

Traffic and the risk of vehicle-related pedestrian injury: a decision analytic support tool

Z Chalabi, I Roberts, P Edwards, J Dowie

London School of Hygiene & Tropical Medicine, Keppel Street, London WC1E 7HT, UK

Correspondence to:
Dr Z Chalabi, Department of Public Health and Policy, London School of Hygiene & Tropical Medicine, Keppel Street, London WC1E 7HT, UK; zaid.chalabi@lshtm.ac.uk

Accepted 4 February 2008

ABSTRACT

Background: Pedestrian injuries are a leading cause of death and disability. Transport policy decisions have a major impact on the risk of pedestrian injury, but the effects cannot usually be quantified in controlled studies. However, mathematical modeling can help to establish the injury consequences of transport policy decisions.

Methods: A stochastic mathematical model was developed to estimate the effect of alternative transport scenarios on pedestrian injury risk. The model is based on a mechanistic description of pedestrian injury causation and comprises four sub-models: vehicle dynamics, pedestrian dynamics, collision incidence, and injury severity.

Results: The model was used to estimate the yearly pedestrian injury rate for a baseline scenario, corresponding to current traffic conditions in London, UK, and three alternative scenarios, comprising reductions in vehicle speed, traffic volume, and vehicle mass. The model simulated a baseline injury rate of 88 per 100 000. Compared with baseline, a 15% reduction in mean speed resulted in a 21% reduction in injury rate and a 75% reduction in fatality rate. A 15% reduction in traffic volume resulted in a 14% reduction in injury rate and a 25% reduction in fatality rate. Reducing vehicle mass by 15% did not reduce the number of injuries, but a 25% reduction resulted in less severe injuries.

Conclusions: The model simulated well the rates and severity of pedestrian injury corresponding to the baseline scenario and made predictions for different transport policy scenarios. However, it is offered primarily as a generic decision support tool for the assessment of alternative policies by transport authorities.

Worldwide, road traffic crashes account for over one million deaths each year.¹ Most of the victims are pedestrians and cyclists, and a large proportion of injuries occur in cities. Urban transport policy decisions impact importantly on pedestrian injury risk, but it is difficult to quantify these effects.² Although the effects of transport policies can sometimes be assessed in controlled trials, there are practical and financial obstacles to conducting trials of transport policies, and so decisions have to be made without such evidence. In these situations, mathematical modeling provides a way of evaluating the consequences of different policies. We describe a mathematical model of pedestrian injury risk that can be used to evaluate the effect of transport policies on the incidence and severity of pedestrian injuries.

METHODS

Model description

A mechanistic model of pedestrian injury was developed on the basis of a mathematical-physics

description of pedestrian injury causation (fig 1). The road network is abstracted as a straight line of length equal to that of the urban road network. Figure 1 shows two vehicles (incoming and outgoing) and a pedestrian crossing the road in the gap between the vehicles. The inter-vehicle distance depends on traffic density, and pedestrian exposure to an incoming vehicle depends on traffic flow. A collision occurs if the time taken by a pedestrian to cross the road is less than that taken by the incoming vehicle to travel the distance between it and the pedestrian as he/she starts crossing.

Although the model seems simplistic, it can be made to capture mathematically the complexity of the causal pathway of pedestrian injury by assuming that all the factors (eg, width of roads, vehicle speed, pedestrian speed) that influence pedestrian injury incidence and the subsequent severity of injury are stochastic (probabilistic). The alternative would be a detailed deterministic description of the road network and vehicle and pedestrian flow, which would be computationally very demanding. Because the geometric configuration is described by parameters that are random variables, non-perpendicular type collisions between a vehicle and a pedestrian are implicitly catered for in the model. Collisions at road junctions are not considered in the present model but will be addressed in the future.

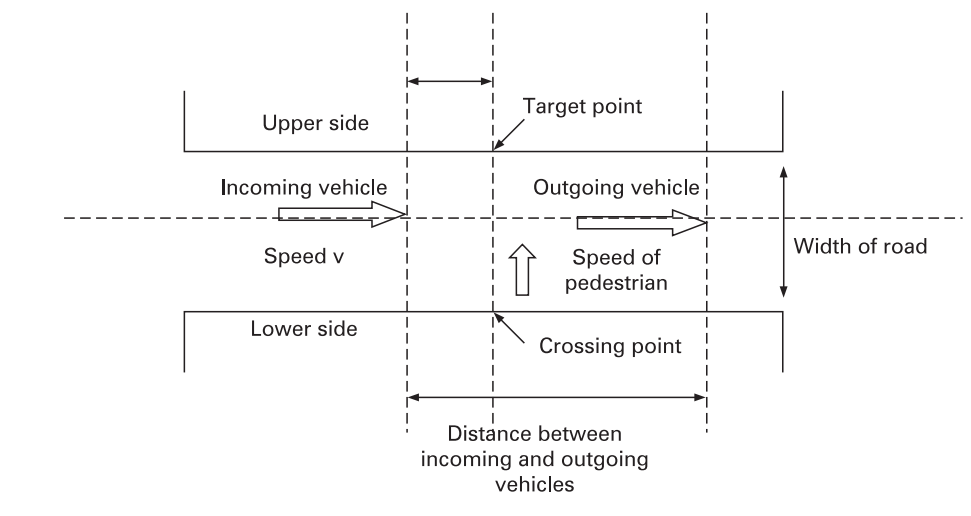
The model has four sub-models—(1) traffic dynamics, (2) pedestrian dynamics, (3) collision incidence, and (4) injury severity—the parameters of which are assumed to be random variables characterized by probability distributions. The propagation of uncertainty between the sub-models leading to the overall model outputs is carried out using Monte Carlo (MC) simulations. MC simulations are widely used in propagating parametric uncertainties in environmental exposure models.^{3–4} In each MC simulation, numerical values of the model parameters are drawn from their respective probability distributions, and the model outputs are computed for that set of parameters. Histograms of the outputs characterize their uncertainty, and their expected values are used for comparative evaluations of health benefits.

Sub-models

Traffic dynamics

Models of traffic dynamics can be classified as microscopic or macroscopic.^{5–7} Microscopic models^{6–10} describe traffic dynamics in terms of individual vehicle behavior. In one-dimensional geometries, the behavior of a vehicle is defined in terms of its speed and rate of change and the

Figure 1 A schematic diagram describing the conditions for a pedestrian-vehicle collision.



distance separating it from the vehicle it follows. Macroscopic models on the other hand describe traffic dynamics in terms of the collective behavior of vehicles.^{8–11} The collective behavior of vehicles is defined in terms of traffic speed, traffic density (number of vehicles per unit distance), and traffic flow (number of vehicles per unit time). In this study, we used a simple model to describe traffic dynamics. The model is defined in terms of two variables: traffic speed and traffic volume. Traffic volume (number of vehicles \times average distance traveled by each vehicle, per unit time) was used because in practice it is easier to monitor traffic volume than traffic density.

Pedestrian dynamics

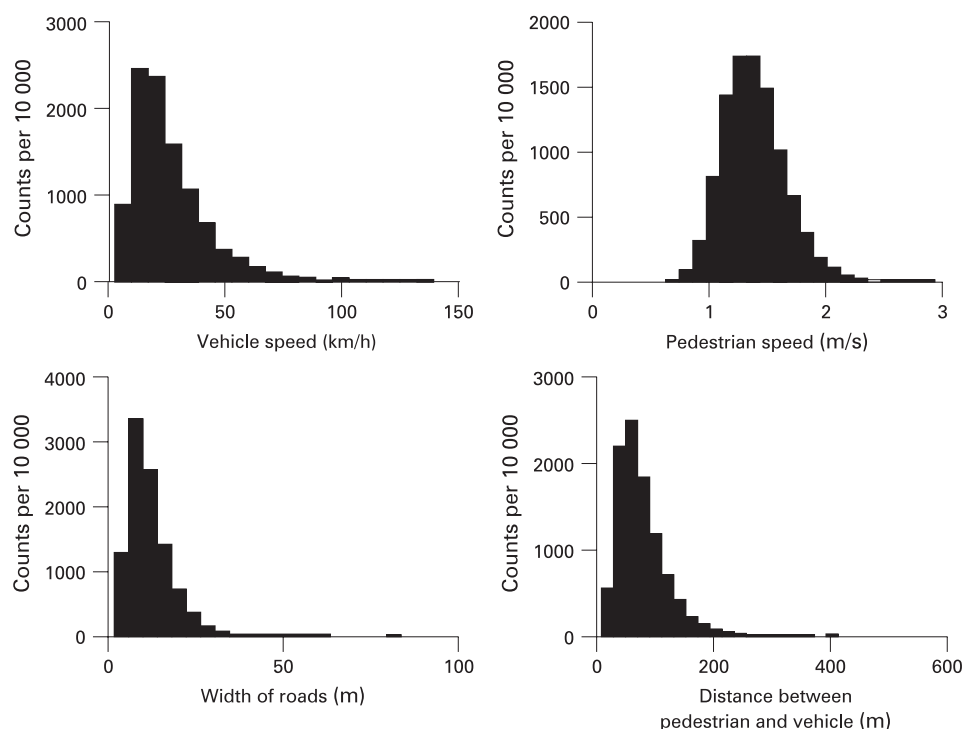
Several models have been developed to describe pedestrian dynamics.^{12–18} They are of two types: cellular automata models and continuum models. Cellular automata models¹² divide the

space into grids and use rules to govern the movement of pedestrians from one grid to a neighboring one. Continuum models¹⁶ take a Newtonian perspective: pedestrians are driven by “behavioral forces” which are either attractive or repellent. For obvious reasons, these models are known as “social force models”. Our pedestrian dynamics model differs from others,^{16,19} as those models were aimed primarily at investigating the impact of pedestrian crossing on traffic flow in vehicle-pedestrian-collision-free scenarios. It is defined in terms of three variables: pedestrian crossing rate, distance between the pedestrian and the incoming vehicle at the initiation of crossing, and the speed of pedestrian crossing.

Severity of pedestrian injury at collisions

There are several mathematical models of the severity of pedestrian injury in vehicle-pedestrian collisions.^{20–24} The

Figure 2 Histograms of the main parameters used in the Monte Carlo simulations (10 000) in the baseline scenario.



Methodologic issues

models are of two types: mechanistic^{22–24} and empirical.^{21, 22} Because our overall model is stochastic, Davis²¹ empirical probabilistic model is used here. In the Davis²¹ model, the severity of pedestrian injury is divided into three categories: “fatal”, “serious”, and “slight”. An injury was classified as fatal if the pedestrian died within 30 days, serious if the pedestrian required hospitalization (or suffered from one or more particular types of injury), and slight otherwise. The model gives the probabilities of severity of injury for three age groups (0–14 years, 15–59 years, and ≥ 60 years) as empirical functions of vehicle speed at impact. In addition to the speed of the vehicle, the geometry of front-end vehicle structure affects injury severity^{25–27} and so, to a lesser extent, does vehicle mass. Davis’ model was modified to take into account the effect of vehicle mass only. Although in vehicle–pedestrian collisions it could be argued that vehicle mass is less important than front-end structure, because it is so much larger than the mass of a pedestrian,²⁷ it is relevant in this study to allow for future trends in manufacturing significantly lighter energy-efficient vehicles. Furthermore, the mass of a vehicle affects the probability of collision incidence: lighter vehicles require less distance to stop when breaks are applied and thus have lower odds of crashing with pedestrians.²⁸ This aspect, however, was not taken into account in this model.

The overall model

The overall model is constructed from the sub-models described above. In its basic form, the overall model outputs the probability of severity of injury per age group per unit time. Each of the model’s output probabilities is the product of several probability terms: the probability of a pedestrian crossing the road per unit length of road per unit time, the probability of a pedestrian crossing the road at some speed, the probability of an incoming vehicle traveling at some velocity, the probability of a pedestrian encountering an incoming vehicle when crossing the road, the probability of a pedestrian and an incoming vehicle colliding, and the probability of severity of injury conditional on collision incidence.

Each of the model’s input probabilities is a function of environmental, traffic-related and/or behavioral factors. The probability of a pedestrian crossing the road per unit length of road per unit time depends for example on the availability of designated pedestrian crossings, the routing of pedestrian traffic over or under roads, the proximity of residences to schools (in the case of young pedestrians) and work places (in the case of adult pedestrians), the number of trips made by a pedestrian per unit time, the distance traveled by a pedestrian per trip, and the number of roads crossed per trip. The probability of a pedestrian encountering an incoming vehicle at the time of crossing depends on factors such as traffic volume, presence of traffic calming measures, and number of traffic signals per unit length of road. The probability of collision incidence depends on the time taken by a pedestrian to cross the road and the time taken

by an incoming vehicle to travel the distance between it and the pedestrian at the time of crossing the road. The probability of severity of injury (conditional on collision incidence) is obtained from Davis’ model. For brevity, the data sources used to determine a very few of the factors are described below.

Distance between pedestrians and incoming vehicles at time of crossing

With the unavailability of direct data, guidelines on the location and timing control of signaled pedestrian crossings can be used indirectly to estimate the mean distance between an incoming vehicle and the time of pedestrian crossing. Traffic engineers have worked out minimum distances to locate signaled crossings to ensure visibility of these crossings to drivers.²⁹ These distances (*d*) are a function of the expected incoming speed of vehicles, and they range from 40 m to 115 m. *d* is assumed to be log-normally distributed, with mean 79 m and variance 1792 m².

Crossing speed of pedestrians

The default distribution of the speed of pedestrians is based on an empirical study.³⁰ Pedestrian crossing rate is setting-specific. In this model, population surveys on pedestrian behavior in London³¹ were used to determine the default distribution of the pedestrian crossing rate. Empirical data give the mean road crossing speed of young adults as 1.51 m/s and of older adults as 1.25 m/s.³⁰ The road crossing speed of pedestrians, *w*, is assumed to be log-normally distributed, with mean 1.4 m/s and variance 0.0671 m²/s².

Width of roads

There are no direct data on the distribution of the width of roads, but secondary data obtained from guidelines on the design of pedestrian crossings in urban areas for pedestrian safety^{29, 30} indicate that the range of road widths vary from 8 to 35 m. In this model, the road width is assumed to follow a log-normal distribution, with mean 12 m and variance 41 m².

RESULTS

Simulation scenarios

Baseline scenario

The data on the baseline scenario for Greater London could be summarized in many ways, but are presented here in a form to suit the model. (Unless otherwise stated, we used Stats 19 data for all road traffic injury collisions in London between 1993 and 2004, obtained from the London Road Safety Unit, Transport for London (TfL). Traffic flow and speed data were supplied by Road Network Monitoring (also TfL).) The total number of pedestrian casualties of all severities for Greater London in 2003 was 7127, of which 23% were 0–15 years old, 58% were 16–59 years, 13% were 60 years and older. The remaining 6% of casualties were of unknown age. On the basis of estimates of

Table 1 Baseline scenario

Age group (years)	Fatal injury	Serious injury	Slight injury	Total
0–14	0.45	3.43	12.62	~17
15–59	1.87	10.87	43.29	~56
≥ 60	1.50	4.59	8.11	~14
Total	~4	~19	~64	~87

Number of casualties per 100 000. Totals rounded up to the nearest integer for ease of presentation.

Table 2 Scenario 1 (mean traffic speed reduced by 15%)

Age group (years)	Fatal injury	Serious injury	Slight injury	Total
0–14	0.17	1.96	10.90	~13
15–59	0.69	6.14	37.36	~44
≥ 60	0.63	2.92	7.66	~11
Total	~1	~11	~56	~68

Number of casualties per 100 000. Totals rounded up to the nearest integer for ease of presentation.

Table 3 Scenario 2 (traffic volume reduced by 15%)

Age group (years)	Fatal injury	Serious injury	Slight injury	Total
0–14	0.41	2.97	10.81	~14
15–59	1.70	9.38	37.08	~48
≥60	1.33	3.93	6.95	~12
Total	~3	~16	~55	~74

Number of casualties per 100 000. Totals rounded up to the nearest integer for ease of presentation.

the residential population in Greater London, this translates to 99 pedestrian casualties per 100 000. The distribution of casualties among injury severity categories was: 2% fatal, 19% serious, and 79% slight. In terms of characterizing pedestrian exposure to road traffic in London, the traffic flow in 2004 was 20 000 million vehicles/km, and the mean traffic speed was 26 km/h. The total length of the road network in Greater London is 1719 km of A roads (main roads other than motorways) and 232 km of B roads (secondary roads).

Policy scenarios

To demonstrate the use of the model, three scenarios are considered. The first evaluates an intervention that reduces mean speed by 15% (eg, traffic calming or speed restrictions). The second evaluates an intervention that reduces traffic volume by 15% (eg, the introduction of congestion charging³²). The third evaluates an intervention that reduces vehicle mass by 15% (eg, the manufacture of smaller energy-efficient vehicles).

Simulation results

Figure 2 shows histograms of the main parameters used in the baseline simulations.

Table 1 shows estimated casualties by age group and severity per 100 000 population. The data were obtained by multiplying three probability terms to give the absolute probability of severity of injury per age group: the probability of pedestrian exposure to an incoming vehicle, the probability of a vehicle–pedestrian collision occurring conditional on pedestrian exposure to an incoming vehicle, and the probability of severity of pedestrian injury conditional on a vehicle–pedestrian collision. The absolute probabilities are scaled by 100 000 to give injury rates per 100 000 (table 1).

Without any data fitting, the model estimated the total number of pedestrian casualties to be about 87 per 100 000. This compares with 99 pedestrian casualties per 100 000 reported for Greater London in 2003. The estimated distribution of casualties across injury categories is: 4.4% fatal, 21.8% serious, and 73.8% slight (reported values were 1.65% fatal, 19.35% serious, and 79.0% slight). The estimated distribution of casualties across age groups is: 19.0% for 0–15 years old, 64.6% for 16–59 years old, and 16.4% for ≥60 years (reported values were 22.9%, 58.0%, and 13.1% respectively; 5.9% were unclassified). The calibration

Table 4 Scenario 3 (vehicle mass reduced by 15%)

Age group (years)	Fatal injury	Serious injury	Slight injury	Total
0–14	0.50	3.43	12.80	~17
15–59	2.04	10.84	43.88	~57
≥60	1.55	4.59	8.25	~14
Total	~4	~19	~65	~88

Number of casualties per 100 000. Totals rounded up to the nearest integer for ease of presentation.

of the model therefore appears reasonable. The results of the baseline scenario were then used for comparative evaluation against policy scenarios.

In the first scenario, the mean traffic speed is reduced by 15% (ie, from 26 to 22.1 km/h), but its variance maintained. All other parameters are assumed to have the same distribution as in the baseline scenario. Table 2 gives the corresponding number of casualties per 100 000 population across age groups and severity of injury categories. Compared with the baseline scenario, the total number of casualties was reduced by 21.2% and the distribution of severity of injury becomes 2.2% fatal, 16.1% serious, and 81.7% slight. In addition to reducing the total number of injuries, the distribution across injuries categories is therefore, as expected, shifted towards less severe injuries. It is interesting to note that because of non-linearity, the estimated reduction in the total number of pedestrian casualties (21.2%) is more than would be expected (had the relationship between traffic speed and the number of pedestrian casualties been linear, a reduction of ~15% in the number of casualties would have been expected).

In the second scenario, traffic volume is reduced by 15% (ie, from 20×10^9 vehicles/km to 17×10^9 vehicles/km). Table 3 gives the corresponding distribution of casualties per age group and injury category. Compared with the baseline scenario, the total number of casualties was reduced by 14.1% and the distribution of severity of injury is now 4.6% fatal, 21.8% serious, and 73.6% slight. It is worth noting that the distribution of casualties across injury categories is approximately the same as the baseline case. This is expected as decreasing vehicle volume would decrease pedestrian exposure but, under the assumption of the model, would not affect traffic speed. It is also worth noting that unlike traffic speed, the relationship between traffic volume and the number of pedestrian casualties is almost linear.

The third scenario estimates pedestrian injuries when vehicle mass is reduced by 15%. Table 4 gives the corresponding estimates. The total number of casualties remains almost the same as in the baseline scenario and the distribution of injuries is also the same (4.6% fatal, 21.5% serious, and 73.9% slight). Table 5 shows the result of reducing vehicle mass by 25%. The trend in pedestrian injury is in the logical direction, with total number of casualties remaining the same as expected (as this intervention would not affect the number of collisions) but the distribution in pedestrian injuries is shifted to less serious injuries (4.4% fatal, 21.1% serious, and 74.5% slight).

Each of the above tables was based on an independent set of 10 000 MC simulation runs. In the simulations, the sequence of random numbers depends on the “internal state” of the random number generator and different sequences of random numbers were generated in each scenario. To determine the uncertainty associated with some of the estimates in the tables, 100 independent sets of 10 000 MC simulation runs were performed for each scenario. The mean of the total number of casualties and its 95% CI obtained from the 100 sets of MC simulations are given in table 6. It is clear that by taking uncertainty into account, scenarios 1 and 2 represent important (statistically significant) reductions in total number of pedestrian injuries, whereas scenarios 3 and 4 are, as expected, on the borderline of showing an effect.

DISCUSSION

Main findings

We have developed a mathematical model that can be used to evaluate the impact on pedestrian injury of some urban

Methodologic issues

Table 5 Scenario 4 (vehicle mass reduced by 25%)

Age group (years)	Fatal injury	Serious injury	Slight injury	Total
0–14	0.45	3.26	12.46	~16
15–59	1.83	10.29	42.73	~55
≥60	1.44	4.35	8.12	~14
Total	~4	~18	~63	~85

Number of casualties per 100 000. Totals rounded up to the nearest integer for ease of presentation.

transport policies. Preliminary simulations with a specific dataset show substantial injury reductions from lower vehicle speeds and also from reductions in traffic volume.

Strengths and weaknesses of the model

The model is mechanistic so that it can be adapted to different urban settings and therefore fulfill its aim of being a practical generic decision support tool. It is also stochastic, reflecting the inherent uncertainty and complexity of the system being modeled. For the selected illustrative dataset, the model produced numerical results in line with the broad epidemiological evidence for the baseline scenario. Although the 95% CI of the model's mean estimate of the number of casualties per 100 000 inhabitants (85 to 90) does not include the reported value for Greater London (99), this is not surprising because the model is not statistically based in the classical sense that parameters are estimated by fitting a model to data observations. The model is informed by data from different sources. The correspondence between the estimated and observed value is therefore reasonable and encouraging.

Because the model consists of several sub-models, developments can be made on each of the sub-models independently. Judged by idealized scientific standards, the model has a number of limitations due to simplifications in its construction. These can be divided into four areas reflecting the model's constituent components: traffic dynamics, pedestrian dynamics, collision incidence, and injury severity.

One of the strong assumptions of the model is that traffic density (and traffic volume) is independent of traffic speed. It is well known that traffic density and traffic speed are inversely related, however the exact form of this relationship depends on many factors and was determined primarily for highway conditions.^{5 8 11} Although a simple inverse linear relationship between traffic speed and traffic density could have been used,⁸ a more robust relationship appropriate for cities is desirable. The current model cannot be used to evaluate the impact of interventions aimed simultaneously at traffic speed and traffic volume because of the decoupling of the two variables. This will be addressed in future developments of the model. Consideration should also be given to whether interventions aimed at traffic speed (or traffic volume) affect separately its distributional properties (eg, mean and variance).

Another limitation of the model is that it represents steady-state conditions, which ignore situations during rush hours and differences between day-time and night-time. Non-steady-state conditions will also be considered in subsequent model developments.

The pedestrian dynamics model is characterized by three parameters that reflect pedestrian behavior. The parameters were assumed to be independent of each other (and of the vehicle traffic parameters), but some of them could be correlated (eg, speed of pedestrian crossing and the distance between a pedestrian and an incoming vehicle at the moment of crossing

Table 6 Number of casualties per 100 000 population obtained from 100 independent sets of 10 000 MC simulations

Scenario	No of casualties/100 000 population
Baseline	87.5 (85.1 to 89.9)
1 (Traffic speed)	67.2 (65.0 to 69.4)
2 (Traffic volume)	74.4 (72.0 to 76.4)
3 (Vehicle mass – 15%)	86.4 (84.0 to 88.8)
4 (Vehicle mass – 25%)	85.6 (83.3 to 87.9)

Values are mean (95% CI).

initiation). “Erratic” driver behavior can be modeled, for example, by choosing a probability distribution function that emphasizes multiple modes to describe erratic fluctuations in vehicle speed.

In the severity of pedestrian injury model, vehicle speed at impact was considered to be the main determinant of severity. A mechanistic model of severity of pedestrian injury during a crash could be constructed to take into account the main determinants of injury severity other than vehicle speed such as front-end structure of the vehicle^{25–27} and vehicle mass.²⁸

The model caters for a wide range of interventions in addition to those aimed at traffic speed and traffic volume. The model comprises many parameters that depend on environmental and behavior factors. Interventions targeted at those factors can be modeled mathematically by changing the distributional properties of the relevant parameters. For example, the effect of providing road safety literature to school children would be modeled through modification of the distributional parameters of the crossing rate and speed of crossing. When implemented using a user-friendly interface, the model can be used by policy makers as a decision support tool by varying the parameters of the model and analyzing the changes in injury rates.

While fully acknowledging the desirability of reducing the above limitations in future developments of the model, we stress that our aim is to provide a generic decision support tool for use at present. Therefore, the appropriate comparator for any evaluation is the best alternative model with the same

Key points

- ▶ Transport policy decisions can have a major impact on pedestrian injury risk. Controlled trials can be conducted to determine the impact but there are many practical, political, and financial obstacles to conducting such studies, and decisions usually have to be made in their absence.
- ▶ Mathematical models can be used to evaluate and compare the health effects of alternative transport policies on pedestrian injury risk. However, if they are to support a typical transport authority in making decisions within its normal time, resource, and evidence constraints, there will be an inevitable trade-off between the scientific completeness and rigor of the model and its practical usefulness.
- ▶ A model has been developed to simulate pedestrian injury under different scenarios as part of a generic decision analytic support tool for the assessment of alternative policies by transport authorities.
- ▶ Model simulations with a specific dataset showed substantial injury reductions from lower vehicle speeds but also from reductions in traffic volume.

practical aim—of which we are aware of none—rather than a hypothetical model that is ideal by scientific standards for a particular situation.

IMPLICATIONS FOR PREVENTION

The above model is a first step towards constructing a full decision analytic support tool for evaluation of the effectiveness and cost-effectiveness of alternative transport policies under time, resource, and evidence constraints. In its present form, the model can be used to compare the health impacts of abstract policies (eg, reducing traffic speed) rather than concrete interventions (eg, imposing traffic speed restrictions). Quantifying the effectiveness of the latter of course requires a further layer of modeling.

Acknowledgements: This work was carried out as part of a European Commission (EC) grant on “Strategies and best practices for the reduction of injuries” (Apollo) under Grant Agreement 2004119. The financial support of the EC is greatly acknowledged. We are grateful to our colleagues in Work package 5 of the Apollo Project for their support in the development of the model. London road casualty data were supplied by the London Road Safety Unit, Transport for London.

Competing interests: None declared.

REFERENCES

- Jacobs G, Aeron-Thomas A, Astrop A. *Estimating global road fatalities*. Crowthorne: Transport Research Laboratory, 2000:TRL Report Number 445
- Dora C, Racioppi F. Including health in transport policy agendas: the role of the health impact assessment analyses and procedures in the European experience. *Bull World Health Organ* 2003;**81**:399–403.
- Babendreier JE, Castleton KJ. Investigating uncertainty and sensitivity in integrated, multimedia environmental models: tools for FRAMES-3MIRA. *Environmental Modelling & Software* 2005;**20**:1043–55.
- Price PS, Curry CL, Goodrum PE, et al. Monte Carlo modelling of time-dependent exposures using a microexposure event approach. *Risk Anal* 1996;**16**:339–48.
- Ceder A. *Transportation and traffic theory*. Amsterdam: Pergamon, 1999.
- Chowdhury D, Santen L, Schadschneider A. Statistical physics of vehicular traffic and some related systems. *Phys Rep* 2000;**329**:199–329.
- Schadschneider A. Traffic flow: a statistical physics point of view. *Physica A* 2002;**313**:153–87.
- Kachroo P, Ozbay K. *Feedback control theory for dynamic traffic assignment*. London: Springer, 1999.
- Tang T-Q, Huang H-J, Gao Z-Y. Stability of the car-following model on two lanes. *Phys Rev E* 2005;**72**:066124 (1–12).
- Treiber M, Kesting A, Helbing D. Delays, inaccuracies and anticipation in microscopic traffic models. *Physica A* 2006;**360**:71–88.
- Lebacque JP, Lesort JB. Macroscopic traffic flow models: a question of order. In: Ceder A, ed. *Transportation and traffic theory*. Amsterdam: Pergamon, 1999:3–25.
- Burstedde C, Klauck K, Schadschneider A, et al. Simulation of pedestrian dynamics using a two-dimensional cellular automaton. *Physica A* 2001;**295**:507–25.
- Helbing D, Buzna L, Johansson A, et al. Self-organized pedestrian crowd dynamics: experiments, simulations, and design solutions. *Transportation Science* 2005;**39**:1–24.
- Helbing D, Farkas I, Vicsek T. Simulating dynamical features of escape panic. *Nature* 2000;**407**:487–90.
- Helbing D, Farkas I, Vicsek T. Freezing by heating in a driven mesoscopic system. *Phys Rev Lett* 2000;**84**:1240–3.
- Helbing D, Molnar P. Social force model for pedestrian dynamics. *Phys Rev E* 1995;**51**:4282–5.
- Schreckenberg M, Sharma SD. *Pedestrian and evacuation dynamics*. Berlin: Springer-Verlag, 2002.
- Stanley HE. Freezing by heating. *Nature* 2000;**404**:718–19.
- Jiang R, Wu Q, Li X. Capacity drop due to the traverse of pedestrians. *Phys Rev E* 2002;**65**:036120.
- Anderson RWG, McLean AJ, Farmer MJB, et al. Vehicle travel speeds and the incidence of fatal pedestrian crashes. *Accid Anal Prev* 1997;**29**:667–74.
- Davis GA. Relating severity of pedestrian injury to impact speed in vehicle-pedestrian crashes. *Transportation Research Record* 2001;**1773**:108–13.
- Han I, Brach RM. Impact throw model for vehicle-pedestrian collision reconstruction. *Proceedings of the Institution of Mechanical Engineers. Part D: Journal of Automobile Engineering* 2002;**216**:443–53.
- Liu XJ, Yang JK, Lovsund P. A study of influences of vehicle speed and front structure on pedestrian impact responses using mathematical models. *Traffic Inj Prev* 2002;**3**:31–42.
- Wood DP, Simms CK, Walsh DG. Vehicle-pedestrian collisions: validated models for pedestrian impact and projection. *Proceedings of the Institution of Mechanical Engineers. Part D: Journal of Automobile Engineering* 2005;**219**:183–95.
- Lefler DE, Gabler HC. The fatality and injury risk of light truck impacts with pedestrians in the United States. *Accid Anal Prev* 2004;**36**:295–304.
- Roudsari BS, Mock CN, Kaufman R, et al. Pedestrian crashes: higher injury severity and mortality rate for light truck vehicles compared with passenger vehicles. *Inj Prev* 2004;**10**:154–8.
- Simms C, O'Neill D. Sports utility vehicles and older pedestrians. A damaging collision. *BMJ* 2005;**331**:787–8.
- Robertson L. Blood and oil: vehicle characteristics in relation to fatality risk and fuel economy *Am J Public Health* 2006;**96**:1906–9.
- DfT. Local Transport Note 2/95. The design of pedestrian crossings. London: Department for Transport, 1995.
- Dunbar G, Holland CA, Maylor EA. Road Safety Research Report No 37. Older pedestrians: a critical review of the literature. London: Department for Transport, 2004.
- TfL. London Travel Report 2003. London: Transport for London, 2003.
- TfL. Congestion charging: First Annual Report-Congestion. London: Transport for London, 2004.

Access the latest content chosen by our Editors

BMJ Journals editors select an article from each issue to be made free online immediately on publication. Other material is free after 12 months to non-subscribers. Access the Editor's Choice from the home page—or expand your horizons and see what the other BMJ Journals editors have chosen by following the links on any BMJ Journal home page.