the urban-area level on commute mode share by car, truck or van (hereafter referred to as “commute mode share by car” for clarity).

The kinetic energy likelihood/severity subblock consisted of variables that were associated with collision likelihood and/or severity, such as state-level enforcement and education (table 1). NHTSA 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.[11] As a general proxy for traffic enforcement intensity, we included the proportion of residents with a recorded speeding violation. We obtained state-level data from Insurify, an automobile insurance marketplace that compiles driver records from across all fifty states and maintains information on more than ten million drivers. However, enforcement is difficult to measure as a high proportion of residents with speeding tickets could be a measure of enforcement intensity, a measure of driver behaviour, or a combination of both, and such violations may occur outside individuals’ residential areas. Accordingly, this measure should be interpreted as a proxy rather than a direct indicator of enforcement activity. State-level data on the proportion of road fatalities involving at least one driver with a blood alcohol concentration of 0.08 g/dL or higher were provided by NHTSA.

The kinetic energy likelihood/severity subblock also consisted of motor vehicle speeds and motor vehicle age[12] (table 1). To represent motor vehicle speeds for each urban area, 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 API, producing 105 routes for each of the 227 urban areas 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 the total distance and estimated travel time, from which we calculated a speed estimate. Travel times were estimated by OpenStreetsMap (OSM) based on posted speed limits and standard OSM turn penalties. We then computed average speeds 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. These route-based speed estimates largely reflect posted speeds, as we did not include any measures of actual vehicle speeds, such as 85th percentile speeds. Vehicle age was sourced from the 2022 National Household Travel Survey’s online data query system and reported at the census-division level.

For the People block, 5-year estimates from the 2022 ACS provided data at the urban-area level on socioeconomic and demographic variables of urban area residents (table 1). We included the Gini Index as a covariate, which is a statistical measure of economic inequality with higher values representing more unequal income or wealth distribution within urban areas. We initially assembled twelve candidate variables for this block and retained the subset reported here. We excluded median age, proportion of residents aged 0–21 years, proportion of residents aged 15–21 years, educational attainment, proportion of zero-car households, median gross rent and gender based on variance inflation factor (VIF) diagnostics to reduce multicollinearity.

Statistical analysis

After data collection, we converted all independent variables to Z-scores to allow for direct comparison between each variable’s estimate. This is done by subtracting the mean from each observed value and dividing by the SD for that variable, resulting in a distribution with a mean of 0 and a SD of 1.[13] To understand the relationship between the exposure-based variables, we also derived an interaction variable for mode share and VMT. However, because the interaction variable was not significant and weakened the modelling results, we excluded it from our final models.

Given that the dependent variables – fatality rates – were continuous and approximately normally distributed and that 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 used for statistical analysis in this paper was:

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

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*.

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

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

We generated the LMEMs in R (V.4.1.3) using the ‘lmer’ function from the ‘lme4’ package (V.1.1-32). We obtained p values for our independent variables using Satterthwaite’s df method via the ‘lmerTest’ package (V.3.1-3) and obtained marginal (ie, fixed effects alone) and residual (ie, both fixed and random effects) R^2 values using the ‘r.squaredGLMM’ command in the ‘MuMIn’ package (V.1.43.17).

We eliminated variables with high correlation based on Pearson correlation coefficients, VIFs and conceptual redundancy. The models’ residuals indicated approximate normality, supporting the suitability of the LMEM approach.

Patient and public involvement

Patients and members of the public were not directly involved in this study.

RESULTS

For overall transportation fatality rates, exposure-based variables were the strongest transportation predictors with higher car mode share and, to a lesser degree, VMT and commute time associated with higher fatality rates (Model 1 in table 2). The amount of driving (ie, VMT) was more strongly associated with overall fatality rates than commute time. This suggests that increased driving may pose greater overall safety risks than increased time spent travelling more generally by any mode, indicating that the intensity and context of exposure – specifically time spent operating a motor vehicle – may be more consequential for overall fatality risk than total travel time alone.

Table 2 Linear mixed-effects models for road fatality rates in US urban areas accounting for state-level random effects

Variable	Model 1 overall fatalities per capita		Model 2 vehicle occupant fatalities per car commuters		Model 3 pedestrian fatalities per pedestrian commuter		Model 4 bicyclist fatalities per bicyclist commuter	
	Est.	SE	Est.	SE	Est.	SE	Est.	SE
Intercept	23.39	0.73***	13.64	0.43***	8.19	0.55***	7.78	0.75***
Transportation								
Kinetic energy exposure								
Commute time per capita (min)	1.72	0.67**	1.60	0.42***	2.62	0.63***	2.93	1.14**
Commute mode share by car (%)	2.23	0.57***	0.88	0.36**	2.48	0.54***	2.55	0.98***
Daily VMT	2.15	0.57***	1.33	0.35***	0.73	0.52	1.60	0.90*
Kinetic energy likelihood/severity								
Driver education required (0=no)	−1.49	0.65**	−0.86	0.38**	−0.11	0.51	0.79	0.78
Earliest allowable driving age (years)	−1.76	0.74**	−0.98	0.44**	−1.35	0.59**	−0.63	0.92
% Residents w/speed ticket	−2.07	0.86**	−0.79	0.50	−1.14	0.66*	−0.88	0.97
% Fatalities alcohol impaired	0.21	0.75	0.13	0.44	−0.36	0.57	0.26	0.83
Average urban motor vehicle speed (mph)*	1.50	0.48***	0.61	0.30**	0.44	0.46	−0.61	0.83
Vehicle age (years)	1.09	0.83	0.04	0.49	1.17	0.66*	−0.75	0.96
People								
Socioeconomics								
Median household income ($)	−3.01	0.73***	−1.92	0.45***	−3.11	0.69***	−2.20	1.22*
Gini index	0.98	0.59	0.62	0.37*	0.93	0.57	0.21	1.02
Demographics								
% Age 70+ years old	−1.12	0.73	0.12	0.46	0.64	0.69	−0.11	1.21
% White non-Hispanic	−0.35	0.73	−0.08	0.45	−1.85	0.67***	−0.54	1.17
% Families married w/kids	−2.85	0.79***	−1.24	0.49**	0.09	0.74	−1.22	1.30
Model parameters								
Marginal R2	0.540		0.479		0.451		0.194	
Residual R2	0.644		0.575		0.502		0.194	
REML convergence	499.9		299.5		1453.8		1707.8	
No. of observations	227		227		227		227	
No. of groups	45		45		45		45	

*p<0.10; **p<0.05; ***p<0.01.
*Average motor vehicle speeds were calculated from a set of origin and destination points in each urban area (see description in section 2.1).
REML, Restricted maximum likelihood; VMT, vehicle miles travelled.

A lack of driver education requirements, earlier allowable driving ages, lower speeding ticket intensity and higher motor vehicle speeds were associated with higher overall fatality rates (Model 1 in table 2). Overall fatality rates were also strongly associated with the socioeconomic and demographic characteristics of the urban areas' populations, with higher overall fatality rates being associated with lower median household income and fewer families married with children (Model 1 in table 2).

There was additional nuance for safety outcomes of individual modes (Models 2–4 in table 2). Kinetic energy exposure-based variables remained the strongest transportation-related predictors for each individual mode. However, time spent in the system emerged as the strongest predictor when analysing modes individually, with more time spent commuting being associated with higher fatality rates. This likely reflects the most fundamental epidemiological form of exposure: risk accumulates over time. In this sense, time captures total kinetic energy exposure for individual modes more directly than distance-based measures such as VMT or mode share. Time may have been weaker for overall fatality rates because it aggregated kinetic energy exposure across very different risk contexts.

Behind the time variable, the second strongest predictor for individual modes varied between vehicle occupants and vulnerable road users (VRUs; pedestrians and bicyclists) (Models 2–4 in table 2). For pedestrian and bicyclist fatality rates, mode share was the second strongest variable, whereas for drivers, it was VMT. This is likely because for pedestrians and bicyclists, the degree to which a place is auto-dominated is more consequential, whereas for drivers, the total amount of driving is more important.

A lack of driver education requirements was a strong predictor of higher vehicle occupant fatality rates, but was not strong or statistically significant for VRU fatality rates (Models 2–4 in table 2). This could reflect driver education programmes emphasising safely operating a motor vehicle and interacting with other motor vehicles more than safely sharing the roadway with pedestrians and bicyclists.

The vehicle speed variable was a significant predictor for higher vehicle occupant fatality rates but was non-significant for pedestrian and bicyclist fatality rates (Models 3 and 4 in table 2). This does not imply that speed is unimportant for pedestrian and bicyclist safety, but instead likely reflects our use of an area-wide average speed proxy. Small variations in speed regionwide may have had limited explanatory power for pedestrian and bicyclist safety outcomes, which are more sensitive to speed conditions along specific high-conflict corridors than to aggregate, regionwide averages. High-end speeds – such as 85th percentile speeds – may be more strongly related to safety outcomes for bicyclists and pedestrians. In other words, our speed proxy did not necessarily capture the critical delta between target speed and operating speed.[14]

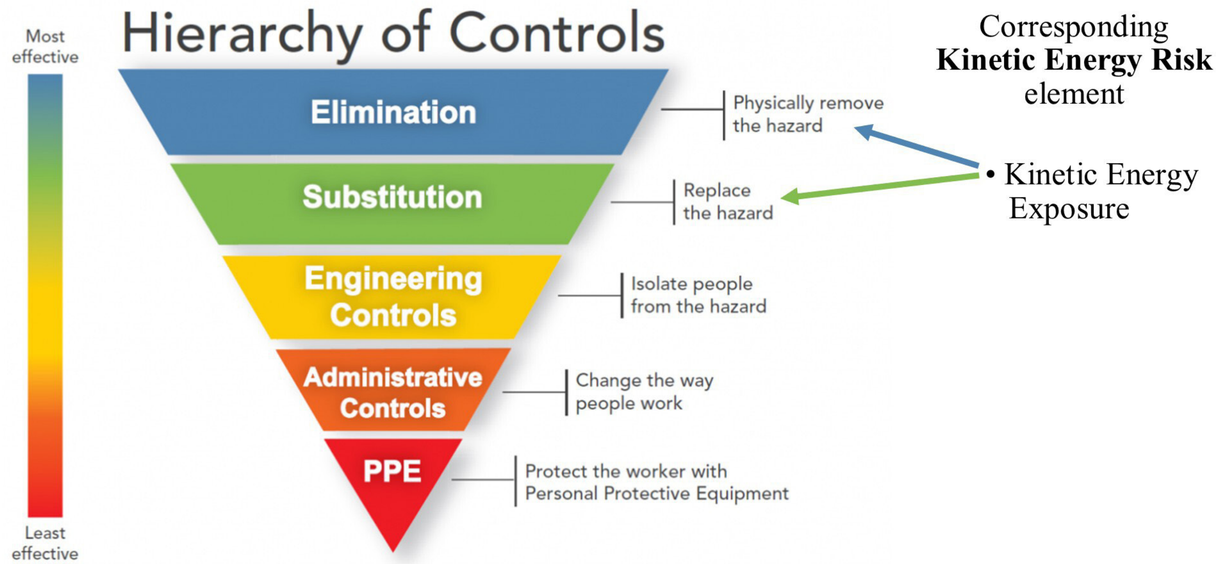

Figure 1 Kinetic energy exposure alignment with the hierarchy of controls.

Lower income levels remained a significant predictor of higher fatality rates across all modes studied (Models 2–4 in table 2). Income was a particularly strong predictor of pedestrian fatality rates, and race/ethnicity was significant for pedestrian fatality rates but not for any other modes. This may reflect differences in travel purpose. For example, biking is often more of a discretionary activity, while walking is undertaken more for necessity and thus can be over-represented among lower-income populations.[15] In addition, prior research suggests that people of colour are more likely to live in areas with roadways that generally have higher pedestrian risk.[16] These socioeconomic and demographic factors may also reflect underlying behavioural factors that we could not directly measure at the scale of this study, as discussed further in Section 4.3.

DISCUSSION AND CONCLUSIONS

Takeaways

This research supports the foundational role of kinetic energy exposure within the three components of kinetic energy risk by being among the first to (1) Identify kinetic energy exposure as a critical pathway to enhancing road safety for motor vehicle occupants, pedestrians and bicyclists and (2) Demonstrating that not all forms of exposure are equivalent: mode share is particularly relevant for VRUs, whereas VMT is more pertinent for motor vehicle occupants.[1 8] The findings also align with the Hierarchy of Controls framework endorsed by the Occupational Safety and Health Administration, which identifies eliminating or substituting hazards as the most effective strategies for improving occupational safety (figure 1). Our results are consistent with this principle, as reducing exposure to kinetic energy represents an approach that targets the hazard at its source. However, additional research is needed to more fully situate the relative roles of kinetic energy likelihood and severity within this framework.

Although our current study uses a per capita exposure metric, conventional safety assessments often rely on VMT–based safety rates, which implicitly normalise higher levels of driving and may frame increased travel as compatible with improved safety outcomes. Much mid-twentieth-century development was shaped within this framework, emphasising land use and roadway designs that facilitate automobile travel. In contrast, our findings suggest that reducing overall exposure to motor vehicle travel may be central to improving safety outcomes, underscoring the need for future research to critically evaluate how exposure metrics influence policy priorities and infrastructure decisions.

Future research topics

Future studies should investigate strategies for influencing travel behaviour and mode choice to achieve exposure-based safety gains, such as transportation demand management and land use policy.[17] Prior studies have shown that more compact land use patterns are associated with improved safety outcomes, likely due to shorter trip distances and lower travel speeds.[18–20] However, additional research is needed to examine whether these safety benefits are also driven by mode shifts or increased trip linking.

Past research supports the idea that mode shift at large scales can be effective by showing that US cities with high non-driving mode share – even high levels of traditionally less safe modes such as biking – are actually safer for all road users.[13 21–24] While less time and VMT in a transportation system is more likely effective at any scale, future research should examine the safety effectiveness of mode shift at different scales. In current US transportation systems, walking and biking are often less safe than driving. Individual-level mode shift away from automobiles may therefore cause those individuals to be at more risk as they navigate still auto-dominated systems. Therefore, it is important to complement community-level mode shift strategies with multimodal roadway safety improvements and other speed and conflict management countermeasures.

Future research might also examine whether there are any strategies that are effective at simultaneously reducing kinetic energy exposure, likelihood and severity. For instance, following the implementation of the bus rapid transit system in Albuquerque, NM, serious injuries and fatalities along the corridor declined by 65%, a reduction that was primarily driven by an 11.5% decrease in 85th-percentile operating speeds (ie, kinetic energy severity reduction) and the introduction of left-turn restrictions (ie, kinetic energy likelihood reduction).[25–27] Future research could explore whether mode shift to transit (ie, kinetic energy exposure reduction) contributed to safety improvements.

A critical open question concerns how autonomous vehicles will influence road safety outcomes. While automation has the potential to substantially reduce kinetic energy likelihood and severity, it may also increase VMT, which could negatively affect safety in terms of exposure.[28 29]

Limitations

Improved measures of vehicle speed are needed beyond the vehicle speed metric used in this study, and particularly metrics that capture the most dangerous speeding behaviour on high-risk corridors rather than average speeds at a broad geographic scale. A future study on a smaller geographic scale would allow for better representation of, for instance, speeds exceeding the 85th percentile speed or the delta between target speeds (eg, posted speed limits) and operating speeds (eg, 85th percentile speeds) and their contribution to kinetic energy severity and likelihood. Better understanding speeding behaviour would also allow us to better understand to what extent enforcement rates are due to high levels of speeding, high levels of enforcement or a combination of both. Additional research should also focus on non-driving exposure measures, including pedestrian and bicycle miles travelled, as alternatives to commonly used mode share indicators, contingent on the availability of such data at scale.

Similarly, although socioeconomic and demographic variables remained strong predictors even after accounting for the transportation factors included in this study – which aligns with the Safe Systems Pyramid's placement of socioeconomic factors at its foundation[3] – they may proxy for additional exposure or demand factors that we were unable to capture at the urban area scale. Future research conducted at a finer spatial resolution could incorporate more detailed measures of exposure and behaviours such as conflicts and near-miss events, which would allow for further definition of the relative importance of kinetic energy exposure, likelihood and severity.

A final limitation of this study is its restricted geographic scope within the US. The extent to which these findings generalise to other contexts remains uncertain. Additional research is needed to evaluate whether similar relationships are observed in other countries, particularly in low- and middle-income settings where transportation systems, travel patterns and road safety conditions may differ substantially.

Final conclusions

Our results suggest that the limited progress toward US road safety goals may be rooted in the automobile-focused development patterns and roadway design standards prioritised since the mid-1900s. The underlying fabric of US land use and transportation systems was built around the assumption that nearly all trips would be made by car, often at relatively high speeds, leading to high levels of exposure to motor vehicle kinetic energy. Efforts to improve safety have therefore operated within a structural context of elevated kinetic energy exposure, making meaningful safety gains more difficult to achieve.

Our findings that exposure-based variables are strongly associated with better road safety outcomes suggest a need to reconsider prevailing approaches to road safety. Rather than focusing primarily on mitigating kinetic energy likelihood and severity after exposure has occurred, greater emphasis should be placed on reducing exposure itself. This includes designing and retrofitting communities to better support mode share by walking, bicycling and transit, and more broadly creating environments that reduce total time spent and VMT within the transportation system. Such an approach expands the set of available safety interventions by incorporating mode shift and VMT mitigation strategies, which have not traditionally been considered as safety tools before, thereby allowing for a more proactive approach to traffic safety. By lowering overall exposure to kinetic energy, such strategies may make safety goals more attainable for all road users.

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