



### Statistical Issues in Road Safety: Evaluation of Safety Measures

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### Why statistics in road safety research?

Our questions are not simple:

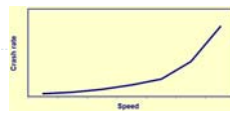
- ▶ When and how accidents occur?
  - ▶ Understanding a situation → observe & estimate
- ▶ Why accidents occur?
  - ▶ Understanding relationships → observe & estimate; association models
- ▶ What can affect occurrence of accidents?
  - ▶ Evaluation of actions → experimental studies; intervene and then observe & estimate; → test effectiveness

Exposure → Outcome  
Action → Outcome

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### Exercise

▶ Research Question:  
Do lower speeds lead to safer roads?



▶ How do we answer this question?

- ▶ What type of study?
- ▶ How we define 'lower'? How do we define 'safer'?
- ▶ Who or what do we study? How many?
- ▶ Who or what do we compare results to? How many?
- ▶ What data do we collect? How do we measure it? When do we measure? For how long do we measure?
- ▶ What is a meaningful relationship?
- ▶ How can we know if what we observe could have been due to chance?

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### RQ: Do lower speeds lead to safer roads?

- ▶ What do you need to do first?
- ▶ Must recognize the 'sources of variability'
  - ▶ Type of road – i.e. 2-way, straight sector, intersection
  - ▶ Traffic volume?
  - ▶ Presence of median?
  - ▶ What other factors? → consider Haddon Matrix

		Haddon Matrix			
		HOST	AGENT	HOSTELITY/ENVIRONMENT	DEFENSIBILITY
Pre-crash	Crash prevention	Education, attitude, experience, police enforcement	Human resources, lighting, signaling, speed management	Road design and road layout, speed limit, pedestrian facilities	
Crash	Crash prevention during the crash	Use of personal equipment	Occupant restraint, other safety, passive restraint, protective design	Crash avoidance, roadside impacts	
Post-crash	Life saving	First aid, first aid, access to medical	Level of access, first aid	Rescue facilities, transportation	

Figure 8.3 The Haddon Matrix for road safety (WHO 2006, Road Safety Training Manual, Unit 2).

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### RQ: Do lower speeds lead to safer roads?

- ▶ What do you need to do next?
- ▶ Type of intervention?
  - ▶ How will you lower speeds? – Traffic calming? Car limits? Road limits?
  - ▶ How much lower?
  - ▶ Other structural aspects may have a confounding effect!
  - ▶ How do you know what works?

A Review of Evidence-Based Traffic Engineering Measures Designed to Reduce Pedestrian–Motor Vehicle Crashes

Evidence-based interventions for road traffic injuries in South Asia. *Mathan D.*

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### RQ: Do lower speeds lead to fewer road transport crashes?

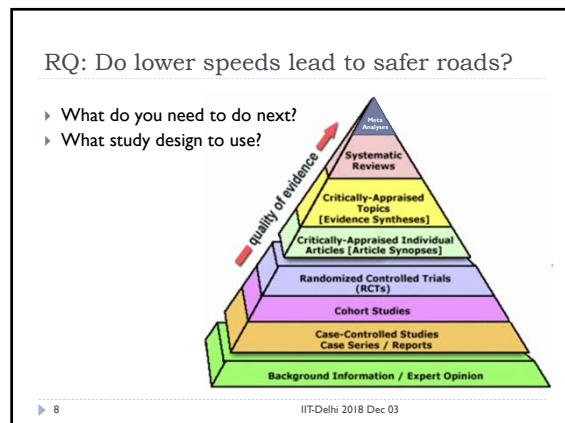
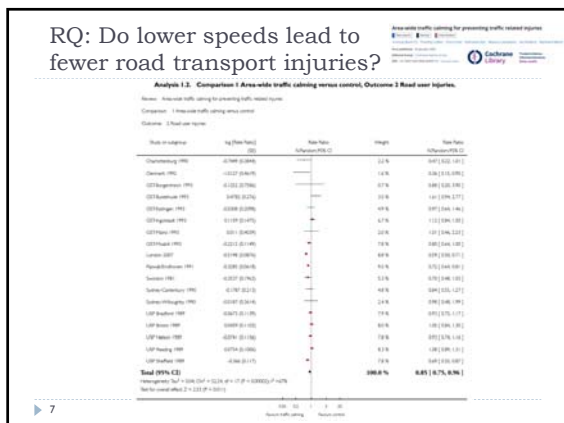
Analysis 1.3. Comparison 1 Area-wide traffic calming versus control, Outcome 3 Road traffic crashes.

Notes: Area-wide traffic calming for preventing traffic-related injuries  
Comparison: 1 Area-wide traffic calming versus control  
Outcome: 3 Road traffic crashes

Study or subgroup	log (Rate Ratio)	SD	Rate Ratio	Weight	Rate Ratio
Cherchenberg 1993	-0.289 (0.140)	0.140	0.75	91%	0.75 (0.57, 0.99)
GST-Burgesswick 1993	0.289 (0.304)	0.304	1.78	3.8%	1.78 (0.86, 3.42)
GST-Burgesswick 1993	-0.289 (0.075)	0.075	0.75	10.4%	0.75 (0.76, 1.12)
GST-Bozinger 1993	0.113 (0.025)	0.025	1.12	10.9%	1.12 (0.96, 1.37)
GST-Engelach 1993	0.276 (0.049)	0.049	1.32	11.3%	1.32 (1.15, 1.51)
GST-Flanze 1993	-0.191 (0.017)	0.017	0.82	11.8%	0.82 (0.75, 1.05)
GST-Flanze 1993	-0.299 (0.042)	0.042	0.74	11.8%	0.74 (0.74, 0.86)
London 2007	-0.503 (0.074)	0.074	0.61	10.4%	0.61 (0.50, 0.75)
PT int. 12001	0.296 (1.024)	1.024	1.34	0.4%	1.34 (0.60, 0.93)
Osaka 1993	-0.411 (0.294)	0.294	0.67	3.4%	0.67 (0.41, 1.04)
Sydney-Camberley 1993	-0.402 (0.170)	0.170	0.67	14.3%	0.67 (0.48, 0.94)
Sydney-Hillheights 1993	-0.302 (0.182)	0.182	0.74	7.4%	0.74 (0.55, 1.00)
<b>Total (95% CI)</b>			<b>0.69</b>	<b>100.0%</b>	<b>0.69 (0.76, 1.05)</b>

Heterogeneity:  $I^2 = 0.0$ ,  $Chi^2 = 74.0$ ,  $df = 11$ ,  $P < 0.00001$ ,  $I^2 = 40.6$   
Test for overall effect:  $Z = 1.38$ ,  $P = 0.17$

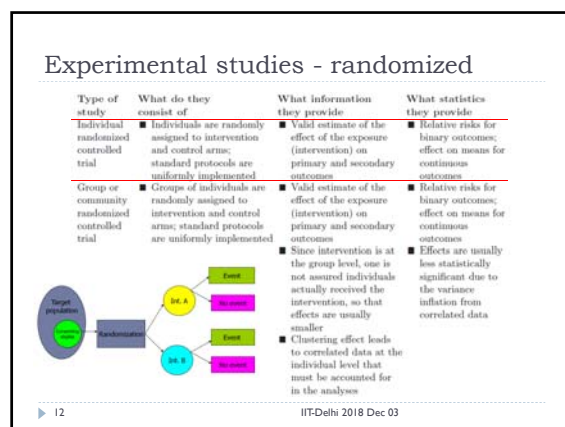
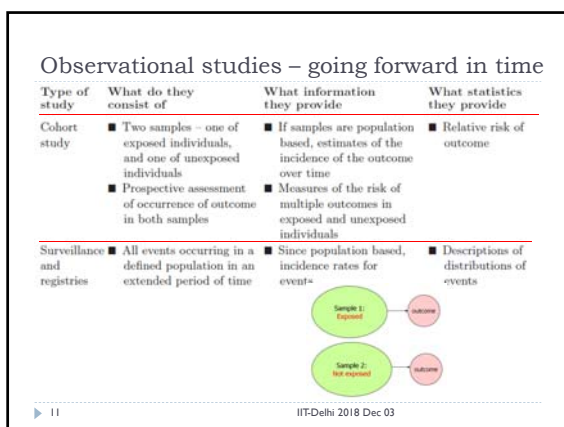
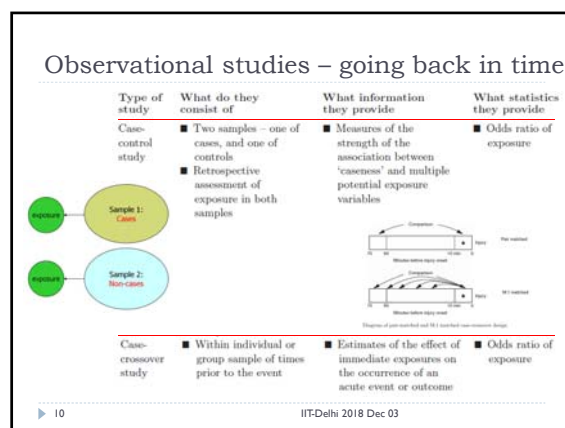
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### Observational studies – in a given time period

Type of study	What do they consist of	What information they provide	What statistics they provide
Case series	In-depth examination of a few number of cases	Presence or absence of multiple factors in cases	Descriptions of distribution of risk factors
Cross-sectional study	A sample from a population at a given moment in time	If sample is population based, estimates of the prevalence of the outcome Measures of the association among concurrently measured variables	Correlations for continuous variables; odds ratio of exposure or of outcome for categorical variables

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### Experimental studies - randomized

Novel group randomized designs for injury research

- Cluster cross-over: reversible policy

- Stepped-wedge: environmental changes

	T0	T1	T2	T3	T4	T5	T6
Control	Int.	Int.	Int.	Int.	Int.	Int.	Int.
Control	Control	Control	Int.	Int.	Int.	Int.	Int.
Control	Control	Control	Control	Int.	Int.	Int.	Int.
Control	Control	Control	Control	Control	Int.	Int.	Int.
Control	Control	Control	Control	Control	Control	Int.	Int.
Control	Control	Control	Control	Control	Control	Control	Int.

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### Experimental studies – non-randomized

Type of study	What do they consist of	What information they provide	What statistics they provide
Non-randomized comparison intervention study	<ul style="list-style-type: none"> <li>Groups or individuals receive different interventions, but are not randomly assigned; they are self-selected to exposure</li> </ul>	<ul style="list-style-type: none"> <li>Biased estimate of the effect of the exposure (intervention) on primary and secondary outcomes</li> </ul>	<ul style="list-style-type: none"> <li>Relative risks for binary outcomes; effect on means for continuous outcomes</li> </ul>
Within-person or within-group before after study	<ul style="list-style-type: none"> <li>A single individual or group acts as its own counterfactual – the outcome after the intervention is compared to the outcome before</li> </ul>	<ul style="list-style-type: none"> <li>Within-person or within-group changes due to the exposure (intervention)</li> <li>If there are multiple measures before and after</li> </ul>	<ul style="list-style-type: none"> <li>Mean change score for continuous outcomes; McNemar's test for binary outcomes</li> <li>Regression trends before and after</li> </ul>

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### RQ: Do lower speeds lead to safer roads?

- What do you need to do next?
- How 'fewer' is meaningful?
- How to account for variability and the role of chance? → sample size !! – HOW MANY?
- It depends!

**For estimation**

The necessary sample size n when estimating the effect of an intervention in a given group is

- higher if want higher level of confidence
- higher if want higher precision = lower half-width of confidence interval
- higher if there is more variability

Conceptually

$$n \propto \frac{(\text{confidence}) (\text{variability})}{(\text{width})^2}$$

**For testing**

The necessary sample size n when testing the effect on an intervention is

- higher if want lower level of significance
- higher if want higher power
- higher if differences to detect are smaller
- higher if there is more variability

Conceptually

$$n \propto \frac{(\text{power}) (\text{variability})}{(\text{significance}) (\text{differences})^2}$$

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### RQ: Do lower speeds lead to safer roads?

- What do you need to do next?
- How analyses will be done?
  - Based on study design
  - Based on types of variables
  - based on research question/hypothesis!

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### Statistical inference

- Estimation** of a parameter in a sample → subject to sampling error, measurement error
- Inference** from the sample information to knowledge about a population → based on the design, but subject to sampling error, measurement error, and chance
  - We quantify this chance by assuming a probability model
    - Using indirect proof → formal statistical hypothesis testing
    - Using imprecision estimates → construction of confidence intervals

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### Statistical analysis - estimation

Understand the effects of variability and chance on what we observe

- e.g. % injured (± variability)
  - Planning - How many events should I study, how long should I study a situation
- e.g. mean time commuting (± variability)
  - Planning – Would a drop in 10minutes be meaningful? Can I achieve this with my actions?

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### Confidence intervals

**Limits on precision:**

- Specify a lower bound and an upper bound within which we are highly confident the true (unknown) value of the parameter lies
- The interval is centered around our point estimate
- The width of the confidence interval
  - Increases with our desire for bigger confidence
  - Is larger if there is larger variability ('noise' in the system)
  - Is smaller if based on larger sample sizes

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### Example

Are 16-year-old drivers with teenager passengers at higher risk of a crash than without other passenger?

$$\text{Relative risk} = \frac{T_{16}A_{30-59}}{T_{30-59}A_{16}}$$

where  
 $T$  = number of crash involvements for the target age driver (e.g. 16-year-old drivers),  
 $A$  = number of crash involvements for adult drivers aged 30-59 (i.e. the base driver group),  
 $f$  = at-fault involvements, and  
 $nf$  = not-at-fault involvements.

Table 5. Relative risk of fatal crash involvement by driver age and passenger presence (FARS, 1995-1995)

Driver age	Relative risk					
	All	95% confidence intervals	Driver alone	95% confidence intervals	With passengers	95% confidence intervals
16	3.28	3.07-3.51	3.28	2.99-3.59	4.72	4.32-5.13
17	2.45	2.32-2.59	1.77	1.68-1.87	3.52	3.29-3.75
18	2.47	2.36-2.59	1.77	1.65-1.90	3.66	3.40-3.93
19	2.19	2.08-2.30	1.61	1.50-1.72	3.23	3.01-3.47
20-24	1.86	1.82-1.91	1.50	1.45-1.55	2.54	2.45-2.64
25-29	1.41	1.38-1.45	1.28	1.24-1.32	1.89	1.82-1.98
30-59*	1.00		1.00		1.00	
60-69	1.03	1.00-1.07	1.13	1.08-1.18	0.91	0.87-0.96
70+	2.09	2.02-2.16	2.27	2.17-2.37	1.93	1.84-2.03

Prusser et al (1998). The effect of teenage passengers on the fatal crash risk of teenage drivers. *Accident Analysis & Prevention*

\*The 30-59 age group is the reference group for relative risk calculations.

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### Example - chance from sampling

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### Statistical hypothesis testing

**Indirect proof:**

- Specify a 'null' hypothesis ('status quo') and an 'alternative' hypothesis (our claim)
  - e.g. risk of 16-year old drivers with teenage passengers
    - $H_0$ : relative risk = 1
    - $H_A$ : relative risk > 1
- Assume the null is correct
- Observe reality (collect data) and see if it conforms with the null being in operation →
  - If probability of observing more  $H_A$  favorable data than what we found is **small**, we have evidence to reject the  $H_0$
  - If probability of observing more  $H_A$  favorable data than what we found is **not small**, our data are consistent with  $H_0$

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### Hypothetical example: Is this driver drunk → evidence?

- Hypotheses**
  - $H_0$ : driver **is not** drunk (innocent)
  - $H_A$ : driver **is** drunk (guilty)
- If evidence is strong supporting drunkenness → declared guilty
- If evidence is weak supporting drunkenness → declared not guilty

**Example of evidence in increasingly incriminating order**

- Non-erratic driving behavior
- Driving behavior was erratic
- Driving behavior led to collision
- Driver cannot write name
- Driver has slurred speech
- Driver smells of alcohol
- Driver cannot do 'nose test'
- Driver cannot write name
- Driver cannot write name
- Driver cannot write name
- Driving behavior was erratic
- Non-erratic driving behavior
- Driver's BAC is high

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### Hypothetical example: Is this driver drunk → evidence?

P-value = probability of an observation that is as or more 'extreme' than the one observed, under the null hypothesis

- Driver's BAC is high
- Driver cannot do 'standing 4 test'
- Driver cannot do 'nose test'
- Driver smells of alcohol
- Driver cannot write name
- Driver cannot write name
- Driver cannot write name
- Driving behavior was erratic
- Non-erratic driving behavior

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### Dealing with multiple factors

- ▶ **By study design**
  - ▶ Experimental designs – control most factors, let few (one) vary
  - ▶ Observational designs – control few factors, most do vary
- ▶ **By analysis methods**
  - ▶ Stratified analysis – study within similar groups – not always possible
  - ▶ Regression modeling – adjust for variation of several factors

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### Design vs. Analysis


- ▶ **When we control a lot of potential explanatory factors by design, it is not necessary to control much in analysis**
  - ▶ e.g. randomized controlled trials
- ▶ **But when we cannot control much by design, as in observational studies, we need to control variability at the analysis**
  - ▶ Stratified analysis
  - ▶ Multivariate regression models

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### Dealing with complexities

- ▶ Multiple factors operate on the systems we study
- ▶ We build models – approximations to reality
  - ▶ Risk models – probability distributions
  - ▶ Sampling models – study designs
  - ▶ Regression models – complex systems, relationships

**"essentially, all models are wrong, but some are useful"**

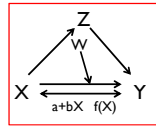


Box, George E. P. & Norman R. Draper (1987). Statistical Model Building and Regression Analysis. 2nd Edition.

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### Modeling relationships

- ▶ Interest is in studying the relationship between two variables:
  - ▶ Y = dependent variable
  - ▶ X = independent variable
- ▶ **How are they related?**
  - ▶ Association vs causation
  - ▶ Directly or indirectly (mediated, confounded)
  - ▶ Unencumbered or moderated (modified, interacted)
  - ▶ Linearly or non-linearly
  - ▶ → Complex system!



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### Techniques used in statistical modeling

- ▶ **The world is complex!!**
  - ▶ Relationships may not be linear: but may be approximately linear in a narrow range of X
  - ▶ There are multiple variables potentially acting on the relationship: control for them by design or by 'excluding' the variable by limiting the population studied
  - ▶ There is lots of variability: study more so that the 'signal' can be detected despite the 'noise'

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### Example of bivariate relationship

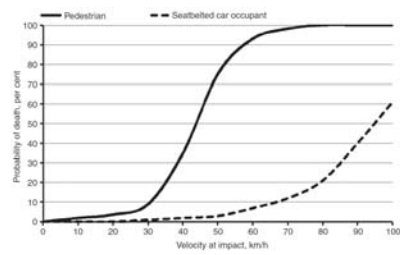


Figure 9.2 Probability of pedestrian and seat-belted car occupant fatality at different impact velocities (adapted from References Peden et al 2004; Anderson et al 1997; Groen 2000; Fisher et al 2011, 1987; Evans 1996).

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### Models

- ▶ **Multiplicative models – linearized to be fitted**
- ▶ **Simple**
  - ▶ Fatality rate = deaths/population
  - ▶ Motorization = vehicles/population
  - ▶ Traffic risk = deaths/vehicles  
→  $D/P = V/P * D/V$
- ▶ **Complex**
  - ▶ Exponential, mathematical: e.g. Oppé/Koornstra/Lassarre models
  - ▶ Linear models with multiple factors: e.g. statistical regression
  - ▶ Non-linear with multiple factors: structural equation models (SEM), classification and regression trees (CART), ...

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### Concepts of a ‘good’ statistical model

- ▶ Concept of ‘model should lie among the observed data points’ → **goodness of fit**
  - ▶ Minimizing ‘residuals’ – specifically the sum of squares of residuals
- ▶ Concept of ‘model should enhance understanding of the relationship’ → **interpretation** must be plausible
  - ▶ Structural equation models
  - ▶ Mathematical relationships based on engineering, physics

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### Comprehensive model

- ▶ Vogt A and JG Bared, “Accident Models for Two-Lane Rural Segments and Intersection,” *Transportation Research Record 1635*, Transportation Research Board, 1998.
- ▶ Developed accident prediction models that take into account the effects of multiple design elements (horizontal, vertical, cross sectional, etc.). The roads are **two-lane rural roads without medians**.

$$\hat{y} = EXPO \times \exp(0.65 + 0.14 STATE - 0.085 LW - 0.059 SIW + 0.067 RHR + 0.0085 DD) \times \left[ \sum_i WH \{i\} \exp(0.045 DEG \{i\}) \right] \times \left[ \sum_j WV \{j\} \exp(0.44 V \{j\}) \right] \times \left[ \sum_k WG \{k\} \exp(0.11 GR \{k\}) \right]$$

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### Width & Speed


Department of Transportation Federal Highway Administration safety.fhwa.dot.gov/geometric/pubs/widthandspeed/Chapter11\_lanewidth.htm

- ▶ Speed is a primary consideration when evaluating potential adverse impacts of lane width on safety. **On high-speed, rural two-lane highways**, an increased risk of cross-centerline head-on or cross-centerline sideswipe crashes is a concern because drivers may have more difficulty staying within the travel lane.
- ▶ **In a reduced-speed urban environment**, the effects of reduced lane width are different. On such facilities, the risk of lane-departure crashes is less. The design objective is often how to best distribute limited cross-sectional width to maximize safety for a wide variety of roadway users. Narrower lane widths may be chosen to manage or reduce speed and shorten crossing distances for pedestrians. Lane widths may be adjusted to incorporate other cross-sectional elements, such as medians for access control, bike lanes, on-street parking, transit stops, and landscaping.

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### Statistical model

**adjustment** vs **interpretation**



predictive model	vs	association models
focus on GOF	vs	focus on plausibility
statisticians	road safety researchers	social scientists

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### Model building

All statistical models are based on **assumptions**:

- ▶ X's measured with no errors
- ▶ Observations are independent
- ▶ Observations are identically distributed

Typically, also

- ▶ **Linearity**
- ▶ A distribution for the errors
  - Homoscedasticity
  - Gaussian, Poisson, Logistic, Negative Binomial, ...

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### Linear, logistic, Poisson and Cox models

- ▶ If outcome is measured on a continuous scale – e.g. AIS score  

$$Y_{AIS} = \beta_0 + \beta_1(\text{speed}) + \beta_2(\text{protective gear}) + \beta_3(\text{age}) + e$$
- ▶ If outcome is a proportion between 0-100 – e.g. probability of seat belt use  

$$\ln \text{Odds of Risk} = \ln[\text{Pr}(Use=1) / \text{Pr}(Use=0)] = \beta_0 + \beta_1(\text{fine\$}) + \beta_2(\text{gender}) + e$$
- ▶ If outcome is a count of events – e.g. number of crashes in a given area over a certain period  

$$\ln Y_{inj} = \beta_0 + \beta_1(\text{traffic mix}) + \beta_2(\text{road}) + e$$
- ▶ If outcome is time to the occurrence on an event – e.g. time to first crash of newly licensed males  

$$\text{Risk} = \text{Pr}(Y_{crash} < t) = 1 - e^{-\int_0^t h(u) du} \quad \text{where } \ln h(t) = \ln h_0(t) + \beta_0 + \beta_1(\text{training}) + e$$

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### Key points

- ▶ Life is complex → Transport systems are complex
- ▶ Must understand **sources of variability that lead to uncertainty** → statistics
- ▶ Statistical considerations determine research study designs appropriate to answer specific research questions
- ▶ Injury information has unique features → appropriate statistical methods are necessary
- ▶ Types of research questions:
  - ▶ Diagnosis → observational studies
  - ▶ Evaluation → experimental studies

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### Key points

- ▶ Statistical methods for inference help us
  - ▶ 'See the signal amidst the noise'
  - ▶ Understand information in the presence of uncertainty from variability and chance
  - ▶ Assuming data is of quality!
- ▶ We construct models to 'make sense out of reality' ("what structures gave us these data")
- ▶ **All models are simplifications of reality → have limitations stemming from assumptions**
  - ▶ Statistical models incorporate **uncertainty (chance) and variability**
- ▶ Models to evaluate effectiveness of interventions

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### Thanks!



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