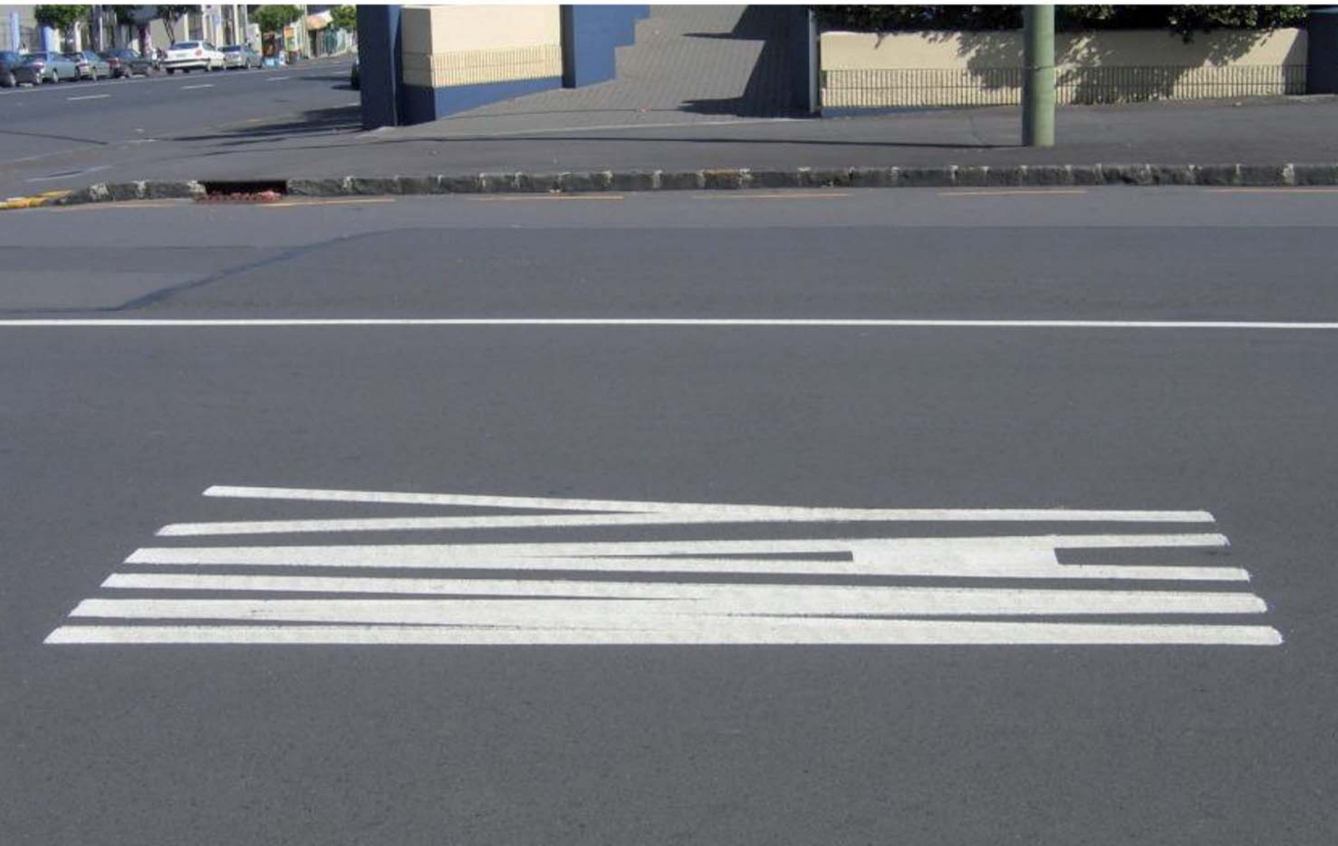
SECOND EDITION

TRAFFIC SAFETY AND HUMAN BEHAVIOR

David Shinar



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Second Edition

BY

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INVESTOR IN PEOPLE

To

Naomi and Yuval, who contributed by just being and by giving me a new perspective on life. May all the safety issues raised here be resolved by the time they can read this.

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Contents

Preface to the Second Edition

> "Understanding the human side of driving is critical for making large-scale improvements in traffic safety." (Njord and Steudle, 2015, p. 3).

This second edition came into being as a result of a confluence of three factors: the publisher's suggestion that it is time for an update, my entry into a new phase of my professional life (emeritus), and my realization that in the past 10 years there has been a most significant expansion in our knowledge about driving and safety. Much of the new research was spurred by changing cultural norms that emphasize sustainability (including sustainable safety), and from gradually evolving perceptions concerning the critical issues of safety and mobility. Let me elaborate here about the last – more substantive – factors: added knowledge, cultural change in our norms, and change in the critical issues of road users' behavior in the context of traffic safety.

In terms of cumulative knowledge, we have experienced (and are still experiencing) an explosion of interest and empirical research related to the safety of mobility: driving, riding, and walking. Prior to the first edition of this book, I was able to find only 17 books that were directly related to road safety. But in the 10 years since the publication of the first edition in 2007, 28 more book have been added to the list. The books, of course, only reflect the tip of the publications iceberg. There is a much greater increase in dedicated scientific conferences and refereed articles of original research. For example, Google Scholar lists approximately 62,000 articles containing all the words "road," "safety," "behavior," and "driving or riding" published prior to 2007, and over 70,000 in the 9 years since then. Narrowing the search scope to the combination of "traffic safety" and "human behavior" yields approximately 2,300 articles published prior to 2007, and over 3,000 since then. As cynical as one might be about the plethora of new and not-so-significant articles, with such a wealth of information there are bound to be some novel and unexpected findings. And there are. Consequently, each of the book chapters has been supplemented with new findings that either confirm previously drawn conclusions or refute them and merit new thinking.

The cultural shift was a gradual one that started in the last century and gained normative acceptance in this last decade. In the past, traffic crashes – invariably labeled as accidents – and injuries were accepted as part of the cost of mobility. But Sweden's 1997 policy shift to "Vision Zero" meaning striving toward zero traffic fatalities, was the harbinger of the new norm of zero tolerance for road fatalities. This has been translated to a practical yet aggressive goal for continued reduction traffic fatalities. This goal, common to both national and international institutions is to cut fatalities by 50 percent every 10 years. Commitment to such a demanding goal requires close cooperation among different agencies and careful considerations of the impact of changes in the traffic system on the behavior of its road users. These implications are discussed in nearly every chapter.

Finally, within the realm of traffic safety and human behavior the specific "hot" issues of concern, and approaches to crash prevention and injury reductions have also changed over the past decade. For example, interest and research in aggressive driving and its contribution to crashes peaked around 2004-2005 while I was writing the first edition of this book. But the interest in distracted driving was nearly nil before 2009 and has been rising fast since then with no signs of abatement as of this writing (based on Google Trends). Distracted driving research – or at least the focus on it – is fueled by the constantly expanding technological communications and advanced driver assistance systems. These are brought into the cars by their manufacturers or by their drivers, and can both aid and impede safety.

Instead of the behavioral crash countermeasures – such as education, public information, and enforcement – that starred in the early part of this century, we are now increasingly looking to technology to solve our problems of speeding, driving while impaired, and distraction. Technological innovations are a rapidly growing part of the arsenal of crash countermeasures and driver assistance systems designed to keep drivers safe in their lanes with safe headways to vehicles and obstacles ahead. But the acceptance, use, and utilization of the new technologies are human behavioral issues that are discussed throughout the book. And as always with people, when their environment changes, it is naïve to assume that "all other things" will stay the same. Behavior will not, and this is illustrated in current research on driver adaptation to new support systems.

Two issues that were hardly addressed in the first edition were bicycling and the emergence of autonomous vehicles; going back to basics (locomotion through pedaling) on the one hand and jumping into the future (commanding the car) on the other hand. Increasing congestion, the desire for environmental sustainability, and renewed interest in health have catapulted bicycling to the fastest growing mode of travel. Bicycling and the interactions of bicyclists with the rest of the traffic – drivers and pedestrians – have spawned many studies that are now discussed in a dedicated chapter on bicycling behavior and safety. A special emphasis in this chapter is how to integrate cyclists into the traffic system while ensuring their safety.

The second new issue is that of the autonomous vehicle. Though autonomous vehicles had been considered nearly a century ago, at the dawn of this century it was still, for most people, a speculative issue worthy of discussion by futurologists. But the vigorous entrance of high-tech companies and automotive manufactures into this arena have made the autonomous vehicle a reality that could change our mobility and life patterns as much as the introduction of the combustion engine changed it a century ago. Contrary to "common sense" the autonomous vehicle does not make driving a non-sequitur. Instead, the expected need of human control and rapid intervention in unforeseen critical situations make this a complex issue as far as human-vehicle interactions (and distraction) are concerned. This has significant implications for injury reduction and crash prevention, which are discussed in the last chapter.

Two significant research methods have contributed greatly to new knowledge and new conclusions concerning driving behavior and traffic safety: the use of naturalistic driving studies (NDS) and the technique of meta-analysis (MA). NDS is the ultimate ecologically valid study of road user behavior because it tracks road users as they move through traffic in their own vehicles going about their own business. Meta-analysis is a technique that synthesizes the results of multiple studies which have addressed the same issue using similar methods and outcome measures, to provide a robust measure of an effect or a countermeasure. As often happens in empirical research, the application of these methods – in different domains – either confirmed previous tentative less robust conclusions or actually debunked earlier misconceptions. The two techniques are described in Chapter 2, and results from their applications are evident in nearly every chapter of the book. Perhaps the most important finding from NDS, is the most recent conclusion emerging from the largest of its kind ever study of crash causation that demonstrated that even today the human factor is a critical element in over 90 percent of traffic crashes (Dingus *et al.*, 2016). In a way this provides prima facie justification for this updated text.

This second edition has the same organization as the previous one, but every chapter has been expanded to include the current relevant issues and the theoretical and empirical research to substantiate them. This edition has over 100 tables and over 200 figures, and cites over 2,500 research papers. Yet even this compendium of approximately 1,200 pages only provides a sample of the studies in this domain. The second edition provides updated research that supports and augments our knowledge of safety-relevant human limitations and capabilities (e.g., in terms of visual perception, and information processing), discusses new research methods and new findings that challenge our previous assumptions and conclusions (e.g., the nature and role of distraction, the risk of drugs, and the safety of older drivers), and discusses new topics that a decade ago did not seem as important (to me at least) as they are today (e.g., bicycling behavior and safety, and in-vehicle driver assistance systems and the autonomous vehicle). For this edition, I have significantly expanded all the chapters of the previous edition and added a chapter on bicycling. Although in the process some of the material of the previous edition was deleted, the new edition is still 50 percent longer than the first edition.

A work of this scope is rarely done without help, and this case was no exception. I would like to thank Tamar Ben-Bassat, John Eberhard, Tsippy Lotan, Ilit Oppenheim, Mike Perel, Edna Schechtman, and my wife Eva Shinar for reading and commenting on the drafts of one or more chapters. They were instrumental in forcing me to clarify some points and in uncovering and helping me correct multiple typographical, syntax, and substantive errors. The ones that remain are obviously mine to own. Finally, I thank the staff of Emerald Publishing, in particular Cristina Irving Turner, Emma Stevenson, Charlotte Hales, Nicki Dennis, and Jen McCall. Their consistent support over the past 3 years made this volume a reality.

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PART A
BACKGROUND, METHODS, AND MODELS

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1

Introduction and Background

"Citizens care about safety. There was a time when we had to force people to be safe, when regulation was the only way. The failed Ford safety campaign of the 1950s is still cited as proof that 'safety doesn't sell', but I'm here to tell you that today safety does sell. We have moved on to market-driven development, with car makers now competing for top safety scores and consumers making real buying decisions based on these scores." (Claes Tingvall, President of European New Car Assessment Program – EuroNCAP – at Transport Research Area – TRA 2006 Conference Göteborg, Norway). (http://ec.europa.eu/research/transport/news/article_4271_en.html)

"Although road traffic injuries have been a leading cause of mortality for many years, most traffic crashes are both predictable and preventable." (WHO, 2015).

Background

On August 17, 1896, Bridget Driscoll, a 44-year-old mother of two, became the first road fatality in the world from a collision with a vehicle powered by an internal combustion engine. She was hit by a car that – according to witnesses – was going at a "tremendous speed" (reported to be 4 mph). The driver of the car was Arthur Edsell who had been driving for only 3 weeks (no driving tests or licenses existed at that time). He was also said to have been talking to the young lady passenger beside him. After a 6-hour inquest, the jury returned a verdict of "Accidental Death." At the inquest, the coroner said: "This must never happen again" (Road Peace, 2004).

Whether or not Bridget Driscoll was indeed the first (true) automobile crash victim is arguable (Fallon and O'Neill, 2005), as Mary Ward was killed 27 years earlier when she fell under the wheels of an experimental steam car in 1869 (Wikipedia, August 26, 2014). The important issue is that in the course of the past 120 years, highway traffic safety has come a long way. Or has it? The purpose of this book is to describe the complexity of the issue of highway safety and the advances and difficulties encountered in this area in the past half century, from the perspective of the driving task. As will be shown in the following chapters, issues that were brought out in the above description of the first traffic accident are remarkably similar to some of the issues plaguing highway safety today: inexperience of novice drivers, speeding, distraction from non-driving tasks, vulnerability of pedestrians, labeling traffic crashes as "accidental," and – most importantly – the desire of everyone involved to eradicate highway traffic injuries and fatalities.

Highway safety and driving behavior as topics of research are much younger than the history of traffic accidents or crashes. Crashes were a very early by-product of the automobile, as illustrated in Figure 1-1, for the first driver fatality crash in England. In fact, crashes and collisions were prophesied long before the automobile actually appeared on our streets. Nearly, 500 years ago the prophetess Mother Shipton proclaimed "A Carriage without a horse shall go/Disaster fill the world with woe" (Wikipedia, 2014). Some early analyses of traffic crashes were published already in the 1930s, but they were limited to technical reports of limited circulation and remained essentially obscured (e.g., Gilutz, 1937). Arguably, the first book on the topic of traffic psychology was the *Psychology and the Motorist* by Toops and Haven, published in 1938. This book cited only three references, and only two of those dealt with driving behavior. Yet, the situation as the authors noted was already alarming. In the U.S., the authors write "some thirty nine thousand Americans annually are killed by the auto." And this was at a time when the U.S. population was below 130 million. In contrast, in 2015 there were 35,200 traffic fatalities (NHTSA, 2016a), and the U.S. population doubled to more than

Figure 1-1. Wall plaque commemorating the site of the first motor vehicle accident in which the driver was fatally injured (courtesy of author).

322 million. Despite the magnitude of the problem, the issue was largely ignored by the academic world at that time. To wit, Toops and Haven's book has been cited only three times since its publication (according to Google Scholar).

Possibly, the first commercially published monograph to focus exclusively on driver and driving behavior was Lauer's (1960) book: *The Psychology of Driving: Factors of Traffic Enforcement*. Since then the number of books and articles have increased in an exponential manner. Books on traffic safety and various aspects of driver behavior that appeared since then include *Aggression on the Road* by Parry (1968), *Vision and Highway Safety* by Allen (1970), *Human Factors in Highway Traffic Safety Research* by Forbes (1972), *Road User Behavior and Traffic Accidents* by Näätänen and Summala (1976), *Psychology on the Road: The Human Factor in Traffic Safety* by Shinar (1978), *Human Behavior and Traffic Safety* by Evans and Schwing (1985), *Traffic Safety and the Driver* by Evans (1991), *Automotive Ergonomics* by Peacock and Karwowski (1993), *Ergonomics and Safety of Intelligent Driver Interfaces* by Noy (1997), *Forensic Aspects of Vision and Highway Safety* by Allen *et al*. (1998), *Understanding Driving: Applying Cognitive Psychology to a Complex Everyday Task* by Groeger (2000), *Human Factors for Highway Engineers* by Fuller and Santos (2002), *Traffic Safety* by Evans (2004), *Handbook of Road Safety Measures* by Elvik and Vaa (2004), *Human Factors of Transport Signs* by Castro and Horberry (2004), *Human Factors in Traffic Safety* by Dewar and Olson (2007), *Traffic Safety and Human Behavior by Shinar* (2007), *The Multisensory Driver: Implications for Ergonomic Car Interface Design* by Ho and Spence (2008), *In the Company of Cars: Driving as a Social and Cultural Practice* by Redshaw (2008), *The Handbook of Road Safety Measures* (2nd edition) by Elvik *et al*. (2009), *Human Factors of Visual and Cognitive Performance in Driving* by Castro (2009), *Maintaining Safe Mobility in an Aging Society* by Eby, Molnar, and Kartje (2009), *Driver Distraction: Theory, Effects, and Mitigation* by Regan, Lee, and Young (2009), *Driver Behaviour and Accident Research Methodology: Unresolved Problems* by Wåhlberg (2009), *Motorcycling and Leisure: Understanding the PTW Rider* by Broughton and Walker (2009), *Forensic Aspects of Driver Perception and Response* by Olson, Dewar, and Farber (2010), *Driver Behaviour and Training* by Dorn (2010), *Handbook of Traffic Psychology* by Porter (2011), *Human Modelling in Assisted Transportation* by Cacciabue *et al*. (2011), *The Safety of Intelligent Driver Support Systems* by Barnard, Risser, and Krems (2011), *The Fast and the Furious: Drivers, Speed Cameras and Control in a Risk Society* by Wells (2011), *Handbook of Driving Simulation for Engineering Medicine and Psychology* by Fisher, Rizzo, *et al*. (2011), *Ergonomics in the Automotive Design Process* by Bhise (2012), *Driver Behavior and Accident Research Methodology* by af Wåhlberg (2012), *Advances in Traffic Psychology* by Sullman and Dorn (2012), *Designing Safe Road Systems: a Human Factors Perspective* by Theeuwes, van der Horst, and Kuiken (2012), *Advances in Human Aspects of Road and Rail Transportation* by Stanton (2013), *Behavioural Adaptation and Road Safety* by Rudin-Brown and Jamson (2013), *Automotive Ergonomics: Driver-Vehicle Interactions* by Gkikas (2013), *Eliminating Serious Injury and Death from Road Transport* by Johnston, Muir, and Howard (2014), *Driver Acceptance of New Technology* by Regan, Horberry, and Stevens (2014), *Communication, Public Discourse, and Road Safety Campaigns* by Guttman (2014), *Driving with Music: Cognitive-Behavioral Implications* by Brodsky (2015), *Increasing Motorcycle Conspicuity* by Rößger, Lenné, and Underwood (2015), *Human Factors in*

Automotive Engineering and Technology by Walker, Stanton, and Salmon (2015), *Human Factors in Traffic Safety* (3rd edition) by Smiley (2015), *Handbook of Driver Assistance Systems* by Winner *et al*. (2016), and *Handbook of Teen and Novice Drivers: Research, Practice, Policy, and Directions* by Fisher, Caird, *et al*. (2016).

Thus, more books have been published in the past decade – since the publication of the first edition of this book – than in all of the previous century and first 7 years of this century! A similar trend also exists in the number of published scientific studies. In an interesting quantitative summary of articles published in the open literature, Hagenzieker, Commandeur, and Bijleveld (2014) found that up until 1950 the total number of journal articles on road safety research was in the single digit range. But since then, there has been an exponential explosion such that by 2010, there were over 2,000 articles in English language alone. Furthermore, the growth was accompanied by a shift in focus from that of accident prone drivers, through multiple crash causes and systems analysis, to today's focus on theories and models of driver behavior in the context of new intelligent transport systems (ITS) and autonomous driving. It is therefore not surprising that the role of psychology and psychological concepts such as risk taking and behavioral adaptation have assumed a central role in this area (Hakkert and Gitelman, 2014; Vaa, 2014).

Definitions: Safety, accidents, and crashes

It is interesting that safety in general and highway traffic safety, in particular, are most commonly defined by their negative outcomes: crashes or accidents. In this book, I will use the two terms interchangeably, though some researchers and safety organizations distinguish between the two and prefer the term "crashes." It appears that even the public – at least the American public – does not view accidents as random uncontrollable events as the word implies. In a national U.S. survey of the term "accident" (and not just traffic accidents), Girasek (2015) found that over 80 percent of the respondents thought that accidents are preventable. Yet, only 25 percent thought that they are predictable and a similar percentage thought that they are controlled by fate. Clearly, at least in the domain of traffic safety, there is a need to distinguish between a neutral and purely descriptive term, like a crash that does not convey any preconceptions about its causes, and an accident that is a random event or an act of God. The term accident is more loaded than a crash and implies a chance event, one that is out of the driver's control and in a sense almost an act of God. If a crash is a chance event ("there but for the grace of God…"), then by implication it cannot be foreseen, and therefore cannot be prevented. If traffic crashes are indeed accidents, then how can they be studied scientifically, and how can science improve traffic safety? As I hope to show in this book crashes most often are not accidents. A similar rationale led the U.S. National Highway Traffic Safety Administration (NHTSA) to replace the term "accident" with the term "crash" in all their official documents and communications in 1996 (NHTSA, 1996). According to the U.S. National HIghway Traffic Safety Administration (NHTSA) office of the Historian, "accidents imply random activity beyond human influence and control," whereas crashes are "predictable results of specific actions." Five years later the editors of the *British Journal of Medicine* declared: "we are banning the inappropriate use of 'accident' in our pages … in favor of the descriptive and more neutral terms 'crash' and 'collision'" (Davis, 2001). Thus, in the past 50 years the use of the term "accident" has been in constant decline in scientific papers, whereas the use of the term crash has been increasing consistently (Hagenzieker *et al*., 2014). Nonetheless, since the term accident is still in common use, the two terms will be used interchangeably in this book.

Before we continue any further, we must agree on a definition of a crash or an accident. Unfortunately, this is very difficult. In the case of traffic accidents, perhaps the most commonly accepted definitions are the ones adopted by the U.S. NHTSA and the UN/ECE. According to NHTSA, a crash is "an unintended event resulting in injury or damage, involving one or more motor vehicles on a highway that is publicly maintained and open to the public for vehicular travel" (NHTSA, 1998). According to the UN/ECE accidents are events "which occurred or originated on a way or street open to public traffic; which resulted in one or more persons being killed or injured and in which at least one moving vehicle was involved" (Berns and Brühning, 1998). Although the definitions seem nearly identical, they are not, as each word that is in them – as well as every word that is not – is critical. For example, the NHTSA definition refers to "motor vehicles," whereas the OECD definition does not mention the word "motor" but does specify "moving vehicles." Thus, a collision between a bicyclist and a pedestrian would qualify as such for the OECD data, but not for the U.S. These kinds of differences create significant problems when we attempt to compare accident statistics across different countries, as done by the International Traffic Safety and Analysis Group that produces the International Road Traffic Accident Data Base (IRTAD) that includes data from all reporting OECD countries and some additional countries, which also vary slightly – but significantly – in their definitions (OECD, 1998). For example, most countries include only injury crashes in their database, but some include property damage crashes too (e.g., Denmark, Israel). However, these data are neither a complete census nor a representative sample. Also, even within countries there are inconsistencies in the inclusion criteria; for example, in cases of crashes resulting from police chases and suspected suicide or loss of consciousness prior to the crash. The similarity but non-identity in definitions means that when looking at international data, we may not be comparing apples and oranges, but we are definitely dealing with a wide variety of oranges (or apples). In addition, most countries do not include vehicle-related non-traffic fatalities on private properties. Thus, being crushed by a backing vehicle on a private driveway is not considered a traffic crash. Although, relative to other traffic crashes their number is small, they are still significant. In the U.S., for example, they claim the lives of approximately 500 people and injure over half a million people each year (NHTSA, 2015c). But because of their psychological impact – the victims being mostly small children – the NHTSA recently issued a regulation requiring a backup video camera and display in all vehicles produced after May 1, 2018.

Safety has come a long way in the past half century

In the western world, over the past 40 years the desire for greater traffic safety has fostered a dramatic social cultural change in norms. Forty years ago the U.S. nationwide front seat safety belt use was 15 percent, alcohol-related crashes accounted for over 50 percent of all fatal crashes, and safety was viewed by the automotive industry as something the public did not care about. In contrast, in 2012 the U.S. safety belt use in the front seats reached 86 percent (NHTSA, 2012), and in some countries (e.g., Australia, Canada, Czech Republic, France, Germany, Japan, Israel, New Zealand, Netherlands, Norway, Sweden, and the United Kingdom) it had reached 95 percent or higher (IRTAD, 2013). In 2012, in the U.S. alcohol impairment was responsible for 31 percent of traffic fatalities (NHTSA, 2013). Not surprisingly, the U.S. Centers for Disease Control listed "increased awareness and response for improving global road safety" as one of the "Ten great public health achievements worldwide: 2001−2010" (CDC, 2011). Perhaps, the most notable change has been in the regulatory and industrial emphasis on safety. In its Research, Development, and Technology Strategic Plan, the U.S. Department of Transportation listed safety as the #1 priority for the fiscal years 2013-2018, ahead of reducing congestion, improving mobility, and preserving the environment (DOT, 2013). On the automotive industry's front, Volvo has stated its safety goal as "no one should be killed or seriously injured in a new Volvo by 2020" (Eugensson, 2009; Eugensson *et al.*, 2011).

Yet, the public's attitude toward traffic safety is complex. A nationally representative survey conducted in the U.S. in 2005 (Mason-Dixon, 2005) found that safety is the single most important feature that Americans value in their personal car. At the same time the majority of the respondents in the same survey also felt that "driving today is less safe than five years ago," and that they are "more likely to be involved in a motor-vehicle collision today than five years ago." Thus, either way one looks at it − from the consumer's desires or the consumer's concerns − and despite the great advances just noted, traffic safety is of great interest to most drivers today. Similarly, in an earlier analysis of a decade of annual polls of the U.S. adult population health habits between the years 1985 and 1995, we found a steady improvement in driving-related safety habits that included significantly fewer people admitting to drinking and driving and significantly more people reporting that they regularly use safety belts (Shinar, Schechtman, and Compton, 1999). The result of all of these changes in driver attitudes and behaviors is reflected in the ever decreasing rate of traffic fatalities, which in the U.S., dropped in one decade, 2004-2014, from 1.44 to its lowest level ever of 1.08 fatalities per million vehicles miles of travel (NHTSA, 2015a, 2015b, 2016b). A similar dramatic trend of increasing highway safety has been observed in the European Union (EU) countries, as reflected in Figure 1-2, where the number of people killed in traffic accidents decreased by nearly 20 percent in the first half of this decade. Though this may be an impressive decline, it falls short of the rate of decline that is needed to meet the EU goal of a 50 percent reduction by the end of the decade.

Traffic safety must come at a cost. While we all want safer cars, safer roads, and safer road users, we often ignore the cost involved. The cost may be in terms of convenience, money, and mobility. From the perspective of driver behavior the cost is most often in terms of mobility and comfort. For example, we would like to "get there" "now" and we would like to get there safely. Well, there is a mathematically simple inverse relationship between speed and the time it takes to get from point "a" to point "b." And we are all aware of that. Unfortunately, there is also a relationship between speed and crash risk, and between speed and crash severity: the higher the speed, the higher the crash risk and crash severity (see Chapter 8). This relationship is more difficult to accept (or easier to

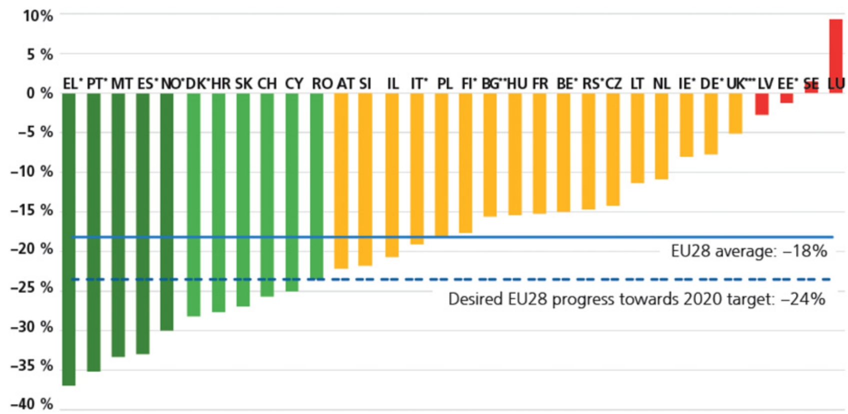

Figure 1-2. Percentage change in road traffic fatalities in 32 European Union and affiliated countries between 2010 and 2014. *Note*: Numbers for starred countries were based on estimates (from ETSC, 2015, with permission from the European Transport Safety Council, Brussels).

challenge) for many people. We can create safer cars with better energy absorption systems, better occupant protection devices (such as airbags), or occupant restraints (such as belts), but the first two cost more money and the third involves some inconvenience. Thus the claim that we all want maximum safety is really not tenable. Instead, what we all desire is to maximize other values, without exceeding a certain (hopefully low) level of crash risk (Evans, 2004; Wilde, 2002).

Scope and Measurement of Traffic Crashes and Injuries

The tremendous impact that crashes have on our society has attracted the attention of scientists, health officials, legislators, and policy makers to this issue, and in most countries significant advances have been made in curtailing accidents. However, to assess the scope of the problem and advances in safety, some standardized – or at least common – measures of the phenomenon must be agreed on.

The scope of the problem in terms of property-damage, injury, and fatal crashes

"Approximately 1.24 million people die every year on the world's roads, and another 20 to 50 million sustain nonfatal injuries as a result of road traffic crashes" (WHO, 2013a, 2013b). Unfortunately, this number has not changed significantly over the past 10 years (WHO, 2015). In contrast, in 2013 terrorists killed approximately 18,000 people worldwide or about 1.5 percent of the number killed by traffic (Kuper, 2015). World-wide traffic accidents are also the leading cause of death for people 15-29 years old, and the ninth leading cause of death across all age groups (WHO, 2015). Thus, there is an elephant in our lives that most people tend to ignore.

Defining severe injury: MAIS3+

In contrast to the specific number of traffic fatalities cited, injuries are expressed in terms of an enormous range of numbers: 20-50 million. This is because documenting and applying a standard common measure for injuries in all countries is a formidable challenge that still has to be met (Tingvall *et al*., 2013) and because relative to fatalities they are quite poorly documented (WHO, 2013a, 2013b). As a start, the EU has embarked on an effort "to devise harmonised methodologies to produce comparable data on serious injuries in due time; (because) only when their true character and frequency is assessed in a sound and uniform way, can effective road safety management mechanisms be employed (such as target setting, implementation, monitoring and evaluation)" (IRTAD, 2014, p. 25). A review of the current practices for documenting injuries in the EU countries revealed that the 23 participating countries had nearly 23 different definitions. Most of these were based on administrative criteria such as hospitalization for 24 hours or more (e.g., Belgium, France, Germany, Ireland, Israel, Portugal, Spain, Switzerland, the United Kingdom), 48 hours or more (Hungary), or overnight (Greece). In very few cases the criteria were actually based on medically accepted measures for injury severity (Finland, Netherlands, and Romania). In short, international comparisons at this stage are practically meaningless. Realizing this, the EU has adopted a common criterion of serious injury: MAIS = 3+. The MAIS is a medically determined evaluation of the Maximum Abbreviated Injury Scale. AIS scores are determined by the injury severity to nine different body regions (head, face, neck, thorax, abdomen, spine, upper extremity, lower extremity, and unspecified) on a 6-level scale of severity, ranging from 1 (minor) to 6 (maximal), where each level corresponds to a probability of death (0 at AIS = 1 and 100 at AIS = 6). The MAIS is the AIS score of the most severely injured body region. MAIS3, the level agreed on by the EU as the threshold for serious injury is associated with an 8-10 percent likelihood of death. As of 2015, most European countries have accepted this new definition of serious injury and are working toward integrating it into their crash documentation (ETSC, 2013, 2015). Once this becomes the norm, comparisons will be meaningful, and the full and true medical, societal, and financial burden will be measurable – and probably very disturbing. Nonetheless, once measured objectively and systematically, a goal for its reduction can be stated.

Consequently, for now at least, we must settle on fatalities as the common comparable measure of national and international road safety. Also, often ignored, but very relevant is the death toll from traffic-based pollution. According to the World Bank (2014), when added to the death toll from road injuries, the total toll of traffic in 2010 was 1.33 million people, making it the sixth leading cause of death.

It is important to refrain from generalizing from fatal crashes to injury and non-injury crashes, as their characteristics are quite different in speed, location, time-of-day, and the people involved. This also means that efforts at reducing traffic fatalities will not necessarily reduce traffic injuries. Because most countries focus on reducing fatalities, the trends are also different. Over long periods of time, the difference is quite dramatic. In the U.S., in the past half century (1964-2013) the death rate per vehicle miles traveled decreased by 80 percent, whereas the number of people injured decreased by 50 percent. The differences in some of the European countries are even more dramatic. For example, in the two decades from 1990 to 2009 the number of fatalities in Spain decreased by approximately

65 percent whereas the number of injuries fluctuated greatly and decreased by approximately 25 percent. In Sweden, a country known for its excellent traffic safety record, over the same period fatalities decreased by approximately 45 percent, whereas the number of injuries actually *increased* by close to 10 percent (OECD, 2010).

As the world population grows, and as cars become more and more commonplace, the number of accidents worldwide increases. According to the World Health Organization (WHO, 2005), worldwide motor vehicle accidents are the second most frequent cause of death for people 5-29 years old and "projections indicate that these figures will increase by about 65 percent over the next 20 years unless there is new commitment to prevention" (WHO, 2004). Also because traffic crashes hit people of all ages, especially young inexperienced drivers, the rising cost of crashes is also reflected in the reduced quality of life as measured by disability-adjusted life years (DALYs – see Table 1-2 for a definition). Using this measure, traffic accidents were ranked as the ninth leading cause of this global burden of disease in 1990, but was projected to become the 3rd by the year 2020 if the trend is not changed (WHO, 2004). So far this prediction seems to be valid, as in 2010 road injuries were the eighth leading cause of deaths worldwide, responsible for the loss of over 75 million DALYs (World Bank, 2014). Furthermore, while the death rate from road crashes has been constantly decreasing in the developed world (Europe and Israel, North America), in the rest of the world it is either stable (Latin America, North Africa, and the Middle East – excluding Israel) or actually increasing (Southeast Asia, Sub-Saharan Africa), as can be gleaned from Figure 1-3.

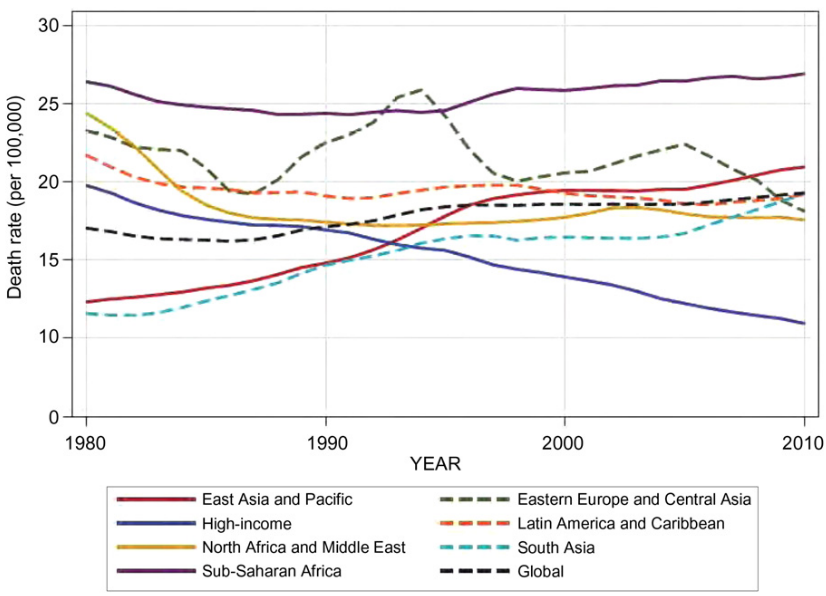

Figure 1-3. Worldwide trends in road injury death rates from 1980 to 2010 (from World Bank, 2014, p. 29, with permission from the World Bank).

Some people see this tremendous and increasing toll as an unavoidable cost of "progress." As the number of cars increases and as the world population increases, so will the number of crashes and victims. Thus, given the current trends, death from a motor vehicle crash worldwide was projected to become the fifth most common cause of death by 2030, versus its 10th place in 2015 (WHO, 2016). The data in Table 1-1, of the leading causes of death in the U.S., show that in the U.S., in terms of estimated years of life lost, this future is almost here. In fact, in 2011 motor vehicle crashes were the number one cause of death in the U.S. for people of ages 8-24 and the seventh leading cause in terms of years of life lost. The measure of "years of life lost" also has significant economic implications, especially when calculated in terms of composite measures that include the quality of life (such as DALY). Furthermore, when the analysis is restricted to unintentional injuries only, then death from motor vehicle crashes rises to the first or second leading cause of death for all age groups! (CDC, 2015).

Finally, though in this book the primary distinction is between crashes of different injury severities, it is important to acknowledge that there are other factors that define crashes, and they have critical implications for crash and injury reductions. Thus, the American National Standards Institute (ANSI, 2007) also classifies (and defines) motor vehicle traffic accidents in terms of damage severity, vehicle type, number of vehicles involved, first harmful event, location, and other variables.

Measuring safety

Since – all other things being equal – the absolute number of crashes is expected to increase over time (as the number of cars and drivers increase), trends in road fatalities are typically measured and tracked in terms of *rates* of crashes and injuries. When rates are used, the number of crashes or injuries is divided by some measure of exposure. Several different rates are often used to track changes in safety over time, each with a different exposure measure, and each providing a different measure of risk. Unfortunately, these measures of risk are often at variance with each other. This is where the use and abuse of statistics can come into play. A simple measure available in most countries is the number of crashes (or injuries or fatalities) divided by the size of the population. This measure gives the average risk per person. Another measure considers the risk per driver, and therefore uses only the number of licensed drivers in the population. However, because not all drivers have cars and by definition (in most countries at least) a traffic accident must involve a motor vehicle, a third exposure measure is the number of registered vehicles (after all, a driver without a car cannot cause a traffic accident). Finally, because only vehicles that are actually moving on the road can be involved in crashes, a fourth common measure of crash rate uses the total number of miles or kilometers driven as the denominator. With four potential denominators and at least three qualitatively different numerators – number of crashes, number of people injured, and number of fatalities – we now have 12 different indices with which we can describe the state of traffic safety in any one country. This gives policy makers a lot of room to either denounce the state of traffic safety or to congratulate themselves for the great improvements achieved on their watch. Table 1-2 provides a list of some of the

Table 1-1. Leading causes of death in the U.S. as a function of age, based on National Center for Health Statistics Mortality Data. Traffic Crashes are highlighted (from Liu, Singh, and Subramanian, 2015).

★★★★★ NHTSA www.nhtsa.gov

Top 10 Leading Causes of Death in the United States in 2011, by Age Group[1]

National Highway Traffic Safety Administration's National Center for Statistics and Analysis

RANK	Cause and Number of Deaths											Years of Life Lost[2]
	Infants Under 1	Toddlers 1–3	Young Children 4–7	Children 8–15	Youth 16–20	Young Adults 21–24	Other Adults 25–34	Other Adults 35–44	Other Adults 45–64	Elderly 65+	All Ages	
1	Perinatal Period 11,931	Congenital Anomalies 448	Malignant Neoplasms 381	**MV Traffic Crashes 785**	**MV Traffic Crashes 3,424**	**MV Traffic Crashes 3,300**	Accidental Poisoning 7,652	Malignant Neoplasms 11,717	Malignant Neoplasms 161,469	Heart Disease 475,100	Heart Disease 596,577	Malignant Neoplasms 24% (9,188,476)
2	Congenital Anomalies 5,013	Accidental Drowning 308	**MV Traffic Crashes 287**	Malignant Neoplasms 693	Suicide 2,167	Homicide 2,449	Suicide 6,100	Heart Disease 10,635	Heart Disease 105,842	Malignant Neoplasms 397,107	Malignant Neoplasms 576,691	Heart Disease 19% (7,291,475)
3	Heart Disease 309	Homicide 363	Congenital Anomalies 158	Suicide 492	Homicide 2,154	Accidental Poisoning 2,301	**MV Traffic Crashes 5,569**	Accidental Poisoning 8,075	CLRD[6] 19,678	CLRD[6] 121,869	CLRD[6] 142,943	CLRD[6] 4% (1,714,895)
4	Homicide 290	Malignant Neoplasms 259	Accidental Drowning 151	Homicide 303	Accidental Poisoning 1,109	Homicide 2,300	Homicide 4,185	Suicide 6,599	Chronic Liver Disease 19,613	Stroke 109,323	Stroke 128,932	Stroke 4% (1,429,919)
5	Influenza/ Pneumonia 204	**MV Traffic Crashes 247**	Homicide 129	Congenital Anomalies 281	Malignant Neoplasms 690	Malignant Neoplasms 801	Malignant Neoplasms 3,499	**MV Traffic Crashes 4,425**	Diabetes 18,700	Alzheimer's 84,032	Alzheimer's 84,974	Accidental Poisioning 4% (1,394,750)
6	Septicemia 178	Heart Disease 138	Exposure to Smoke/Fire 96	Heart Disease 169	Heart Disease 403	Heart Disease 564	Heart Disease 3,301	Homicide 2,519	Stroke 16,910	Diabetes 52,402	Diabetes 73,831	Suicide 4% (1,393,748)
7	Stroke 134	Influenza/ Pneumonia 101	Heart Disease 92	Accidental Drowning 163	Accidental Drowning 173	Accidental Drowning 249	HIV 636	Chronic Liver Disease 2,449	Suicide 15,427	Influenza/ Pneumonia 45,363	Nephritis/ Nephrosis 53,609	**MV Traffic Crashes 3% (1,297,257)**
8	**MV Traffic Crashes 93**	Exposure to Smoke/Fire 89	Influenza/ Pneumonia 52	CLRD[6] 113	Congenital Anomalies 212	Congenital Anomalies 184	Diabetes 666	Diabetes 1,842	Accidental Poisoning 15,379	Nephritis/ Nephrosis 37,796	Nephritis/ Nephrosis 45,591	Diabetes 3% (1,119,576)
9	Nephritis/ Nephrosis 76	MV Nontraffic Crashes[4] 79	CLRD[6] 49	MV Nontraffic Crashes[4] 84	Accidental Falls 86	Pregnancy, Child Birth 119	Influenza/ Pneumonia 530	Stroke 1,718	**MV Traffic Crashes 9,424**	Septicemia 26,746	Suicide 39,518	Perinatal Period 2% (942,864)
10	Malignant Neoplasms 70	Septicemia 55	MV Nontraffic Crashes[4] 37	Influenza/ Pneumonia 79	Influenza/ Pneumonia[5] 81	Influenza/ Pneumonia 116	Stroke 505	HIV 1,619	Nephritis/ Nephrosis 7,414	Hypertension Renal Disease 23,272	Septicemia 36,280	Chronic Liver Disease 2% (761,320)
ALL[3]	23,985	3,572	2,205	4,885	12,983	15,669	43,748	69,893	505,562	1,831,844	2,515,458	All Causes 100% (38,536,588)

Table 1-2. Commonly used measures of crash and injury rates (from WHO, 2004, p. 57, with permission from the World Health Organization).

Measure	**Description**	**Use and Limitations**
Number of injuries	Absolute figure indicating the number of people injured in road traffic crashes. Injuries sustained may be serious or slight.	Useful for planning at the local level for emergency medical services. Useful for calculating the cost of medical care. Not very useful for making comparisons. A large proportion of slight injuries are not reported.
Number of deaths	Absolute figure indicating the number of people who die as a result of a road traffic crash.	Gives a partial estimate of magnitude of the road traffic problem, in terms of deaths. Useful for planning at the local level for emergency medical services. Not useful for making comparisons.
Fatalities per 10,000 vehicles	Relative figure showing ratio of fatalities to motor vehicles.	Shows the relationship between fatalities and motor vehicles. A limited measure of travel exposure because it omits non-motorized transport and other indicators of exposure. Useful for international caparisons.
Fatalities per 100,000 population	Relative figure showing ratio of fatalities to population.	Shows the impact of road traffic crashes on human population. Useful for international comparisons.
Fatalities per vehicle-km traveled	Number of road deaths per billion kilometers traveled.	Useful for international comparisons. Does not take into account non-motorized travel.
DALYs (Disability-Adjusted Life Years)	Healthy life years lost due to disability and mortality. 1 DALY lost = 1 year of healthy life lost, due to premature death/disability.	DALYs combine both mortality and disability.

more common measures and their uses. The important point is not that one measure is better than another, but that each statement of traffic safety has to specify the type of measure used. The intelligent reader can then interpret its meaning. This is not always easy because different measures are affected by different variables that by themselves have no bearing on safety policy. For example, O'Neill and Kyrychenko (2006), demonstrated that the number of deaths per distance traveled is greatly affected by the level of urbanization and demographic characteristics of the road users. Thus, in the U.S. where the fatality rates differ greatly among the 50 states, almost 70 percent of the variance is accounted for by differences in these two factors. The use of the different measures is illustrated below for crash and injury trends over time for specific countries, and at a given time for comparisons among countries.

The choice of a preferred rate goes beyond the immediate meaning of the measure. In recent years, with the dramatic increase in traffic accidents worldwide, traffic safety has come to the attention of health officials, who are now attempting to address it as they would any other disease. From the perspective of public health, traffic accidents are *the* disease of our time, and they are projected to remain in that dubious place of honor in the next few decades at least. As a public health issue the situation is not only grim, but has not improved at all over the past decades. An interesting illustration of this is provided by Sivak (1996) who notes, based on data provided by the U.S. National Safety Council, that between 1923 and 1994 the total number of people killed in the U.S. from traffic accidents annually more than doubled: from 18,400 to 43,000. However, the death rate per million vehicle kilometers decreased by 92 percent (!): from 13.4 to 1.1. During that time, at least part of the reason for the increase in the first measure and the decrease in the second measure was due to the increase in the size of the U.S. population, the number of licensed drivers, and the number of registered vehicles. With all these critical factors affecting the likelihood of traffic accidents, the fatality rate per 100,000 persons living in the U.S. remained essentially unchanged: at 16.5 in both periods. Thus, if we are to treat crashes as a modern day disease, we must look just as epidemiologists evaluate the risk of diseases and epidemics: at its impact relative to the number of people in the affected population; and the news concerning the traffic accident "disease" is not good. Incidentally, despite significant reductions in the U.S. traffic fatality rates, the U.S. is far from being a leader in this domain. Based on data collected by the IRTAD for 2013, the U.S. had 10.3 fatalities per 100,000 inhabitants while seven OECD countries – Denmark, Israel, Netherlands, Norway, Sweden, Switzerland, and the United Kingdom – led the pack with less than four fatalities per 100,000 inhabitants (IRTAD, 2015).

If we look at traffic accidents from the perspective of highway safety administrators and policy makers then we make allowance for all the factors for which the engineers – justifiably – cannot assume responsibility and these include the number of people and vehicles moving on the roads. The differences in philosophies concerning the place of traffic safety – as a unique safety phenomenon versus a public health concern – are also reflected in the different goals set by different countries. Of course, to be immune from criticism for biasing the safety picture, a country can strive to lead on all three rate measures of fatalities: per population, per vehicles, and per kilometers driven. Worldwide as of 2013, three countries excelled and led the rest of the world on all three measures: Sweden (with 27 fatalities per million inhabitants; 58 per million passenger cars, and 2.4 fatalities per billion vehicle kilometers), the United Kingdom (with 28, 59, and 2.8, respectively), and Netherlands (with 28, 60, and 3.3, respectively) (EC, 2015). By comparison, the U.S. which up to the 1970s led the world in traffic safety had 103.5 deaths per million inhabitants, 122.6 per million registered vehicles, and 17.5 per billion vehicle kilometers (NHTSA, 2015a).

The importance of setting measurable goals – regardless of the terms in which they are defined – is well established as a means of improving performance (Locke and Latham, 2002). Setting tough but achievable goals is a great motivating force. Once stated, a goal becomes a measure against which nations, governments, and other institutions can evaluate their performance, and be held accountable. Most European countries – where the population size is relatively stable – set their traffic safety goals in terms of reductions in either absolute number of fatalities or in terms of the rate of fatalities per population (IRTAD, 2015). The most ambitious and challenging goal phrased in absolute terms is the "Vision Zero" adopted by the Swedish parliament in 1997: "that no one would be killed or seriously injured in the road transportation system." This approach explicitly states that "the system designers are invariably ultimately responsible for the design, management and use of the road transport system and thus, they are jointly responsible for the level of safety of the whole system. The road users are obliged to abide by the rules that the system designers decide on for the use of the road transport system. If the road users fail to abide by the rules – for example, due to lack of knowledge, acceptance or ability – or if personal injuries occur, the system designers must take additional measures to prevent people from dying or being seriously injured" (Fahlquist, 2006, p. 1113, quoting the Swedish law).

In contrast, the U.S. Department of Transportation sets its safety goal in terms of the fatality rate per 100 million vehicle miles traveled. The strategic goal that was set in 2003 for 2008 was "not more than 1.0 per 100 million vehicle miles traveled" (U.S. DOT, 2003) or 0.62 deaths per 100 million vehicle kilometers traveled. Unfortunately, this goal was not achieved and instead a new more modest goal was set to "reduce the rate of roadway fatalities per miles traveled from 1.25 per million vehicle miles traveled (VMT) in 2008 to 1.03 per 100 million VMT in 2013" (i.e., 0.64 fatalities per 100 million vehicle kilometers traveled) (U.S. DOT, 2012), and that goal too has not been met (NHTSA, 2015a). In 2015, the fatality rate was 1.12 (NHTSA, 2016a) or 6.96 fatalities per billion kilometers traveled. Note that this is significantly worse than the rate of nearly all Western European countries (Figure 1-5).

Another caveat is the definition of a crash or an injury. For example, one of the more common definitions, used in the U.S. Fatal Analysis System, for a fatal traffic accident is "a police-reported crash involving a motor vehicle in transport on a trafficway in which at least one person dies within 30 days of the crash" (NHTSA, 2000). Not all countries limit recorded crashes in their data files to ones occurring on public roads (by including crashes off the road and on private roads) and motor vehicles in motion (by including crashes involving bicyclists and a parked car), and not all countries use the same time limit of 30 days (the range varies from 24 hours to no time limit at all) to note a fatality or a fatal crash. These differences in definitions make cross-cultural and international comparisons a little more uncertain than they appear. However, some approximations can be derived by factoring some of the differences. For example, the World Health Organization uses a 12-month rule for counting fatalities for vital statistics reporting. In the U.S. according to ANSI (2007) "experience indicates that, of the deaths from motor vehicle accidents which occur within 12 months of those accidents, about 99.5 percent occur within 90 days and about 98.0 percent occur within 30 days" (Section 3.1.3). This difference of 2.0 percent between 30 days and "anytime" (equivalent for all practical purposes to 1 year) has also been obtained for traffic fatalities in Israel (NRSA, 2010).

Perhaps, the most common rate used by traffic safety engineers and transportation experts is the number of crashes or fatalities per total vehicle miles (or kilometers) driven by all cars; that is, the risk per miles or kilometers of driving in any one country. Obviously, a registered vehicle that is not moving, cannot strike anyone, and the more time and distance a vehicle travels on the road the more it is at risk of being involved in an accident. But time-on-the-road is very difficult to evaluate, and we therefore resort to the estimate of total mileage driven. Unfortunately, the measure itself is not as accurate as we would like it to be because it typically depends on survey reports of people's estimates of their driving distances. Distance traveled can be accurate in countries with annual motor vehicle testing, where based on the odometer readings from all vehicles the aggregate measure of the total distance traveled by all vehicles can be calculated. However, this procedure is practiced in very few countries (e.g., Israel). Still, regardless of how it is calculated or estimated, when the change over time is great, the inherent inaccuracy of the measure is less important. Thus, as noted above, in the U.S. the risk of fatality per mile driven has decreased markedly over the half century by approximately 80 percent: from 5.5 fatalities per 100 million vehicle miles in 1966 to 1.1 fatalities per 100 million vehicle miles in 2012 (Figure 1-4). Statistically speaking, this means that in the U.S. a person would have to travel by car an average distance equivalent to over 460 round trips to the moon – which is on the average 238,855 miles from earth – before being killed in a traffic accident.

Using this rate, fatalities per total distance traveled, as a basis for international comparisons, it is easy to see from Figure 1-5 that, in general, the more developed, and more motorized, countries have lower fatality rates, with England and some of the Scandinavian countries leading the way. Note, however, that the U.S., the most motorized country in the world (with approximately eight vehicles for every 10 residents, including infants and children) does not fare well as these countries. This chart, however, does not include countries with fatality rates significantly above 100 such as China (126) and Russia (598).

The rate per miles driven is also oblivious to the impact of alternative modes of transportation on overall travel safety. Public transportation by train or bus is typically safer than travel by car and shifting the public's use to these modes can increase public safety without being reflected in the fatalities per miles driven. Thus, as comforting or disturbing as the rate of fatality per miles driven is (depending on where you live, of course),

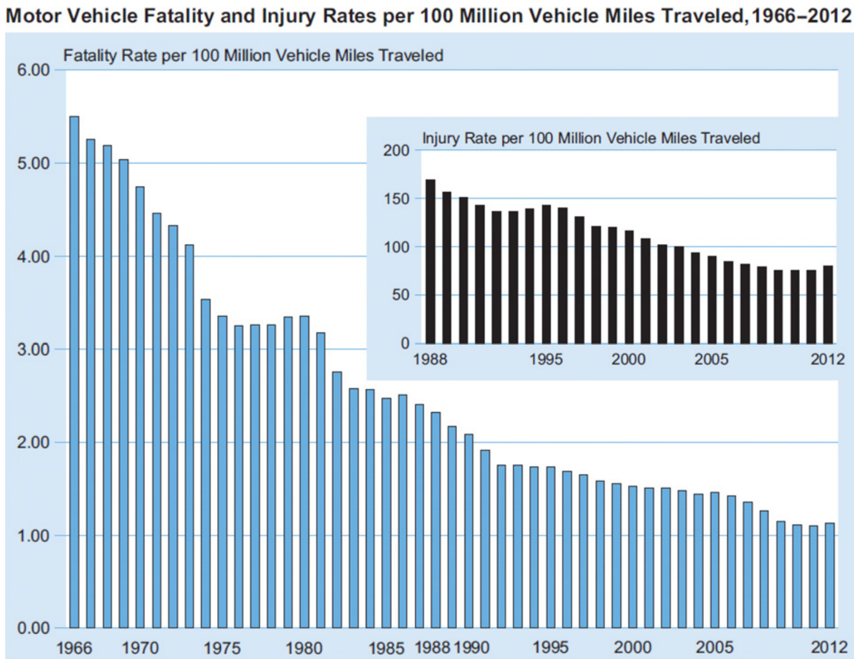

Figure 1-4. Trends in fatalities and injuries per 100 million vehicle miles of travel in the U.S., 1966-2012 (from NHTSA, 2014).

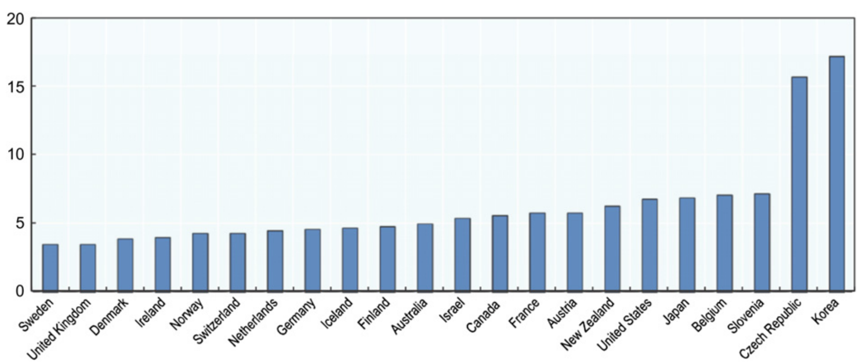

Figure 1-5. Fatalities per billion vehicle kilometers traveled in different countries in 2013. Data for Australia, Canada, Ireland, Lithuania and the U.S. is provisional. Data for the Czech Republic is from 2012 (from IRTAD, 2015, with permission from the OECD Publishing, Paris).

the state of traffic safety looks very different if we consider another common rate: the rate of fatalities per number of people in the population. This is the typical measure used in health statistics to estimate the risk of a person of contracting any disease in any one country.

Unlike the rate per miles driven, in the U.S. the rate of fatalities per population has stayed fairly constant with only a 5 percent drop from 1923 to 2000. Why the great disparity in the behavior of the two statistics? One possibility is that most of the improvement in the rate per miles driven is due to an increase in travel rather than due to a reduction in the number of crashes. Thus, a road segment may be equally safe (or unsafe) regardless of the number of cars traveling on it (within limits) and a car may be equally safe (or unsafe) regardless of the miles driven. Another possibility, raised by Sivak (2002) is that a society has a certain tolerance to traffic injuries, not in absolute terms (because the absolute numbers keep increasing) but relative to population size.

While the rate of involvement per population is a common rate used in the health area, it does not account for the number of drivers or vehicles running on the roads and potentially having the crashes. Obviously, the likelihood of being in a crash should be related to these. Also – especially from the perspective of policy makers – there is very little one can do to control all citizens, but there are a lot of actions that can be taken to regulate and improve the vehicles and the drivers. Therefore, two other common rates are the rate of crashes or fatalities per number of licensed drivers and the number of crashes or fatalities per number of registered vehicles (Figure 1-6). Figure 1-7 demonstrates the difference in the rates of fatalities relative to the number of people and relative to the number of registered vehicles in different countries. Although the data are somewhat dated, they still illustrate the importance of having both measures, and the differences between them. As can be seen from this figure, in the more developed countries of the Western world (in income per capita and the number of vehicles per person),

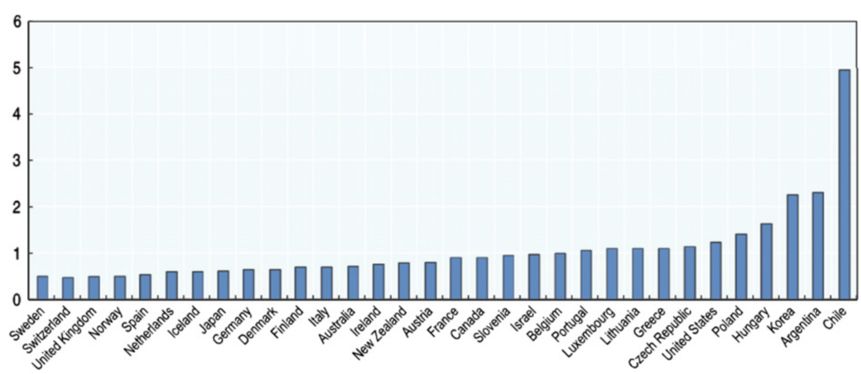

Figure 1-6. Road fatalities per 100,000 registered vehicles in 2013. (Total vehicles include mopeds for Argentina, Australia, Canada, Chile, Iceland, Ireland, Lithuania, and the U.S. Canada: 2012 data. Provisional data for Australia, Ireland, Lithuania, and the U.S.) (from IRTAD, 2015, with permission from the OECD Publishing, Paris).

both rates are relatively low, whereas in the less-developed countries such as Turkey and Korea, the rate per population is much lower than per vehicles. In general, the disparity between the two rates is even greater for poorer, less motorized countries. When we focus on rates per population only, finer distinctions among the countries become apparent, as can be seen for the EU countries in 2010 and 2014 (Figure 1-8).

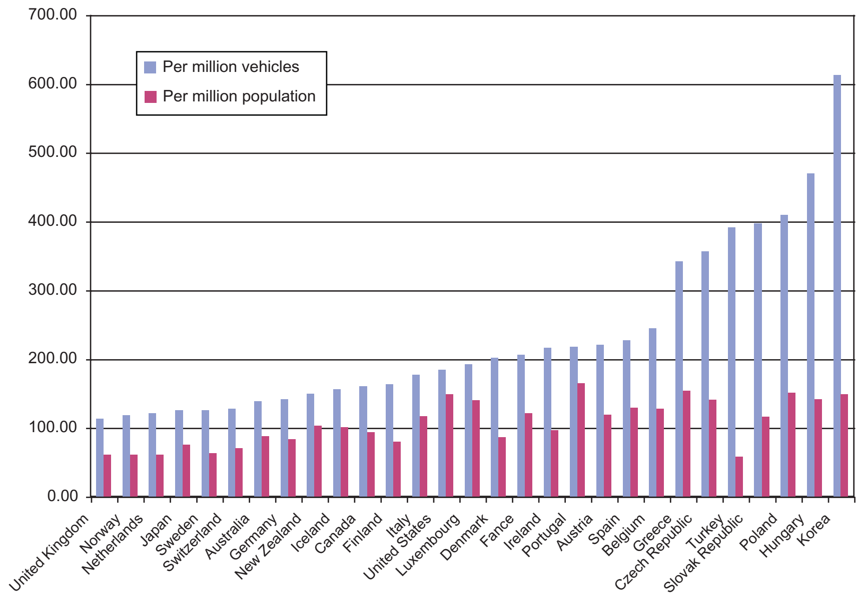

Figure 1-7. Traffic accident fatalities per population size and number of registered vehicles in different countries: 2002 (from OECD, 2006, with permission from the OECD Publishing, Paris).

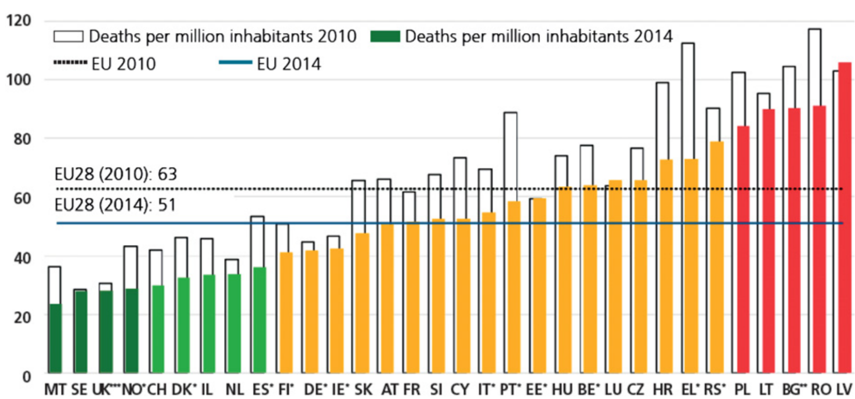

Figure 1-8. Road deaths per million inhabitants in 30 EU and affiliated countries in 2010 and in 2014. *Note*: Starred countries are estimates (from ETSC, 2015, with permission from the European Transport Safety Council).

Of the various measures described above, fatalities per vehicle miles/kilometers driven have evolved to become the gold standard of traffic safety measures. Yet, even for this measure (as well as the others) there are pitfalls in using aggregate data when comparing countries or states. The most common is the one known as "Simpson's Paradox," which states that "a trend that appears in different groups of data disappears when these groups are combined, and the reverse trend appears for the aggregate data" (Wikipedia). Stated with respect to international comparisons in fatality rates, it means that one country may appear safer than another when all of its regions are combined, whereas in fact, it is actually less safe when examined on a regional basis. An illustration from U.S. data is the comparison of the fatality rates of California and South Dakota (SD). California has a fatality rate of 1.27 fatalities per 100 million vehicle miles and SD has a fatality rate that is nearly 70 percent higher, 2.12 fatalities per 100 million vehicle miles. When the fatality rates are disaggregated by the types of roads, we get a completely different picture, as can be seen in Table 1-3. When the data are disaggregated into urban and rural roads, it is obvious that SD is safer on both. Yet, because most of the driving in California is on urban roads (where fatality rates are lower because of lower speeds), while most of the driving in SD is on rural roads, we actually get the misconception that driving on California roads is safer than driving on SD roads.

Given these large differences between the various measures, and the pitfalls that abound in interpreting the aggregate data on each measure, is there a simple way to describe safety levels? The answer is yes and no. Perhaps, the most common way to evaluate safety is to consider change over time in a given country, state, or locality, and then justify the particular measure used. The particular measure used will then depend on the nature, mission, and policy of the institution making the comparison. Health organizations would be more likely to evaluate safety in terms of rates relative to population size, whereas transportation organizations would be more likely to consider rates relative to drivers, vehicles, or total kilometers traveled. Still there remains one caveat: the change in safety may be due to exogenous reasons (confounding factors) that may only surface in comparisons to other locations.

Table 1-3. Demonstration of Simpson's paradox using California and South Dakota fatality rates (per 100 million vehicle miles of travel). Based on 2004 data (from Hedlund, 2008).

State	**Fatality Rate (per 100 Million? VMT)**			**Distribution of VMT**	
	Rural	Urban	Total	Rural	Urban
California	2.68	0.92	1.27	20%	80%
South Dakota	2.49	0.87	2.12	77%	23%

Motorization and Crashes – Smeed's Law

Contrary to appearance, the data in Figure 1-7 do not reflect independence of the two measures of safety. There is another measure that seems to mediate the relationship between safety per population size and safety per number of vehicles: the level of motorization. The level of motorization as an intervening variable was first proposed by Smeed in 1949 and is now known as Smeed's law. According to this "law" the rate of fatalities per number of vehicles decreases exponentially as a function of the number of vehicles per the size of the population. Stated in more intuitive terms, the involvement of each vehicle in a fatal crash decreases as the number of cars in a country increases. Although first formalized by Smeed on the basis of 1938 data from only 20 countries, it has since been validated repeatedly on more recent and larger samples of different countries based on annual statistics from different years (Adams, 1985; Evans, 2004; Smith, 1999). A relatively recent evaluation of this relationship is depicted in Figure 1-9, and it is based on mostly 2002 and 2003 data from 62 countries gathered by Link (2006). When Link's fatality rates (per million vehicles) are plotted relative to the level of motorization (vehicles per 1,000 people), we obtain the typical negative power relationship demonstrated by Smeed on data more than three quarters of a century ago. Further demonstration of the strength of this relationship was shown by Adams (1985) and Evans (2004) when they plotted the data for individual countries over the course of several years.

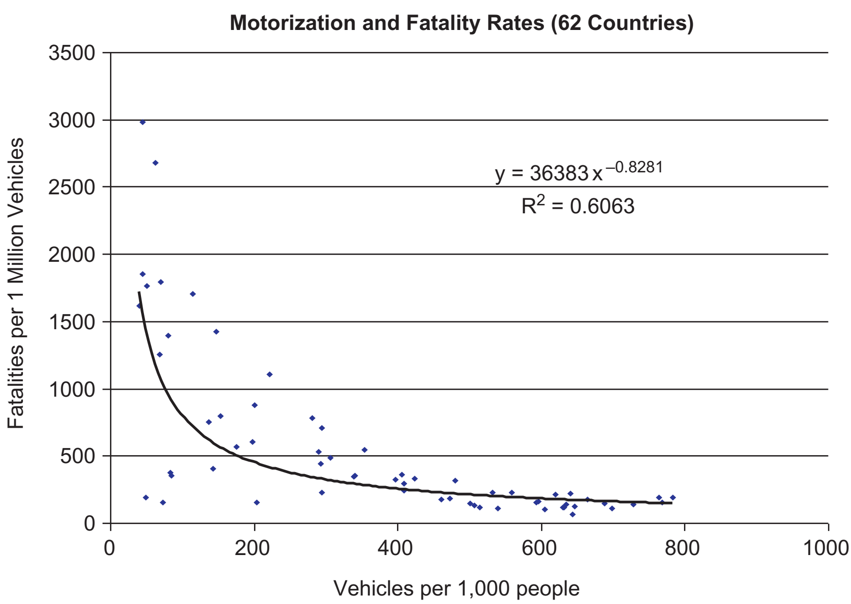

Figure 1-9. Smeed's Law based on data from 62 countries (collated by Link, 2006, with permission).

Various explanations have been offered for the relationship between fatalities per vehicles and the level of motorization (Näätänen and Summala, 1976). Because the relationship is one of association, it is likely that there are multiple factors that together contribute to this phenomenon, and it is their combined effects that are most likely responsible for the stability in this function across countries and across time. Other variables that covary with increasing motorization and that may directly or indirectly influence traffic safety include the increasing proportion of trips taken in motorized vehicles relative to trips taken by walking or bicycling (see Chapters 15 and 17); improvements in the transportation infrastructure (including divided highways, hard shoulders, barriers, etc.) that accompany the increase in vehicles; demographic shifts toward urbanization, where accidents are less severe; increasing traffic density and congestion, leading to reduction in high-speed crashes; improvements in emergency medical services; reductions in the exposure (kilometers driven) of each vehicle as the number of vehicles increases (we can accumulate vehicles, but we still cannot drive more than one vehicle at a time); increases in population risk awareness; and greater level of motorization due to greater government investment in safety in general, including education. Perhaps the most important implication of Smeed's law and the explanations offered for it is that because accidents and highway safety are affected by multiple factors, addressing any one of them without consideration for the others will only constitute a small part of the solution for a complex problem.

For example, we can illustrate the relationship between motorization and the mix of vehicles. The argument is that as the level of motorization increases, the mix of protective vehicles (cars), non-protective vehicles (motorcycles and bicycles), and vulnerable road users (pedestrians) changes, so that there are more of the former and fewer of the latter on the streets and highways. This is illustrated in Figure 1-10 that graphically displays the relative proportions of people killed in motor vehicle crashes as pedestrians, bicyclists, motorcyclists, and occupants of cars and trucks in different countries. Figure 1-11 displays the relevant data collapsed across countries but disaggregated by gross levels of income (which correlates highly with the level of motorization). The differences between highly motorized and high-income countries and the countries with low levels of motorization and income are striking. In motorized countries most of the people killed are car occupants. For example, in the EU countries the range is from close to 70 percent in Norway, Finland, and Sweden, to approximately 50 percent in Cyprus, Romania, and the Czech Republic (ETSC, 2011). In contrast, in low-income countries (especially in Sub-Saharan Africa), pedestrians account for more fatalities than any other mode of transportation (Figure 1-11). Obviously, once a collision occurs, the likelihood of an unprotected pedestrian being killed in a crash is much greater than that of a car driver or a passenger who is protected by their vehicle frame, a safety belt, and an airbag. For example, as detailed in Chapter 15, an analysis of the data from 62 countries revealed that the proportion of pedestrian fatalities is inversely related to the level of motorization ($r = -0.72$) and the level of affluence (gross domestic product/person, $r = -0.71$), which are positively related to each other ($r = 0.82$).

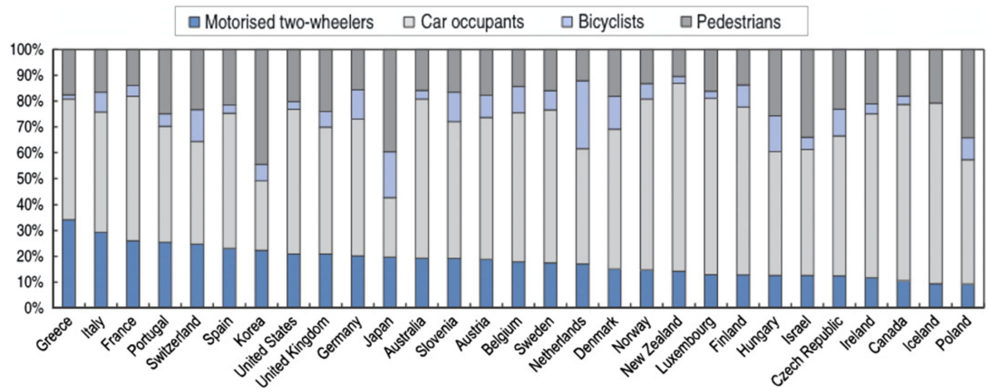

Figure 1-10. Percentage of different types of road users in fatalities (average 2009-2013) share of different road user classes in OECD countries. *Note*: in the U.S. sport utility vehicles are not included in the "car" category, and hence the large proportion of others (from IRTAD, 2015, with permission from the OECD Publishing, Paris).

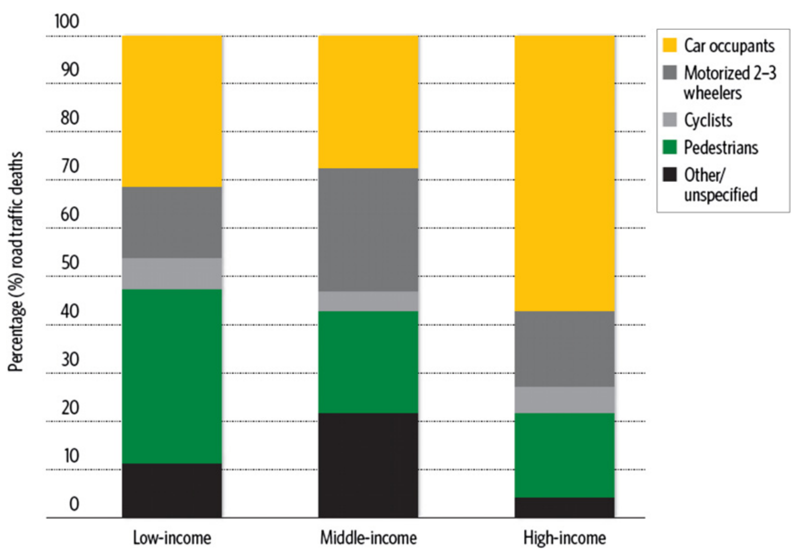

Figure 1-11. Percentages of road users killed as pedestrians, cyclists, mopeds and motorcycles, and cars and trucks, in different countries with different income levels (reprinted from Global Status Report on Road Safety 2013 (p. 7, Copyright World Health Organization, http://apps.who.int/iris/handle/10665/78256).

The Reliability and Validity of Crash Data

Even when crashes are well defined in identical terms, there are significant variations in crash data among sources. Various state agencies, such as police, licensing agencies, safety divisions, insurance companies, trauma centers, and bureaus of statistics do not always agree with each other. Furthermore, in many traffic safety studies, the crash data are based on the drivers' own reports. Needless to say there are many reasons for discrepancies between self-reports of crashes, reports from hospital trauma centers, and police reports.

The most ubiquitous source of crash data is police reports, which constitute the basis for national crash statistics in over 70 percent of the countries surveyed by the World Health Organization (WHO, 2013a, 2013b). However, for various reasons, listed in Table 1-4 (Elvik *et al.*, 2009), there are limitations to police reports.

It is worthwhile to dwell on the reasons for the data loss as they can introduce some significant biases in the data analysis, interpretation, and recommendations based on them. To start with, some accidents are simply not reported to the police for various reasons: poor communications (mostly in remote areas and in less-developed countries) and inadequate police force to record and investigate all crashes. Next, some accidents are "not reportable" according to the police definitions, such as minor injury and property-damage-only crashes. Some of these crashes are actually misclassified because of initial underestimation of injuries (such as those from internal bleeding). For these reasons and others, police records often underreport accidents relative to hospital records, especially pedestrian and bicycle accidents (Derriks and Mak, 2007). Thus, in a cross-country comparison, Elvik and Mysen (1999) estimated that global crash recording rates include only 95 percent of all fatal crashes, 70 percent of serious injury crashes (where at least one person was admitted to a hospital), 25 percent of slight injuries crashes (where no one was treated at a hospital), 10 percent of very slight injury crashes, and 25 percent of

Table 1-4. Reasons for incompleteness and inaccuracy of police accident data in the various stages of information transmission (from Elvik et al., 2009, with permission from Emerald Group Publishing).

Stages in the Recording of Accidents	Reasons for Lost or Inaccurate Information
All accidents on public roads	Not reported to the police
Accidents defined as reportable	Not reportable accidents
Accidents reported	Incomplete reporting
Data elements recorded	Missing data elements
Accuracy of recorded data	Inaccurate data

property-damage-only crashes. In fact in some countries and jurisdictions, police, as a matter of policy, do not become involved in the recording or investigation of property-damage-only crashes (e.g., Israel). Next, even when a crash is investigated some of the needed information may be missing. Finally, clerical and judgment errors often lead to inaccurate data in the final data set. Evaluations of the accuracy of police reports – even those of well-trained officers – often reveal some gross inaccuracies in data recording and interpretation of the evidence. Errors are most common when it comes to attributing the cause of the accident (Shinar, Treat, and McDonald, 1983), exact location, time, and speed (Chung and Chang, 2015). It is important to emphasize that underreporting and errors are not a random process or one that is the same for all countries. The greatest amount of underreporting occurs in the poorest countries where the death toll from road traffic crashes is the greatest (World Bank, 2014). But even in the developed world, underreporting is a significant problem for pedestrian and bicyclist crashes as these often occur on the sidewalk or on foot paths off the road and often do not involve a motorized vehicle (Turner, Roozenburg, and Francis, 2006).

Interestingly, there is no convincing argument for the preference of one data source over the other as they all have some advantages and disadvantages. The intuitive appeal of police reports as a data source for crash involvement is that they are based on police-observed facts. The appeal of self-reports is that they can supply details that police reports often lack. On the other hand, drivers suffer from memory failures and bias and are less reliable in recalling crashes from several years ago. Drivers are also probably less likely to report crashes in which they were culpable, especially if they involve socially unacceptable behaviors such as being intoxicated.

Overall, there is a moderate agreement between the total numbers of police-reported crashes and self-reported crashes, although the two definitely do not provide identical sets of cases. Marottoli, Cooney, and Tinetti (1997) consider the two sets complementary, but others are more skeptical. Owsley *et al.* (1991) compared crash frequencies in state records and self-reports and found a near zero correlation between the two sources ($r = 0.11$), although when the frequencies were grouped, and the measure of association was changed (to Kappa coefficient of agreement) a greater – although still low – level of agreement was obtained ($K = 0.40$). McGwin, Owsley, and Ball (1998) compared the two sources on a sample of 278 drivers 55+ years old and found a moderate agreement on whether or not the drivers had a crash in the past 5 years ($K = 0.45$), but poor agreement in terms of the number of crashes a driver had ($K = 0.25$). The discrepancies are not random, but biased in a specific manner. In their sample McGwin and his associates found that the amount of discrepancy depended on the driver demographics, driving exposure, and visual impairments. This creates a caveat that may account for some of the inconsistencies among studies and even within a single study. Thus, in their own study McGwin *et al.* (1998) found that performance on some driving-related skills (such as "useful field of view," discussed in Chapter 4) was associated with crashes on both data sets, whereas others (such as presence or absence of glaucoma) were significantly associated only with one only (police-reported crashes). In general, they also found that drivers tended to underreport crashes, omitting some of the crashes in the police-based files.

In many studies the source of the data is based on convenience. When available, police data are sought as the "more objective" source. But in some cases – such as the study by Maycock, Lockwood, and Lester (1991) on the relationship between age, experience, and crashes and the study by McCartt, Shabanova, and Leaf (2003) on the effects of graduated driver license on crash involvement – the researchers actually preferred to rely on drivers' self-reports because they are considered to be more valid for the specific issues examined in these studies (both studies are described in detail in Chapter 6 on young drivers).

A third source of crash data are hospital records. Obviously, this applies only to injury crashes above a certain level of severity. Also, because hospital injury records are not typically centralized in a national data file, an accurate comparison is difficult. Still, hospital records can be indicative of lacunas in police data. Studies conducted in several countries have consistently shown that when compared to hospital data, there is fairly a good agreement on fatalities, but an underreporting by the police, especially in accidents involving bicyclists (Amoros, Martin, and Laumon 2006; Broughton *et al.*, 2010; Rosman, 2001). Some of the underreporting stems from different definitions of "road accident" (police typically require the involvement of a motor vehicle) and injury severity (police use administrative criteria such as length of hospitalization, whereas hospitals use medical criteria such as the MAIS based on actual injury severity) (Broughton *et al.*, 2010). Still some of the discrepancies stem from differences in actual reporting where the driver fails to stop and the bicyclist is taken (or goes himself/herself) to the hospital without anyone notifying the police. These shortcomings of the police data relative to data from hospital records do not imply that the latter should substitute for the former, but that "because of underreporting problems and possible bias (e.g., with differing rates of reporting by vehicle type), police data should be complemented by hospital data, which are the next most useful source" (OECD, 2010, p. 8). Unfortunately, most countries do not have linked hospital, vital registry, and police data on traffic fatalities. When data from all sources are available, the police data often underestimate the scope of the problem (WHO, 2015).

The Concern for Traffic Safety

Despite the statement by Tingvall (quoted at the beginning of this chapter), the concern about traffic safety is not shared by all road users everywhere. A multi-nation Social Attitudes to Road Traffic Risk in Europe (SARTRE) (SARTRE 4, 2012) conducted in 2010 on a representative sample of 1,000 adults in 19 countries (17 European countries plus Cyprus, plus Israel) demonstrated very large differences among the people of different countries in their concern about traffic safety. Figure 1-12 shows the percentage of respondents who expressed different levels of concern about the road safety in their country. Although there were very large differences in the percentage of people who were "very concerned" – ranging from less than 20 percent in Germany to over 75 percent in Israel – only a very few people in all other countries stated that they were not concerned at all. Interestingly, the level of concern did not parallel the level of traffic

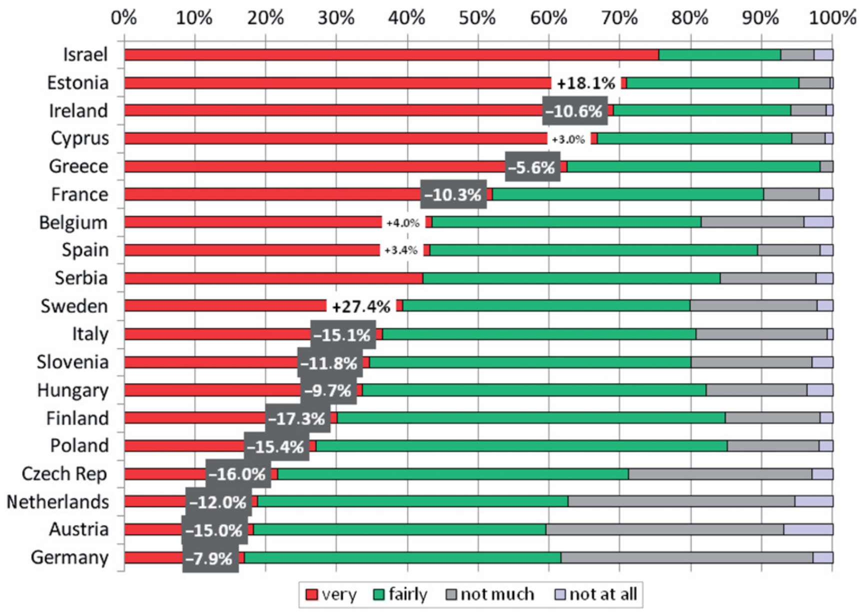

Figure 1-12. Concern about road safety in 2010. Frequency distribution in percentage of road users who are "very concerned" in 2010 (SARTRE 4) and the change from 2001 (SARTRE 3) noted in percentage points to SARTRE 4 (significant changes in bold) (from SARTRE, 2012, p. 47, with permission from J. Cestac, SARTRE 4 Coordinator and Final Report Editor).

safety: r = 0.07. It was highest (Israel) and lowest (Germany, Austria, Netherlands) in countries that rank quite high on most measures of traffic safety (as reflected in Figures 1-5 to 1-8). The absence of such a relationship is underscored when the concern for safety is plotted against the fatality rate relative to the number of people in the country (Figure 1-13). Sweden is quite consistently ranked as the safest country, yet it was in the middle in the ranking on "very concerned." Thus, it appears that concern for safety is not closely related to the actual level of safety. To the extent that being concerned drives the behavioral norms and the governments' investment in safety, it is a good thing to be very concerned. In Israel there is a false public perception – often shared by tourists who view Israelis as very aggressive drivers – that the road safety level in Israel is low, and definitely lower than it should be relative to other OECD countries, independently of all objective data (Figures 1-5 to 1-8). Relative to the previous SARTRE survey conducted in 2001, the change in the percentage of people who were "very concerned" was mostly negative (although not statistically significant). Thus, as road safety increased in nearly all EU countries over that period, the level of concern declined. The most notable exception is Sweden, where there was a statistically significant *increase* in concern despite its excellent road safety records. This supports the speculation that heightened concern is a good thing in a country where the government is attentive to the concern of its constituents. One of the most visible means of that attentiveness is the state of the country's roadway infrastructure. Thus, it should be no surprise that when

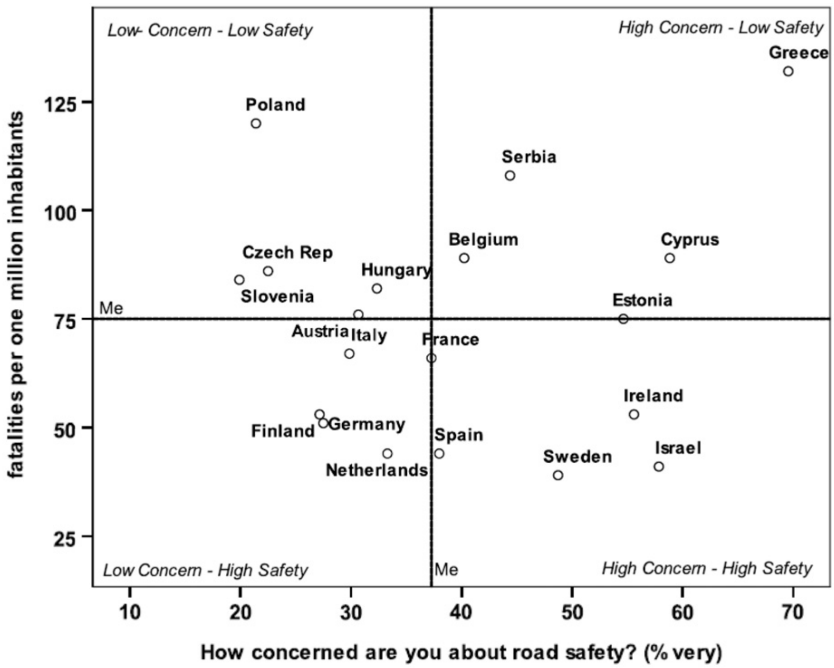

Figure 1-13. Personal concern about road safety versus fatality rate. The center lines indicate the medians of percentage of people who are "very concerned" and the fatality rate (from SARTRE 4, 2012, p. 49, with permission from J. Cestac, SARTRE 4 Coordinator and Final Report Editor).

the fatality rate was plotted relative to the percentage of people who rated the roads as "very" or "fairly" safe, a strong negative relationship emerged (r = –0.72). The higher the fatality rate the lower the percentage of people satisfied with their roads, with Sweden having the lowest fatality rate and highest level of satisfaction (Figure 1-14). It is probably also relevant to note that Volvo – that has always carved safety on its mission – is a dominant factor in the Swedish economy.

Organization of This Book, Additional Resources, and the Rationale for the New Edition

Book organization

In the remainder of the book, I will explore the reasons why highway safety is improving – and the reasons why it isn't, especially from the perspective of the road user behavior. Because the road user – driver, cyclist, or pedestrian – has been historically viewed as the only decision maker in the driver-vehicle-highway system, his or her role is critical. But the driver does not behave in vacuum. The roadway environment and the vehicle characteristics are crucial components in the highway traffic system as are other vehicles and road

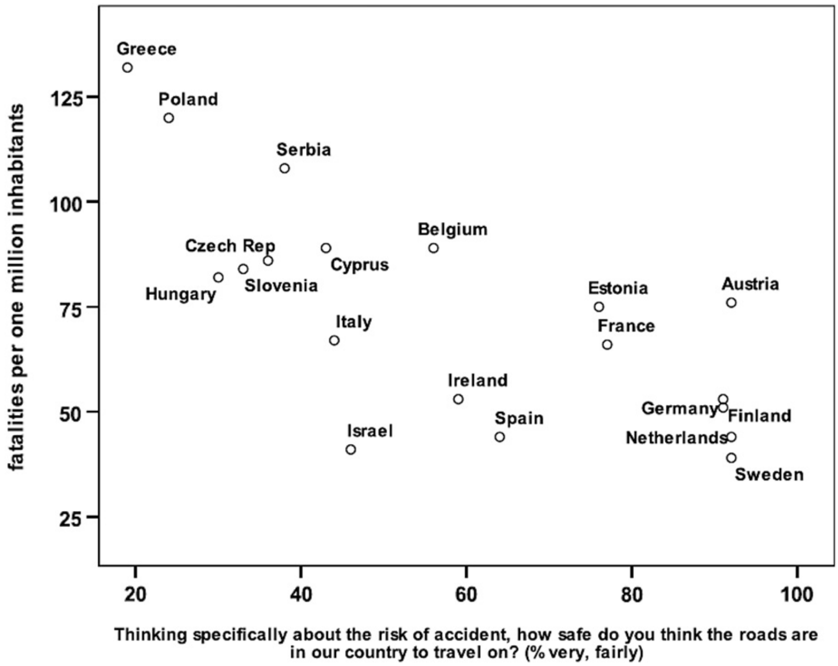

Figure 1-14. Perception of the safety of the roads versus the fatality rates (per one million in population) (from SARTRE 4, 2012, p. 51, with permission from J. Cestac, SARTRE 4 Coordinator and Final Report Editor).

users, the legal and social environment, and the enforcement that is or is not applied. When a crash occurs, it is not necessarily the "nut behind the wheel" that is responsible for it but many other "nuts and bolts" in this complex system that may be loose or missing at the critical moment. Nonetheless, the focus of this book will be on the driver and the driver's behavior as the significant element in highway safety.

The contents of the book are divided into six major parts, each further divided into 2-4 chapters, totaling 19 chapters. The first part, Background, Methods, Models (Chapters 1-3), essentially sets the stage for discussing the substantive issues of this book. Like any discipline, traffic safety has its own jargon, its own measures, and its own theoretical models within which the discussion of the issues is framed. The Methods chapter provides some very basic information on research design, independent and dependent measures, and statistics that are commonly used in behavioral research on highway safety.

The remainder of the book focuses on specific safety-related issues and, as much as possible, defines the nature of the issue, problem, or behavior, its scope and impact on traffic safety, and potential countermeasures that can reduce the magnitude of the problem.

The second part, Driver Capacities and Individual Differences (Chapters 4-7), focuses on four aspects of driver characteristics that have been studied extensively in their relation to safety: driver vision, driver information processing, and driver age. Age-wise the two groups that have received most of the attention – although they definitely constitute a minority of all drivers – are the young drivers (typically under 25 years) and the older drivers (typically 65 years old and older). Because the nature of their crash involvement differs and because they differ greatly in their experience, skills, and information processing abilities, they are treated separately in two chapters.

The third part, Driving Style, (Chapters 8-10) focuses on two aspects of driving style: speeding behavior and aggressive driving. Obviously, as most people would suspect, the two are related to other driver characteristics such as age and gender, and therefore the relationship of speeding and aggressive driving to age and gender is discussed in this context. In addition, this section also discusses the benefits of occupant protection and the road-users' tendencies to use them.

The fourth part, Driver Temporary Impairments (Chapters 11-14), focuses on the four types of impairments that most researchers associate with the greatest involvement in crashes: impairments from alcohol, impairments from (other) drugs, impairments from fatigue, and impairments from distraction and attentional lapses. Unlike the more stable individual differences of personality, gender, age, and visual and information processing abilities, these can change drastically within short intervals (on the order of minutes), and then their effects are often interactive with the person's more stable characteristics. When such interactions have been studied they will be discussed in these chapters.

The fifth part, Vulnerable Road Users (Chapters 15-17), implicitly acknowledges that most of the previous discussion was focused on car drivers and occupants. But these are not the only road users that contribute to and suffer from crashes. The others, often labeled as the "vulnerable" road users, consist of primarily riders of powered two-wheel vehicles (mopeds and motorcycles), bicyclists, and pedestrians. They are considered vulnerable for an obvious reason: They do not have the protective seat belts and shield of the car. Although most of the readers of this book probably think of themselves primarily as drivers of passenger cars, we are all at times vulnerable road users as well. In many countries the combined "contribution" of the vulnerable road users to the traffic death toll is greater than that of all car occupants (drivers and passengers). According to the World Health Organization "Half of the world's road traffic deaths occur among motorcyclists (23 percent), pedestrians (22 percent), and cyclists (5 percent)." Car occupants constitute (only) 31 percent of the deaths and the remaining 19 percent are "unspecified road users" (WHO, 2013a, 2013b, p. 6). The three groups making up the vulnerable road users are also distinctly different from each other on at least two dimensions. These include regulation: motorcyclists are regulated through licensing, whereas bicyclists and pedestrians are not, and age: motorcyclists essentially mimic the driver population in their age distribution (with greater frequencies of young riders), whereas bicyclists extend to much younger age groups (teens and preteens) and pedestrians – at least in terms of their crash involvement tend to concentrate on the very young and very old. Consequently, these three types of road users are treated in separate chapters.

The last part, Crash Causation and Countermeasures (Chapters 18 and 19), focuses on what we have learned over the past 100 years – and especially over the past few decades – about the causes of traffic accidents, their relative frequencies, and the means that have proven successful in combating accidents. The crash causation chapter also has a methodology component because often the relative frequency of various causes of traffic accidents is methodology-bound, meaning that different methods of analyses yield different conclusions. The countermeasures chapter is divided into four domains in which countermeasures can and have been applied: organizational actions (such as "Vision Zero" mentioned above), behavioral changes in drivers and other road users, environmental treatments of the roadway and its "furniture," and vehicular changes in both crash prevention and injury reduction. A significant conceptual change that has occurred over the past decade is reconsideration of the role of the driver as the controlling element in the vehicle. Recent innovations in in-vehicle safety systems transform the driver more and more into a monitor of the car and traffic and less of a continuous controller of the vehicle. In its most extreme form, we see the autonomous vehicle (often known as the Google Car, http://en.wikipedia.org/wiki/Google_driverless_car) that, within some limitations, can safely navigate itself in traffic. This approach involves numerous systems that regulate the speed and lateral control of the car while responding to various crash-related sensors that are sensitive to the prevailing roadway and traffic conditions. While autonomous vehicles would seem to negate even the presence of the driver (let alone the need to change the name), they do involve multiple aspects of the human driver and vehicle interactions that are critical to safety. These issues are discussed in the last part of Chapter 19.

Additional resources

Nearly 40 years ago, I published a small (212 pp.) book on this topic entitled *Psychology on the Road: The Human Factor in Traffic Safety*. At the time, the challenge was to find scientifically valid published research in this area. Ten years ago, while working on the first edition of this book, the challenge was to select the most pertinent research from a wealth of scientific reports published in refereed journals and other technical publications that cover the field. By that time the emphasis in reviewing the state-of-the-art shifted from searching for literature to selecting the most relevant literature. The emphasis in the current version was again on selection. But it was much more difficult now. As noted in the beginning of this chapter, in the last decade alone there were more books written on the topic of human behavior and traffic safety than in all the previous years since the appearance of the motorized vehicle. The same applies to refereed articles of original research and to technical reports. Although most of the studies have been published in a few journals that focus on safety and road user behavior (for example, *Accident Analysis and Prevention*, *Applied Ergonomics, Ergonomics, Human Factors, Injury Prevention*, *Journal of Safety Research*, *Journal of Traffic Medicine*, *Traffic Injury Prevention*, *Transportation Research Part F*, and *Transportation Research Record*), the internet search engines now reveal additional studies published in medicine, engineering, law, policy, and public administration journals. In addition much of the research is only published as technical reports of government and public research agencies, such as the NHTSA, the Federal Highway Administration (FHWA), and the Federal Motor Vehicle Carrier Safety Administration (FMVCSA) in the U.S.; the Road and Transport Research Institute (VTI) in Sweden; Institute for Transport Economics (TOI) in Norway; the Institute for Road Safety Research (SWOV) in Netherlands; the Department for Transport (DfT) in the United Kingdom; Institut Français Sciences et Technologies Transport a Ménagement Réseaux (IFSTAR) in France; and similar bodies.

There are also non-government organizations that are very active in research in this area such as the Insurance Institute of Highway Safety (IIHS) in the U.S., the Traffic Injury Research Foundation (TIRF) in Canada, and the Transport Research Laboratory (TRL) in England. Finally, there are university-based research centers that focus on highway safety such as the University of Michigan Transportation Research Institute, the Texas Transportation Institute at Texas A&M University, the Highway Safety Research Center of the University of North Carolina, the Institute of Transport Studies at the University of Leeds, the Monash University Accident Research Center, and the Centre for Accident Research and Road Safety at the Queensland University of Technology in Australia. All of these and many others have websites that describe their research activities and reports.

The rationale for a new edition

There were several reasons why I felt it was time to update the first edition of the book. First and foremost, the increasing interest in road safety beyond the domain of safety and into the domain of public health has generated an explosive growth in the number of research studies in this area. Second, the emergence of new study methods – specifically Field Operational Technique and Naturalistic Driving Studies – that brings research much closer to the actual driving context. Third, the plethora of electronic driver assistive systems that are designed to increase safety and infotainment systems that are designed to enhance the drivers' abilities to engage in non-driving tasks, at once improving and compromising driving safety. Fourth, the rapid shifting in urban transport from the car to the traditional and electric bicycles. Fifth, the shift toward sustainable lifestyle that is sweeping the world has also changed mobility patterns with a move toward cleaner vehicles, but more importantly with a shift toward alternative modes of transport such as bicycling, motorcycling, and walking, as well as combinations of the different modes of transport. All of these required updating all of the chapters in the first addition, as well as adding a chapter on the increasing role of bicycling (and electric bicycles) in the transportation system.

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2

Research Methods

"In God we trust. All others must bring data." (W. Edwards Deming).

The purpose of this chapter is to set a level field for all readers, by briefly describing the various methods used in driving and highway safety research. Most – but not all – of the methods and concepts described below should be familiar to anyone with behavioral research background or to an advanced student in the behavioral sciences background. Because the terms are repeatedly used in the following chapters, and some readers may not be familiar with all of them, they are defined here for reference.

Most people feel that they know a lot about driving. I am yet to encounter a taxi driver who does not have a "simple" solution to the "accident problem." Admittedly, most taxi drivers have extensive experience in driving, and may be more skillful than most non-professional drivers. Yet someone's personal feeling or idea is not a substitute for good research data. Interestingly, we feel that we can easily tell who is a good and who is a bad driver, who is an aggressive driver and who is a considerate driver, who is a careful and safe driver, and who is a reckless and dangerous driver. Many of us also feel they "know" the reason for most crashes, and what needs to be done (typically by the government) to "fix" the accident problem. Also, at one time or another most people had some formal driving instruction, have read some newspaper articles, or seen a television program about driving, and – most importantly – have been driving.

To support these gut-level convictions with good research is a lot more difficult. Research on driver, motorcyclist, bicyclist, and pedestrian behavior is complex because human behavior is complex and variable, and the driving context is complex and variable. For this reason, in order to understand road users' behavior we must conduct or rely on research at different levels of complexity – beginning with basic research on human behavior, in which the situation is quite simplified and well controlled, and ending with observational on-the-road studies where the situation is most complex and almost nothing is under the control of the researcher. Between the two extremes, there are laboratory studies with various levels of complexity that mimic the driving environment through the use of simulators, and there are controlled on-the-road studies with instrumented vehicles and drivers who are constantly aware of the fact that they are participating in a study.

The results of the various studies, when considered together can provide us with necessary insights and advances in highway safety. In brief, the main benefits of the laboratory studies are that they are safe, they can recreate many repetitions of situations that in real life occur rarely, and – most important of all – they afford us the opportunity to study the effects of specific factors on a person's response, without the presence of many other factors that may co-exist on the road. For example, a laboratory study can be designed to study the driver's reaction time to a brake light ahead in the absence of any distractions. In this case the driver (often referred to as subject) may be seated in front of a red light and asked to push a button whenever it goes on. The result – called simple reaction time – can be a good approximation of the minimum time a person needs to react to such a stimulus. Obviously, this minimum time is rarely achieved in a complex situation such as a real road with moving traffic and various sources of distraction. Therefore, it is not surprising that on the road we can observe reaction times to brake lights that are actually tenfold as long, such as when a tired driver is approaching a partially obscured traffic light while engaged in a conversation on the phone or attending to a pedestrian about to cross the street. Thus, a laboratory study has some use – because it provides us with a notion of "best possible" behavior under controlled conditions, but the ability to extrapolate its results to real life is limited. At the other extreme, on-the-road observational studies focus on driver behavior in the environment as it is. This makes the road study an obvious choice, except that the real environment changes all the time and a particular type of behavior obtained in one environment (e.g., on a rural road at night in England, with English drivers) may not be very relevant to the behavior of other drivers in countries with other driving cultures, on different types of roads, and at different hours of the day. Thus, an on-the-road study tells us a lot about behavior in the very specific environment in which it was tested, but very little about behavior in other environments. To complicate things, many factors – some of which are not even known to the researchers – are not controlled, and may account for the specific results that are obtained.

The remainder of this chapter defines some of the key terms that are relevant to behavioral research and the principal research methods. They are all illustrated with some examples from driving behavior research. Most of the concepts and methods are not restricted to driving or highway safety research, but they will be illustrated here with examples from highway safety research.

Key Concepts in Behavioral Research

The purpose of this section is to present some concepts and terms that will be used in the rest of the book. They include various measures that relate to highway safety, validity and reliability of the measures, experimental versus observational studies, between-subject versus within-subject experimental designs, and statistical versus practical significance.

Variables of interest

Whenever we conduct a study we have at least two variables of interest: a predictor, or an independent variable (such as driving style or type of road), and a dependent variable, which is a behavior (such as violations) or a phenomena (such as crashes) that occurs and is assumed to be caused by it. But things are typically not that simple. Other variables – depicted in Figure 2-1, intervene in the process. They include control, confounding, moderating, and intervening variables that can either explain or complicate the results of most studies. Their definitions and effects are described below.

Independent and dependent variables
The goal of most studies is to determine how one factor affects another. We call the factors that are presumed to exercise an effect the independent variables, in the sense that they can be independently manipulated by the experimenter. The factor on which we examine the effects of the independent variable is called the dependent variable in the sense that its outcome depends on the independent variable or variables. For example, if

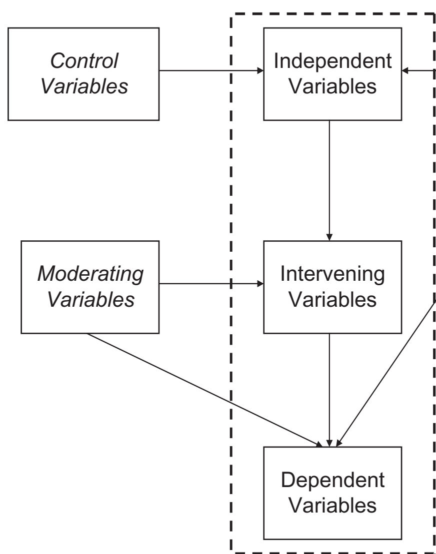

Figure 2-1. The relationships among various variables that are involved in empirical and experimental scientific research.

we wanted to study the effects of uncertainty on driver brake reaction time, we could set up mockup of a vehicle and then under various conditions turn the brake lights on and measure the driver reaction time. "Uncertainty" would be our independent variable and "reaction time" would be our dependent variable. We can vary the level of uncertainty by manipulating the predictability of the appearance of the light. Thus, in one situation, the timing of the onset of the lights would always be constant so the driver would know almost exactly when they will come on. In that case expectancy would be high and uncertainty would be minimal. This is the situation we have when the car ahead of us stops in response to a light that changed to red. In this situation the timing of the brake light onset is almost completely certain. In other situations the timing of the light could be highly variable so the driver would not know when to expect it. In that case the level of the independent variable – uncertainty – would be high. An example is an unexpected braking of a car ahead in stop-and-go traffic. It turns out that when such a study is conducted the level of uncertainty has a significant effect on reaction time: the greater the uncertainty the longer the reaction time (Warshawsky-Livne and Shinar, 2002). Similarly, we study the effects of alcohol blood concentrations, glare, drugs, hours of sleep, distractions from cell phones, and a host of other independent variables on dependent variables such as target detection, reaction time to obstacles, and crash involvement.

In highway safety, the dependent variable of greatest interest is some measure of crashes. We typically would like to know how everything affects safety and the ultimate measure of safety is a reduction in the number or rate of crashes. For various reasons measuring crashes (the dependent variable) is not always practical. Therefore, in many studies our dependent measures are intermediate or surrogate measures of safety that are related to accidents. For example, it is commonly accepted – at least by researchers in the area – that the risk of an accident and the level of injury in an accident (dependent variables) increase with increasing speed (independent variable). We may therefore decide to investigate means of reducing drivers' speed. We can then examine the effects of behavioral interventions (such as enforcement), environmental interventions (such as speed bumps), and in-vehicle devices (such as speed governors) on drivers' speed (which has now become the dependent variable).

When we cannot actually manipulate the independent variable, as when we wish to determine the effect of gender (independent variable) on crash involvement (dependent variable), we consider the first as the "predictor" variable and the latter as the "predicted" variable. The statistical relationship per se does not indicate causality, or which variable influences the other, but our basic understanding of human nature (or in some cases a theory that we have on human nature), indicates to us that gender is much more likely to affect crash involvement, than crash involvement can change gender.

Control variables

Control variables are factors that could affect the dependent measure, but for various reasons their level is held constant. In a typical controlled study when we focus on the effects of one or two independent variables (such as speed and headway) on one dependent variable (such as crash likelihood), we want to control all other variables that might increase the noise in the data; or technically speaking increase the variance. Thus, control variables are those variables that might have an effect on the dependent variables, but they are controlled by keeping their values constant and are not varied in the study. For example, in a driving simulation study on the effects of speed on crash likelihood, we may want to employ both male and female subjects. However, to reduce the noise/variance the researcher may decide to use gender as a control variable and include only males. The rationale would be that males are much more likely to speed and assume other risk-taking behaviors. Similarly the researcher can decide to control other variables that may increase the variance in the driving behavior and the effect on crash involvement such as driving experience, socio-economic level, the roads and traffic selected for the drive, the visibility, etc. The more variables that we can control, the more confident we are in our conclusions. So why not control for as many variables as we can? The reason is that as we add control variables we also limit the level of generalization of our findings to the particular driver and situational characteristics that were tested. For example, when we decide to restrict our study only to males, our conclusion must also be limited to males only. So, as often in life, we have a trade-off between the strength of our results in the situation in which they were obtained and the degree of generalization to other situations.

Intervening variables: Mediation between the independent and dependent variables
An intervening variable is one that – as its name implies – intervenes between the independent variables that we manipulate and the dependent variables that we measure. When I described the effects of uncertainty on reaction time, I also used the term expectancy. In fact, to understand the relationship we posit a psychological, latent (unobservable) term that we believe intervenes between the independent and dependent variables. We assume that the physical measure of uncertainty is related to the unobservable variable of expectancy. Expectancy, in turn, is assumed to directly affect the dependent variable. Thus, the vertical chain of independent → intervening → dependent variables in Figure 2-1 constitutes the basic relationships that are the focus of most experimental research.

Intervening variables – because they are not directly observed – are tricky. For example, there is currently overwhelming evidence that the use of cell phones while driving is dangerous. It impairs cognitive functioning and proper visual scanning of the road ahead, and increases the likelihood of crashes (Chapter 13 contains a detailed discussion of this area). But what is it about cell phones that make them so dangerous? What is the intervening variable? One possibility is that holding the phone limits the driver's control of the vehicle to the use of one hand. This implies that the intervening variable is the motor control of the vehicle. With this explanation in mind, many jurisdictions prohibit the use of hand-held cell phones. However, further research demonstrates that hands-free phones interfere with a host of driving tasks just as much as hand-held phones, and both increase the likelihood of a crash by similar degree. These findings have led many researchers to conclude that the intervening variable in this phone → driving performance → accidents chain is mediated by the intervening variable of attention: the phone, regardless of how it is used, simply creates a cognitive load that distracts too much attention from the road. However, "attention" is not an observable variable, and so we use surrogate measures to define the level of attention a task or a device requires, such as the amount of time drivers redirect their eye glances from the road ahead to the distracting (cell phone) task (Victor, Harbluk, and Engström, 2005), or performance on a secondary task (Strayer *et al.*, 2015). The plot does not end here, as studies using a new research methodology — namely naturalistic driving studies (see below) — that record driver behavior and glance behavior continuously, have shown that the only significant increase in the crash risk as a result of using a cell phone is during the brief periods when the driver's gaze is directed away from the road and the traffic (Fitch *et al.*, 2013; Klauer *et al.*, 2014). Thus, in the search for the intervening variable responsible for the deleterious effects of cell phones on driving safety, we have moved from an unobservable concept of cognitive distraction or overload to an observable variable of visual distraction.

The labels "independent," "intervening," and "dependent" are not part of a definition of a variable. Instead they represent the role that a variable plays in a particular experimental design. Occasionally, after we speculate about the role of an intervening variable in a particular relationship between independent and dependent variable, we can conduct another study to actually observe the effects of this variable. For example it has been repeatedly demonstrated that young novice drivers have the greatest crash risk. This is despite the fact that these drivers have the best vision and shortest reaction times. However, what these drivers do not have is the skill of effectively scanning their visual field in order to anticipate imminent accidents. To test for the effects of this intervening variable directly, Mourant and Rockwell (1972) compared the eye movement patterns of novice drivers as they accumulate more and more experience and showed that the visual search pattern becomes more efficient with increasing driving experience.

Confounding variables

A confounding variable is a variable that is not manipulated or controlled by the researcher and it is typically one of which the researcher is unaware at the time the study is designed. What makes one a confounding variable is that it behaves in a way that is similar to the independent variable, and thus, in retrospect, makes it impossible to determine whether the effect that was measured is due to the manipulation of the independent variable of interest or to the effect of the confounding variable that correlated with it. For example, if we measure the amount of ice cream sold on the beach and the number of drownings each day of the summer season, we may observe that the number of drownings is directly related to ice cream sales. We could then speculate on various intervening variables that would cause eating ice cream to drown (and many parents may already have that in their minds). In fact, a much simpler explanation is available: ice cream sales are directly related to the number of kids on the beach, and the more kids that there are on the beach, the more kids there are in the water, and the greater the number that may drown. Thus, the obviously confounding variable here is the number of kids in the water.

Confounding variables are actually not part of the study design, but they still have an effect on the results. They are less common in a laboratory setting where the situation is highly controlled, than in a field study where the researcher has very little control and a myriad of variables may be at work.

In highway safety research "exposure" or the extent to which a study group is exposed to a certain situation is a common confounding variable that always has to be considered. The literature is replete with examples, so we will pick three. The first example is a very costly one and stems from crash data obtained over 50 years ago. At that time some researchers and insurance actuaries noted that American teenagers who took formal driving instruction before getting their license were involved in fewer crashes than those who did not (meaning they were taught by their licensed family members or friends). This led to the premature conclusion that formal instruction improves safety and most insurance companies then offered reduced premiums to young drivers who took formal driving lessons. This resulted in an increase in demand to include driving instruction as part of the high school education program. A massive research effort was then launched by the U.S. National Highway Traffic Safety Administration to determine the actual benefits of structured instruction by professional instructors. The program, nicknamed Driver Education Evaluation Program (DEEP), randomly assigned teenagers to either formal training or not. Detailed tracking of the ensuing rates of violations and crashes failed to show the hoped-for benefits of the formal instruction. It turned out that the early findings were based on simple comparisons of crash and violation records of drivers who took driving instruction and drivers who did not take driving instruction. What these comparisons failed to take into account was the confounding variables of socio-economic status and safety orientation of the parents: the drivers who took the formal lessons came from families with lower crash rates, higher socio-economic levels, and greater concerns for safety than the ones who did not take the formal instruction (which, of course, cost money). Thus, the safety orientation of the young driver's family was suspected as a confounding variable that may have been responsible for the effect attributed to the driving instruction. Indeed, several evaluation studies of various driver education programs, where the allocation of teenagers to the instruction and non-instruction groups was randomized, failed to show any significant differences among the groups (see Chapter 6). Since then several studies have shown that the behavior of teen drivers is to a significant extent modeled after that of their parents (Bianchi and Summala, 2004; Miller and Taubman – Ben-Ari, 2010; Prato, Toledo, Lotan, and Taubman - Ben-Ari, 2010).

The second example is more recent and much less consequential. A study publicized in a daily newspaper in Israel claimed that young women are less careful when they drive close to home than when they drive further away, because they have more violations near their home than elsewhere (Barak, 2005). Unfortunately, the study did not control for exposure: the extent to which the women drove in the different vicinities. Since we spend more hours – in and out of our cars – in and close to home, it is obvious that we get more chances close to home for just about everything! This includes accidents, headaches, and misplacing our keys.

The third example is of a confounding variable that is well known but hard to control. It is almost axiomatic that young novice drivers are highly accident prone and that as they age and acquire more experience their crash risk diminishes. This is a statistical fact that insurance companies rely on when they set their higher premiums for young drivers. But is the effect due to age – or immaturity? Or is it due to the lack of safe driving skills that are acquired through experience? Thus, because in the general population age and driving experience are highly correlated, it appears that one of these two variables is a confounding variable, relative to the other. However, which is the true independent variable and which is the confounding one? The difficulty from the researcher's perspective is that age and experience greatly overlap since most drivers get their license almost as soon as they legally qualify. Nonetheless, a careful researcher will find a way to disentangle the two. When this is done, we find that the over-involvement of teenagers is actually due to both; indicating that neither is a confounding variable, and both actually affect the dependent variable (crashes) (Cooper, Pinili, and Wenjun, 1995; Maycock, Lockwood, and Lester, 1991; see also Chapter 6). These three examples demonstrate that the benefit of well-planned and carefully controlled research is that it considers potential confounding variables and tries to nullify or control for their effects by various experimental and statistical means.

Moderating variables

Moderating variables, as can be seen in Figure 2-1, are variables that affect the intervening variables, and therefore also affect the results observed on the dependent variables. These variables attenuate the effects of the independent variable by exerting an influence on – or moderating – the intervening variable. For example in the study cited above on the relationship between the uncertainty of a stimulus and the reaction time to it (Warshawsky-Livne and Shinar, 2002), the effects of the expectancy could be moderated by fatigue and motivation to excel. Therefore, the experimenter can control them by holding them constant or by experimentally manipulating them. For example, we can hold fatigue constant – meaning the same for everyone under all conditions – by making sure all participants had the same amount of sleep and the order of the different levels of uncertainty was randomly varied so that a given level of uncertainty would not always be at the end of the experiment when the participant is already tired. We can also manipulate the moderating variable and see its joint effects with expectancy. For example, we could run the same study twice: once in the morning and once in the evening and then see if the effects of expectancy are diminished or magnified at the end of the day when people are more fatigued.

Validity and reliability

Any time we do a study or read about a study there are two issues that determine our faith in the study's findings: (1) did the study actually and appropriately measure the things it reportedly measured, and (2) are the findings stable so that if other researchers in other places and other times were to replicate the study they would get the same results? These two issues define the study's validity – the extent to which the study actually measured what the researchers thought it did – and its reliability – the stability of the results across time and place. Thus, the early findings of the "effects" of driver education on driving safety mentioned above were actually quite reliable since the same results were obtained in several evaluations. However, as it turned out, the conclusions were not valid because the studies did not isolate the effects of the education program by themselves, but instead measured a host of other things that invalidated the early conclusions. Because most of the research in highway safety is of statistical nature, and the issue of confounding variables is always lurking in the background, we often seek more than one study to develop confidence in our conclusions. The ability to replicate a study by different researchers at different places around the globe gives the findings the needed reliability. This is critical in behavioral research – and that includes human factors in highway safety – because human behavior is quite variable, and often the results of a single study are not easily replicable. As an illustration, in a recent evaluation of the reliability of the results of 100 behavioral studies, in which 97 percent obtained statistically significant effects, 36 percent of the replications obtained statistically significant effects. In other words, nearly two-thirds of the findings could not be replicated (Open Science Collaboration, 2015).

But simply replicating the results does not validate them. The issue of validity is most often involved when we assume intervening variables and rely on surrogate measures of safety (rather than crash involvement). Thus, we should always question the validity of findings that are based on research in driving simulators and in studies relying on drivers' self-reports or responses to questionnaires. In neither instance do we measure actual driving behavior, and in neither case do we know how to consider the "accidents" relative to real ones.

Even the data we have on accidents should be examined for its validity. For example, given the proven effectiveness of seat belts and the overwhelming evidence for the effects of alcohol in crashes, we routinely accept the notion that an increase in seat belt use and a reduction in driving while intoxicated are intervening measures that mediate crash severity and involvement, respectively. The implication being that as seat belt use goes up and as driving under the influence of alcohol goes down, overall injury and crash rates should go down. Unfortunately, we often do not know the exact number of crashes a person had. The most common sources for data on crashes in every country are the police records. However, many crashes are not reported to the police, and many crashes that are reported do not merit a police investigation, and are therefore not recorded either (see discussion in Chapter 1). Most often these are crashes with either minor or no injuries and relatively little property damage. For example, repeated surveys conducted annually for three years on over 7,000 novice drivers in England revealed that only 35 percent of the accidents reported in the survey were also reported to the police, and even among the more serious accidents – the injury accidents – 10-20 percent were not reported to the police (Forsyth, Maycock, and Sexton, 1995). Detailed comparisons between records from trauma units in hospitals and police reports often show significant under-reporting by the police. This is especially so for non-fatal accidents. Furthermore, the under-reporting is not uniform across different variables. Police are less likely to report minor injury cases than severe injury cases, and less likely to report motorcycle and bicycle injury accidents than car accidents. (Amoros, Martin, and Laumon, 2006; Dhillon *et al.*, 2001; Janstrup *et al.*, 2016; Peleg and Aharonson-Daniel, 2004). This biased under-reporting then results not only in an unduly rosy picture of the level of traffic safety, but in incorrect proportion of different types of crashes, with potentially significant policy implications. Does that mean that we should rely on hospital records for all injury crashes? Not necessarily. Hospital staffs do not investigate crashes, and their records that a documented injury indeed was caused by a crash are not necessarily valid.

People may wish to report that injuries were incurred in a traffic accident in order to mask other kinds of violent events such as spouse abuse.

Given the shortcomings of police accident data, a significant body of research relies on self-reports to document crashes. Do self-reports and police reports reflect the same thing? The answer is a qualified yes. In terms of the number of crashes reported, people tend to report similar number of crashes as the police records reveal. However, these are not always the same crashes. As expected, people tend to report crashes that were not reported to or were not documented by the police, but then people sometime tend not to report significant crashes – such as ones involving driving under the influence of alcohol – even when these crashes were investigated and documented by the police.

When the criterion for validity is what happens in the "real world," it is often referred to as ecological validity. The results of two popular research methods that are often questioned in terms of their ecological validity are those based on self-reports and on behavior in driving simulators.

The ecological validity of self-reported behavior in general, not just with respect to crashes, is always suspect and cannot be assumed to reflect actual behavior. What people say they do and what people actually do may be slightly different, somewhat different, or even very different. However, the lure of using questionnaires and interviews to obtain information is great because they are both much cheaper, and often more detailed than obtaining similar information from direct objective observations or records. Furthermore, interviews can also provide insights to the respondents' reasons for their behavior.

The use of seat belts is a good example to demonstrate the complex issue of the validity of self-reports. To obtain an accurate observation-based estimate of belt use by front seat passengers under various conditions through a representative sample of observations in different parts of the U.S. is very expensive. To obtain responses over the phone from the same number of people in a representative sample of the U.S. driving population would cost a fraction of that. But are the two types of information the same? Obviously, the "socially desirable" answer to the direct question "do you use the seat belt when you drive?" is "yes." But is it the true answer? Several researchers in different parts of the world have compared the responses that people gave to this and similar questions after they were unobtrusively observed (Fahner and Hane, 1973, in Sweden; Stulginskas, Verreault, and Pless, 1985, in Canada; Streff and Wagenaar, 1989, in the U.S., and Özkan *et al*., 2012, in Turkey). The results of all the studies were consistent in showing that although there is a significant correlation between the actual use and the reported use, the reported use was significantly higher than the actual use. In an attempt to improve the validity of reported belt use, Streff and Wagenaar from the University of Michigan Transportation Research Institute tried to provide a "correction factor" that could be applied to self-reports to obtain an estimate of actual belt use. They compared the results of unobtrusive observations with roadside interviews (with two different questionnaires) of the same drivers, and with the answers from a telephone survey of a similar sample. Their findings were somewhat complex. In essence they found that self-reports provide an over-estimate of the actual use, but there was no single correction factor that could be applied. This is because the similarity of the reported use to the actual use depended on the specific wording of the question asked and the circumstances. For example, the reported use in roadside interview was nearly identical to the observed use, when the percent of people responding that they "always" use seat belt was used as a comparison measure. In contrast, the same question in a telephone interview yielded a significant over-estimate of the belt use, relative to the observed, showing that the more dissimilar the situation (in time and place) the greater the disparity between the observed use and the reported use. Still, to provide an easy rule of thumb, at least with respect to the specific issue of estimating seat belt use, Streff and Wagenaar recommend that self-reported seat belt use be discounted by about 12 percent to approximate actual belt use. Thus, the implication from their finding and those of the other researchers is that because the two are correlated, and the gap can be estimated, reported use of seat belt can be a good and valid surrogate measure of actual belt use. Unfortunately that rule of thumb turns out to be inappropriate in some circumstances. Parada *et al.* (2001) compared the observed behavior of drivers entering various parking lots of gas stations' convenience stores in El Paso, Texas with the self-reported use based on a question imbedded in a driver opinion questionnaire on "drivers" opinions of Texas roadways." In their study, self-reports over-estimated the actual use by 27 percent for Hispanic drivers and by 21 percent for "white non-Hispanic" drivers. Such findings might suggest that under-reporting bias may be greater the lower the actual belt use (Türker *et al.*, 2012) and a valid correction factor would then be not a single number but a function.

Still, even with such gross correction factors, the results of these seat belt studies are important in two respects. First, they demonstrate the existence of a caveat that should be attached to self-reports. Second, they can provide specific correction factors once the relevant mediating variables (actual observed rate of the specific behavior, the population demographics, and the particular measure of interest – e.g., crashes versus seat belt usage) are established. Finally, in some evaluations self-reports are better than "objective" data. This was demonstrated by a study in Australia where performance of older drivers on a road test correlated with self-reports of past accidents but not with the police records of past accidents (Anstey *et al.*, 2009). This does not mean that self-reports are more accurate but only that the inaccuracies in one (poor memory and social desirability bias in self-reports) are still better than the inaccuracies in the other (non-reporting of less severe crashes in police records).

The second domain with serious concerns about its ecological validity is the use of simulators in research on driving behaviors (Shinar and Ronen, 2007). The need to validate measures obtained in a simulator against real world measures of driver behavior and crashes cannot be ignored, and as illustrated below is often addressed in simulation research. However, not all simulation measures can be validated. We can easily design situations that result in a crash in a simulator (for example by intoxicating people before they drive), but no one would consider replicating the same conditions in the true world to see if a crash will actually happen there. Thus, in interpreting the results of research reported in this book – or in any other venue, for that matter – a prudent reader should always ask whether or not the specific measure used warrants the conclusions drawn.

Obviously, it is best if we can combine multiple data sources to estimate an effect. For example, to obtain good crash data it would be desirable to combine police records, hospital records, and drivers' reports; desirable but prohibitively expensive and logistically complicated. Consequently, most studies use one of these sources and try to justify its validity. It is then up to the reader to judge whether or not the measures used are indeed valid or not. The rule of thumb here is "caveat emptor."

Study Design

The design of a study determines the conclusions that can be drawn from it. The ultimate study does not exist. Every study design is a compromise between the desirable and the practical, and it is important to understand what we can and cannot conclude from different study designs.

Experimental versus observational studies

In the best of all possible worlds we would very much like to be able to control all the independent variables and then be able to tell exactly how they affect the outcome measures or dependent variables. Unfortunately this is never the case. When we conduct an experimental evaluation we can control many of the variables, but not all of them. For example, to study the effects of drugs on driving we might consider two approaches. The first approach is to do a naturalistic study in which we stop drivers on the road, assess their driving and driving record, and test their blood and/or urine for illicit drugs. This study is more ethical and feasible than the second approach which involves a controlled study in which we actually administer drugs to some people (treatment group) and not to others (control group) and then test for differences between the two groups in their driving behavior. The first approach is an observational study because all it does is observe existing differences in the independent variable (presence/absence of drugs) and the dependent variable (driving behavior). The second approach is one that involves random drug administration to one of two groups that are matched on as many characteristics as possible. This is the experimental approach.

As one may easily surmise, the conclusions drawn from the experimental approach are much more valid than those drawn from observational research because in the former we actually control and manipulate the situation, whereas in the observational approach there may be many differences between those with drugs and those without drugs that may have nothing to do with the effects of drugs. These differences may be acting as confounding variables. For example, the drivers with drugs are more likely to be young males, who are more prone to risky behaviors to begin with (after all, they demonstrate that by taking drugs!), and be caught at night when driving is more dangerous to begin with, than the drivers not taking drugs. The disadvantage of the experimental approach is that it is impossible to simultaneously examine all the variables that actually operate in real life, and it is sometimes unethical to create the situations that occur "naturally" in real life. Very often a study will be mixed in the sense that some variables will be controlled and others will be observed. An example could be a study on the effects of varying amounts of alcohol on driving-related behaviors of male and female drivers. While we can experimentally control the amount of alcohol (making it an experimentally controlled independent variable), we cannot (at least in most situations) control the gender of the subjects, and so we select a group of males and a group of females as participants.

Between subjects versus within subjects study designs, and treatment versus control conditions

Within the controlled environment of experimental studies, one important distinction is between studies in which the different levels of the independent variables are administered to different people, versus the situation where all the different levels are administered to the same people but at different times. In the "between subjects" design we typically have one or more treatment groups (such as different groups of subjects each getting a different amount of alcohol) and one control group (people who are being given nothing or a placebo – a substance that appears like the treatment but does not contain its active ingredient; e.g., an alcohol-looking drink that has no alcohol in it). In the "within subjects" design instead of having several treatment groups we have one treatment group in which everyone is administered several treatment *conditions* so that all study participants get the same conditions (but typically in different order to cancel out "order" or "learning" effects), and one of the conditions, where the "treatment" is not administered at all is the control *condition*. The within-subject design in which the order of the conditions is counter-balanced is also called a cross-over design (for a detailed description of different cross-over designs, see Pocock, 1983). The benefits of the between subjects approach is that each person gets tested for a shorter period of time and there is no need to worry about the order effects. However, when the individual differences – the differences among the people in their reaction to the variable of interest – are high, as they are with alcohol, this creates a lot of "noise" in the data making it difficult to discern the effects of the independent variable. On the other hand, within subjects designs suffer from the need to control for order effects (e.g., would a person with three drinks perform any differently if he/she were previously evaluated after four drinks than if they previously had two drinks or none?), and from the fact that it is often impractical to have all the people experience all of the experimental conditions. The benefits of the within subjects design is that it actually enables us to see how changes in the level of the independent variable (such as the amount of alcohol) affect a person as he or she experiences more or less of that variable. In the context of studies of the effects of alcohol on driving we will often find both types of studies yielding similar results, thereby strengthening our conclusions (see Chapter 11).

There are some independent variables whose effects can be studied either in a within or a between-subject design, and others that must be studied only in a between subjects or a within subjects design, with different implications for each. If we wish to study the effect of learning, we can either study a single group who is exposed to training (e.g., looking at novice drivers immediately after receiving their license and then periodically every

2 months) or study the effect of training by observing different groups of drivers with various levels of training. In the latter case we must ensure that experience is not confounded with any other variables, and it is therefore less conclusive, so a preferred method would be to track a group of cohorts over a period of their first two years of driving (when most of the safety skills and habits are acquired). If we wanted to study the effects of age or aging on driving behavior and crash risk that would be a different story. Here the temporal sequence is much longer. To track the same drivers from their early teenage days of driving to their old age (whatever definition we use for "old") is very difficult for obvious reasons, so we often compare groups of drivers of different ages, trying to control for various generational differences, trying not to forget that the different generations also grew up under different social, health, demographic, and technological conditions.

One variation of the between subjects design that has some of the benefits of the within subjects design without its shortcomings is known as a "case control" design. In this case, instead of comparing two (or more) groups that are drawn at random from the same population, each subject in each group is matched with a specific subject (or subjects) in the other group. This method eliminates many potentially confounding variables that may otherwise distinguish between the groups and thus yield spurious results. As an example, in the fleet study described below that evaluated the crash reduction potential of an advance brake light system, for each vehicle (in the treatment group) equipped with the advance brake light system, another vehicle (in the control group) was selected that was of the same make and model, and driven for the same purpose in a similar environment. Thus, if an effect were to be found it would not be an artifact of any of these matching variables (though it could be due to unknown confounding variables). However, even in studies defined as case-control, the matching is not perfect and various sources of error that can affect the validity of the results have to be considered (see Houwing *et al.* (2013) for a review.

Statistical versus practical significance

Significance means different things to different people – especially statisticians. In everyday use, a "significant" finding is synonymous with an important, noteworthy, major, or momentous finding. In fact, these are the synonyms you will get if you use Microsoft, tools > language > thesaurus. We can consider that as a "practical" definition of significance. The statistical definition for a significant finding in the context of behavioral research is the degree to which this finding would not have been obtained by chance alone. In other words, if a given study were conducted repeatedly many times, in what percent of the trials would the same effect be obtained by chance; that is, when there is no real effect? How reliable is the initial finding? Thus, in the statistical sense significance is a measure of the reliability of the results.

We seek statistical significance because human behavior is very variable, and people do not consistently respond in the same way to the same stimulus. For example, do you always stop at an intersection when the "Don't Walk" red signal is on? To answer this question we use statistical tests of significance that tell us – for a given result – the likelihood of obtaining the same finding if the same study were run many times. A conventional rule of thumb is to consider a result as statistically significant if the likelihood of obtaining it by chance is five percent or less. Throughout this book, whenever a result will be reported, it will be implied that it was statistically significant at a level of 5 percent or less. What we strive for in research are results that have both statistical significance and practical significance; that is, they are both reliable and important. Statistical significance does not imply practical significance. Practical significance typically means that the size of the effect is large and not necessarily that it is consistent. When sample size in a study is large, we can find small differences that are highly reliable – therefore highly statistically significant – yet their size is small for all practical purposes (Hauer, 2004).

Research Methods: From Basic/Laboratory to Applied/Field

The most robust knowledge that we have about human behavior in highway safety comes from multiple studies employing multiple methods, all leading to the same conclusions. This means performing converging research operations to answer the same question. There are not many examples of this. Most often converging operations do not all support each other for various reasons, and often a promising idea that is based on one or two similar studies is not followed up with additional studies employing different methods or is simply not pursued further. However, occasionally a specific issue becomes sufficiently important that it is pursued by different researchers using different methods. A salient example, discussed in depth in Chapter 13, is the impact of cell phone use on driving performance and crash involvement. The remainder of this chapter will be devoted to demonstrating some of the research methods used in highway safety to evaluate the benefits of two different approaches to help drivers avoid rear-end collisions. These two approaches involve two different technologies: the center high-mounted stop lamp (CHMSL) and the advance brake warning (ABW) system.

A case in point: Reducing rear-end collisions

The most important cue that a driver has to indicate that the car ahead is braking is the onset of its brake lights. Regrettably, that cue may sometimes arrive too late, in the sense that by the time the following driver realizes that the car ahead is braking, he or she does not have enough time to brake in order to avoid a rear-end collision. The most dramatic and extreme situations of that type are the chain accidents on the high-speed freeways and motorways. The question is, is there a way to speed up that realization so that we can brake more rapidly in response to the lead car's deceleration?

The first approach, and one with which nearly all drivers are now familiar, is that of the Center High-Mounted Stop Lamp (CHMSL). The CHMSL is the product of years of research that culminated in a change in the U.S. Federal Motor Vehicle Safety Standard (NHTSA, 2004) that requires the addition of the CHMSL to all passenger cars registered in the U.S. as of 1986, and all vans and trucks as of 1994. Other countries followed suit with Canada requiring the CHMSL in 1986, Australia and New Zealand in 1990, Israel in 1994, and finally in Eurasia in 1998. The CHMSL is the red light located in the center rear of the car either just behind or in front of the rear windshield or at the top of the trunk, so it is higher than the two brake lights. It is connected to the brake pedal so that whenever the driver activates the brakes the light goes on. The goal of the various studies that led to the CHMSL was to improve communications among drivers so that the driver of a following car would be able to respond more quickly to the braking of the driver ahead, and even to the braking of drivers farther ahead. Prior to the introduction of the CHMSL, the following driver had to detect the onset of the two brake lights, which (as everyone knows) are located on the sides of the car near the ground and off the following driver's direct line of view. Thus, the standard brake lights are not in the center of the driver's field of view, but rather in the driver's visual periphery where target detection is poorer (see Chapter 4). Furthermore, the closer a driver is to the car ahead, the greater the angle between the gaze ahead and the location of the brake lights, and therefore the poorer the detection of the brake lights. Thus, the three benefits of the CHMSL are that (1) it is in the driver's direct line of sight, (2) it enables a following driver to see braking of several cars ahead (through the windshields), and (3) at night, it changes from being totally "off" to "on" (in contrast to the standard brake lights that from a distance appear to just make the rear lights brighter).

The time from the onset of the lead driver's brake lights till the activation of the brakes by the following driver is known as the brake reaction time. Obviously, the shorter the reaction time, the larger the gap between the cars when the lead car starts to brake, and the greater the safety margin to avoid a rear-end collision. When the brake reaction time exceeds the temporal gap between two cars (the distance between the cars divided by the speed of the following car), a collision is inevitable. So the goal of improving communications in this particular case was essentially one of reducing the brake reaction time by providing drivers with a brake light system that would be more conspicuous and quicker to detect than the standard configuration, thereby reducing the rate of rear-end collisions.

The second series of studies was designed to evaluate an innovative approach to reduce rear-end crashes by reducing the lag time between the lead driver's *decision* to brake and the response of the driver behind that car. The idea was that somehow the following driver would respond to the lead driver's decision rather than to the motor response (i.e., braking) that follows that decision. The concept behind the particular system, labeled an ABW (Advance Brake Warning) system – was based on an assumption that in case of emergency braking, the driver removes the foot from the accelerator pedal to the brake pedal in an automatic "reflexive" manner that is much quicker than in the case of the more typical premeditated controlled braking. It is well known, that automatic actions are generally much quicker than controlled actions (Shiffrin and Schneider, 1977). Given that, the technological challenge was to devise a sensor that would detect the speed of the retracting accelerator pedal, and whenever that speed exceeded a certain threshold, the sensor would trigger the onset of the brake lights. In that case the driver in the following car would see the brake lights of the lead car come on *before* they are actually activated by the brake pedals. In a sense the brake lights would come on in response to reading the driver's mind! This is an interesting idea but it requires answering a host of different questions. Is the release of the accelerator in an emergency braking situation really different from that involved in normal braking? If so, then what speed of accelerator release characterizes emergency braking? When the accelerator pedal is moved at that speed or faster, is it always followed by actual brake activation? If quick release of the accelerator pedal does not always involve braking, how often does it happen? Does this create a dangerous false alarm ("cry wolf") situation that may cause following drivers to habituate to the system and not respond to the onset of brake lights as a real braking of the lead drivers? If the quick release is always or almost always followed by actual braking, how much time does it take to move the foot from the accelerator to the brake pedal; that is, how much of an advance warning will that give the following driver relative to the current situation when he/she first sees the brake light after the brake pedal has been activated? Finally – and most important – given the advance warning, how many rear-end crashes are likely to be prevented by such a device? Several different studies, utilizing different approaches, are needed to answer all of these questions and several different methods were in fact employed to answer them.

The following sections briefly discuss the various research methods that are used to study human behavior in the context of highway safety, and each method is illustrated by a different study used to answer a different question related to the CHMSL or the ABW. The methods reviewed below include basic laboratory studies, digital simulations, physical simulations (also known as simulator studies), on-the-road experiments, and controlled field studies.

Laboratory "Basic" Research

The principal benefit of research conducted in the laboratory is that the experimenter has complete control of the situation. It is then easy to study the effect of one or more independent variables on one or more dependent variables, while controlling for potential confounding effects, and, if desired, manipulating various moderating variables. The flip side of this advantage is that we cannot control all of the variables that may be operating in the real world. Thus the ability to generalize from the lab to the real world may be quite limited, but that limited generalization is equally applicable to many different real situations. For example, to assess the advance warning time that can be provided by the ABW, we (Warshawsky-Livne and Shinar, 2002) designed a simple laboratory study in which a subject – representing a following driver – sat behind a mockup of a rear of a car with his or her right foot resting on an accelerator pedal. The subject's task was to release the accelerator and depress the brake pedal right next to it as soon as the red brake lights of the mockup car flashed. There were two dependent measures: (1) the reaction time to the light – measured in terms of the time from the onset of the brake lights until the start of the release of the accelerator pedal and (2) the movement time – measured as the time it took the subject to move the foot from the accelerator pedal to the brake pedal. The sum of the two times was the total brake reaction time.

The study involved four independent variables: the subject's gender and age, the number of times the task was performed, and the level of expectancy for the red brake lights.

Let's consider the definition and the rationale for each one in turn. Driver age was important because older drivers are susceptible to performance degradations in multiple driving-related manners: beginning with their vision (Shinar and Schieber, 1991) and ending with their motor responses and coordination (Seidler and Stelmach, 1995; Stelmach and Homberg, 1993). Thus, the study evaluated the performance of both young drivers (students ranging in age from 18 to 25) adult drivers (26-49), and older drivers (ranging in age from 50 to 82). Gender is always an interesting issue, especially since there are many differences between the amount, type, and style of driving of men and women. For obvious reasons both age and gender were between-subject variables (we still cannot manipulate age and – in most cases – gender).

The other two variables were manipulated in a within-subject design so each person experienced all of the different conditions. Because reaction time is not constant, and people's reaction times increase significantly when the stimulus is unexpected (Fitts and Posner, 1967), it was necessary to control the level of expectancy of the lights. This was done by having the people respond to the light under three conditions of temporal uncertainty (a more technical term for expectancy): (1) with the interval between the response and the beginning of the next trial short and constant (minimal level of uncertainty), (2) with the interval varying from 2 to 10 seconds in a random manner (intermediate level of uncertainty), and (3) with varying intervals and on a certain proportion of the trials the lights were not turned on at all (maximal level of uncertainty). These situations roughly correspond to actual driving situations with varying levels of uncertainty: (1) when a driver expects the car in front of him or her to brake as when it is close to a traffic light that has just turned yellow, (2) in a stop-and-go traffic when the car ahead brakes but it's braking action is not at a fixed pace, and (3) when the car ahead is close to a traffic signal so that it sometimes proceeds to cross the intersection and at other times it brakes (known as the amber light dilemma zone). The final independent variable was the learning process. It is well known that reaction time improves with practice, at least initially. This is also well known to most people from their own experience and it is supported by many controlled experimental studies (see Fitts and Posner, 1967, for a review). It is therefore common to examine the changes in reaction time as a function of the amount of practice, or in our case the number of trials. So each subject performed the task ten times in each of the three conditions of temporal uncertainty.

The results of the study are illustrated in Figure 5-2. In that figure the reaction times and movement times are plotted on the Y-axis and the trial number is presented on the X-axis. Several observations can be made from these results: movement time is much shorter than reaction time (approximately 0.17-0.18 seconds versus 0.36-0.43 seconds), and it is essentially unaffected by the temporal uncertainty, while reaction time is. It appears that the uncertainty affects the initial decision to brake, but once the brain issues a command to move the foot to the brake pedal, the movement itself is quite automatic. Thus, only the reaction time changes from approximately 0.36 seconds in the condition with least uncertainty to approximately 0.43 in the condition with the most uncertainty. Furthermore, it appears that both actions (the reaction and the movement) are so overlearned, that there is essentially no learning effect and the performance on the first trials is essentially the same as it is on the last trials. Not presented in the figure are the findings that the differences between the men and the women in the study were negligible (and statistically not significant), but the age effect was quite noticeable: the average reaction time of the young drivers was 0.35 seconds while the average reaction time of the oldest drivers was 0.43 seconds. Although these numbers appear very small, one should keep in mind that at a speed of 100 km/hr (62.5 mph) a car travels 27.8 meters/second (90 feet per second). This means that in the time that our average subject moved his or her foot from the accelerator pedal to the brake pedal a car going at 100 km/hr would travel an average of 4.8 meters (15 feet and 9 inches); a distance that may mean the difference between a near accident and a real accident or between a minor collision and a serious collision.

This simple laboratory study does tell us how much of an advance warning the ABW can provide, but it leaves many unanswered questions such as what headways do drivers maintain when traveling at different speeds? If the headways are always such that they exceed the total brake reaction time, then there is no benefit to the added warning. In a real world situation when a car brakes, its actual braking distance depends on the amount of friction between the tires and the road: good tires on dry road can provide a short stopping distance while bald tires on a wet road will result in much longer stopping distance. Also, in the real world driver reaction times are typically much longer; 3-5 times as long as those observed in the laboratory under optimal conditions (Johansson and Rumar, 1971). Furthermore, under conditions of low expectancy (surprise!) they may exceed two seconds (McGee *et al*., 1983). So how do we evaluate the effects of all of these differences between the lab and the real world? One approach is to conduct a digital simulation, to which we now turn.

Digital Simulation Studies

A digital simulation study is a virtual study in the sense that we conjure up hypothetical situations and then let a computer program – based on previous mathematical and statistical functions – "run" the situation and determine its outcome. The benefit of a simulation study is that other than programming, it is free! Therefore simulation can be a great tool in exploring an issue "on the cheap." To illustrate the use of this approach we (Shinar, Rotenberg, and Cohen, 1997) used a simulation called Monte Carlo to estimate the potential benefits of the ABW with thousands of simulated runs of two vehicles following each other. Each run consisted of a pair of cars traveling in the same direction, one behind the other. At a certain point, the lead car braked as hard as possible, and the simulation program then determined whether or not the following car would hit the lead car or whether or not it would be able to brake in time to avoid it. In order to arrive at this conclusion, the simulation had to consider the reaction time of the following driver and the movement time to the brake. Reaction time distributions based on real-world driver braking reaction times were used, and on each run a data point from that distribution was sampled. The simulation also had to consider the conditions of the road (dry, wet, or icy), because they affect the coefficient of friction that determines the time it would take both vehicles to come to a stop. Finally, of course, it also had to consider the speed of the two cars and the headway (gap) between them at the time that the lead car started to brake. On half of the runs the lead car did not have an ABW and on half of the runs it had one and therefore the braking reaction time of the following driver was shortened by subtracting from it the movement time that would be saved. Thus, the study had four independent variables: the presence or absence of the ABW, the speed of the cars, the weather conditions, and the headway between the cars. The dependent variable was a dichotomous one: was a collision prevented or not. Some of the results of this study are presented in Table 2-1.

Table 2-1. Percent of rear-end crashes prevented with and without ABW at different vehicle headways (from Shinar *et al.*, 1997, reprinted with permission from the Human Factors and Ergonomics Society).

Private Headway	**With ABWS**	**Without ABWS**
0.50 seconds	50	0
0.75 seconds	95	32
1.00 seconds	100	50
Total	82	27

The table shows the percent of crashes prevented with the ABW and without the ABW as a function of the time headway (the temporal gap between the cars). The results are based on a total of 4,320 runs (720 in each cell) and are quite dramatic: with very short headways, none of the crashes would have been prevented without the ABW, while with the ABW 50 percent of the rear-end crashes would have been prevented. As the headway between the two cars increases, the overall number of crashes prevented in both situations increases, so that with ¾ of a second headway nearly all the crashes are prevented with the ABW and only 32 percent are prevented without it. If the headway is further increased to 1.0 second then all crashes are prevented with the ABW and 50 percent are prevented without it. When the headway is 1.5 seconds or higher (not included in the table) all crashes were prevented regardless of the presence or absence of the ABW.

Driving Simulator Studies

Physical simulation studies involve "driving" a mockup of a real vehicle inside a laboratory. This is achieved by projecting the driving scene on a screen in front of the car and by having the driver control the apparent movement of the scene via the vehicle's pedals and steering wheel. Most such simulators are based on computer-generated images. The rate and manner in which the projected images change are then determined by the activation of the pedals and steering wheel, which are also connected to the computer. The computer responds to the driver's actions by slowing down or speeding up the changes in the scene. Beyond this communality the differences among simulators are greater than the differences among cars.

But there is one other communality to all simulator studies – it is in their basic assumption that performance in a driving simulator is a good description of one or more aspects of real driving behavior. Given the discrepant results that are sometimes obtained with other methodologies, this assumption may not always be warranted; for example, in the case of distracted driving from cell phones when measured in naturalistic driving studies (see Chapter 13). A challenge to that assumption is the fact that unlike driving your own car, driving in a simulator is almost always a new experience. As such there is a learning or adaptation curve that must be considered, as driving in the first few minutes of a drive is probably very different than driving at the end of a drive. Obviously, it would be impractical to drive hundreds of hours before a person is considered equally familiar with the simulator as with his or her own car. So how much practice is enough? Most driving simulator research is done after a few minutes of practice or a few kilometers of driving, or until the driver "feels comfortable" with the task. However, recent studies (Ronen and Yair, 2013; Sahami and Sayed, 2013), have shown that the three criteria are very different from each other, and that the amount of practice at which performance on various indicators levels off is different for different measures of performance (such as stabilization of speed and lane position) and for different types of driving environments (such as rural versus urban, straight versus curved road). Thus, while simulators as a tool may be valid for comparisons among various conditions (relative validity), one must still be careful in interpreting the results given the many differences between driving a simulator and driving one's own car.

Despite the caveats listed above, there are different reasons why a study can best be conducted in a simulator. Some situations are dangerous to study in a controlled fashion on the road and are difficult to replicate in a valid manner in a rudimentary laboratory test. These include controlled studies of the effects of alcohol and drugs on driving or studies of drivers' reactions to unexpected obstacles to study the likelihood of collision. Other situations are the kinds that rarely occur on the road and collecting enough data may be prohibitively expensive. These include studies on the effects of extreme road, traffic, and weather conditions such as the behavior of drivers in fog and congestion (which, unfortunately, is not a very rare event in urban driving), or situations that are difficult to create on the road in a controlled manner even though they may occur quite frequently. To illustrate the latter, a study by Bar-Gera and Shinar (2005) sought to determine whether drivers tend to pass other vehicles because they impede their speed or because they do not like to drive behind another car and are therefore willing to increase their speed just in order to pass it. To determine this it was necessary to study the passing behavior of drivers, driving at different speeds, behind cars moving at different speeds relative to theirs. To manipulate and record the data from such situations on the actual road is quite difficult but to study it in a driving simulation is quite easy. In this particular example the simulation was designed so that while a driver drove down the road at a speed of his choice, a car appeared up ahead. That car then slowed down until it was closer to the driver and then it speeded up to a constant speed that was slightly below, at, or slightly above that of the driver. The results were quite surprising and they are reproduced in Figure 2-2. They show that the mere presence of a vehicle ahead causes some drivers to pass it, even if to do so they have to increase their speed. Thus, even when the vehicle ahead maintained a speed that was faster than that of the following driver by three km/hr, approximately 50 percent of the drivers still passed the car. Interestingly, on most of these occasions, after they passed the vehicle, the drivers slowed down to their previously preferred speed.

Another type of situations for which simulation studies are uniquely applicable is to evaluate systems that do not yet exist in the real-world, such as innovative safety devices. An example is the study of the effects of an innovative aid to keep safe headways while driving in long tunnels. Driving in tunnels is very different than driving on the open road: there are very few peripheral stimuli to give the driver an accurate sense of speed, there are no scenery to provide distraction and the darkness and proximity of the walls can give drivers a sense of claustrophobia. More important, perhaps, are the dangers of tunnel crashes. When a crash occurs in a tunnel, it often results in a fire and the fumes, flames, and smoke have no escape route other than up and down the tunnel. This, of course, poses a great risk to drivers and occupants of all vehicles who are often trapped inside the tunnel. One approach to reduce this risk is to require vehicles to maintain large headways. Unfortunately drivers are quite poor at estimating headways (Taieb-Maimon and Shinar, 2001). Therefore, as part of a European Union multi-national project we evaluated a technologically feasible – but non-existing – system in which a moving point of light would travel along the tunnel wall at a fixed distance behind each vehicle, and the task of a following driver would be to assure that he/she stayed behind

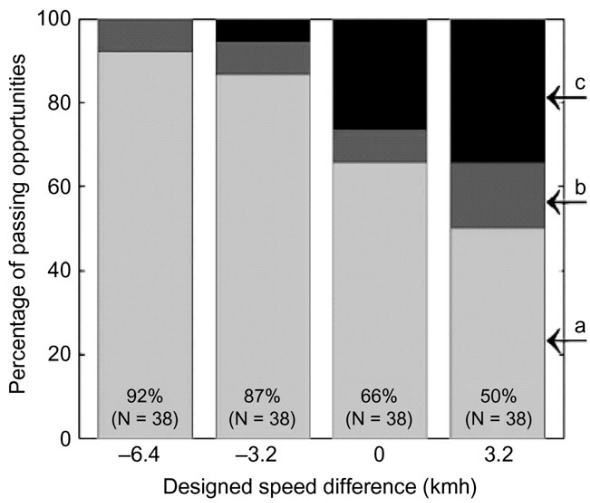

Figure 2-2. The distribution of drivers' actions as a function of designed speed difference between the lead car and the driver. Negative difference indicates that the lead car traveled at a lower speed when the driver (a) passed the lead car, (b) did not pass but wanted to, (c) did not pass (reprinted from Bar-Gera and Shinar, 2005, with permission from Elsevier).

that spot of light. A simulation study was designed in which the geometric features and dimensions of specific 13-kilometer Alpine tunnel connecting Leon in France with Bardonecchia in Italy was replicated and drivers were tested while driving the tunnel with this and other means of maintaining the desired headway. The system proved to be much better than no indicator and also significantly better than the traditional approach of painting equally-spaced markers on the road pavement or on the walls (Shinar and Shaham, 2003). With the rapid infusion of electronics into new vehicles, simulators are often utilized to guide and evaluate the design of advance driver support systems and minimize distraction from new infotainment systems (Boyle and Lee, 2010). The use of simulators in such cases is critical to safety because the effects of these technological innovations on actual crash data are slow and difficult to assess.

In general we distinguish between two types of simulators: fixed base and moving base. In a fixed base simulator the driver and vehicle are stationary and only the scene on the screen moves. Thus, there is only an apparent movement effect provided by the changing visual sense. Figure 2-3 is a schematic drawing and picture of the fixed base simulator at Ben Gurion University of the Negev, Israel. In contrast, a moving base simulator is designed to provide the additional cues of actual movement that we get when we move in a real car. These include the effects of the movement on our sense of equilibrium (generated by organs in the inner ear) that is affected by the pitch of the vehicle (the forward lurching when we brake and the backward lurching when we accelerate), proprioceptive stimulation caused by the yaw of the car (when it takes a curve), and the vibrations

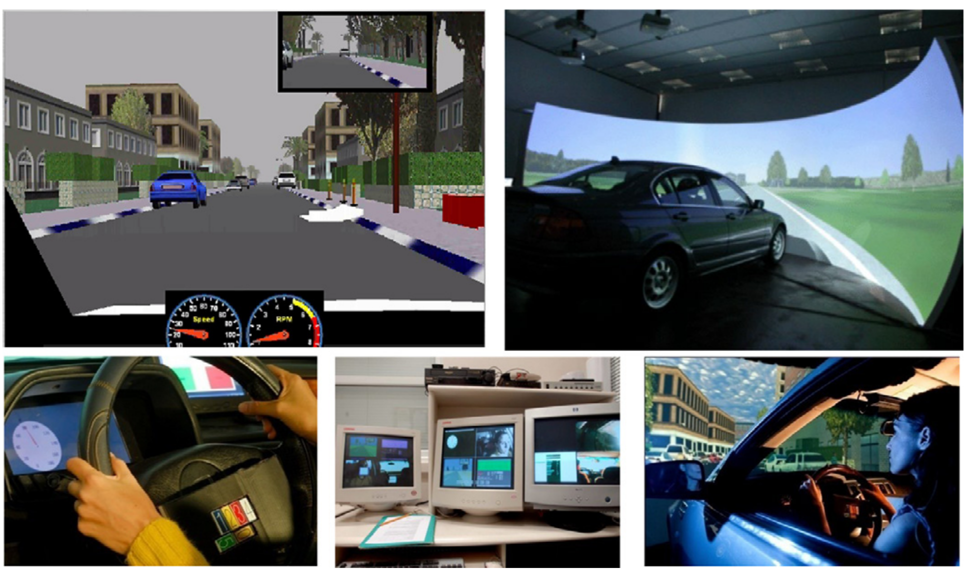

Figure 2-3. A fixed base simulator at the Ben Gurion University Ergonomics Laboratory. Clockwise from top left: partial view of a simulated street scene, the full-size car and the 140-degree curved screen, driver connected to EEG electrodes, monitors in the control room, and steering and dashboard console.

caused by deformation in the road and the type of the road pavement (heave). To provide the driver with all of these cues moving base simulators consist of a vehicle cab that actually moves within a limited space so as to provide the "driver" with the non-visual cues of the movement. The most advanced moving base simulator – the U.S. National Advanced Driving Simulator (NADS), housed at the University of Iowa – is shown in Figure 2-4. This simulator is currently promoted as "the world's highest fidelity simulator" (NADS, 2014). It consists of a large building that houses a moveable 24 feet diameter dome. Inside the dome is a full-size vehicle that the driver "drives." The visual scene is projected on a circular 360-degree screen via 15 computer-synchronized projectors. The visual scene is interactive and can be designed to show various environments under various roads, time of day, precipitation, and traffic conditions. More complicated are the non-visual cues that are provided to the driver, including sound, and vehicle movements in response to speed, acceleration and deceleration, and turning curves. Studies with the NADS enable recording of a multiple array of driver behaviors, eye movements, speed, and lane keeping performance. To appreciate the level of sophistication and complexity of this simulation, take a virtual tour that is available on the web (http://www.nads-sc.uiowa.edu/sim_nads1.php).

While it would be nice to conduct all simulation studies in NADS-like simulators, the difference in cost between a rudimentary fixed base simulator and a moving base simulator such as the NADS is over 1,000 fold! Thus, research with a driving simulator has to consider the ecological validity of the simulator relative to the task that the driver has to perform. To measure reaction time to a traffic light that turns red directly in front of a driver it is probably sufficient to simply present a light that changes from green to red on a computer screen, but to measure a driver's reaction to a light that changes from red to green while the driver is moving in traffic approaching an intersection at various

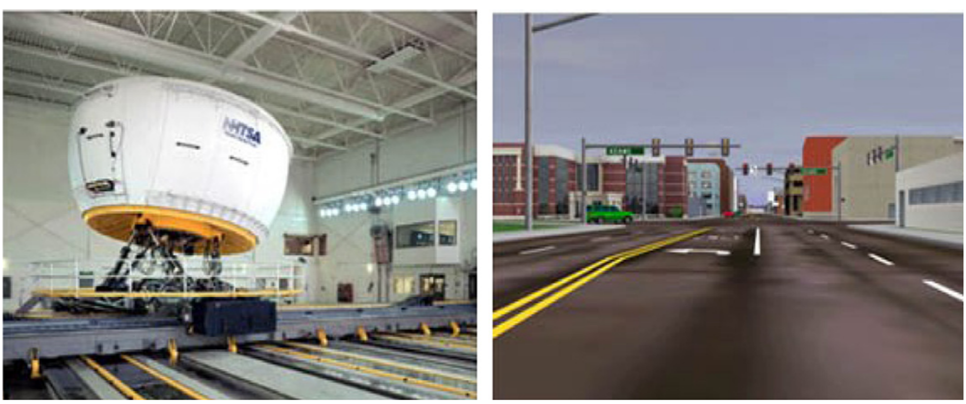

Figure 2-4. The U.S. National Advanced Driving Simulator (NADS) at the University of Iowa. The left panel shows the moving dome that contains the vehicle and driver and the right panel shows a scene on the front screen as seen by the driver (from NHTSA, 2007).

speeds and may be at different distances from the intersection when the light changes – for this a more sophisticated simulator is needed.

Validity of driving simulators

Regardless of the level of sophistication of the simulator, its use always raises the question of its validity: how relevant are the results obtained with it to results that would be obtained in a similar task on the real road. Because each simulation is unique in some aspects, each simulator must be validated independently. One feature that is relatively easy to evaluate is the sense of speed in a simulator versus the real road. To evaluate the validity of speed perception in the fixed base driving simulator at Ben Gurion University of the Negev, drivers drove in both the simulator and on the road. For that particular evaluation, licensed drivers were asked to drive a car on a rural road outside the city, and while their view of the speedometer was occluded they were given two types of tasks. In one type – speed production – the task was to drive at different speeds ranging from 40 to 100 km/hr. Once the driver said that he or she reached designated speed, the actual speed was recorded. The second type – speed estimation – involved having the drivers accelerate or decelerate until they were told to maintain that speed, and then they were asked to estimate that speed. For the simulator validation, a scenario consisting of a road with identical geometric properties (width, lanes, and curves) and similar roadside features was designed and the drivers were asked to perform the identical speed production and speed estimation tasks in the simulator. Figure 2-5 shows the results from the speed estimation task. The Y-axis shows the estimated speeds and the X-axis shows the actual speeds. As can be easily seen there is a very strong linear relationship between the estimated speed and the actual speed. This is not surprising on the road where people have thousands of hours of driving experience, but it is gratifying to obtain in the simulator: in both cases, the faster one drives, the faster the perceived speed. More important perhaps is the similarity of the simulator estimation to the actual speed. The dashed line indicates a perfect identity relationship. In the simulator the rate of change in speed is very similar

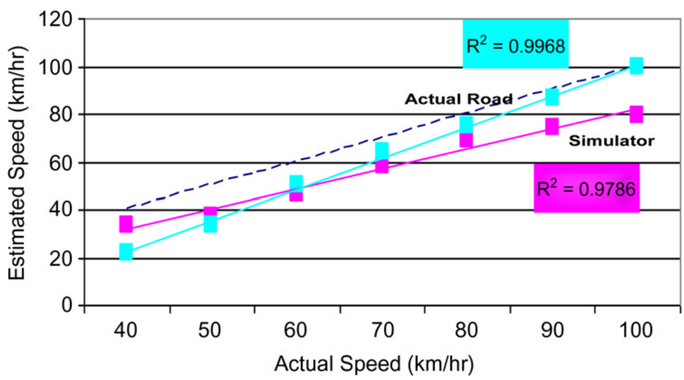

Figure 2-5. The relationship between actual speed and estimated/perceived speed in Ben Gurion University's simulator and on the road (from Shinar and Ronen, 2007).

to that on the road (represented by the similar slopes of the lines), but the simulated speed appears lower than the real one by approximately 10-20 km/hr. This difference can then be used to adjust the simulation speed in order to provide a sensation of the actual speed on the road. Interestingly, even on the road, the estimated speed was lower than the true speed, though as the speed increased, the estimate became closer to the actual speed. In the simulator the relationship was actually "cleaner" in the sense that the estimated speed was almost a constant underestimate of approximately 7 km/hr. Thus, these results demonstrate that studies with this particular simulator are valid as far as the drivers' relative speed perceptions are concerned. Furthermore, these results can also be applied to other studies with the same simulator, by supplying a transfer function to use in order to achieve any perceived speed. Similar results – demonstrating the relative – but not the absolute – validity of perceived speed in a simulator relative to real-world driving were obtained in an Australian simulator (Godley, Triggs, and Fildes, 2002).

In another type of simulator validation, McGehee, Mazzaae, and Baldwin (2000) compared the brake and steering reaction times of drivers when they encountered an unexpected vehicle that crossed their path as they approached an intersection. The simulator used was a highly advanced moving base simulator with six degrees of movement, and with 190 degrees visual field in front and 60 degrees visual field in the rear-view mirrors. Thus, the simulator provided the driver with both a visual and a kinesthetic environment that are nearly identical to that experienced in real driving. The validation evaluation revealed that in the sophisticated simulator the average steering reaction times were 1.64 seconds and on the road they were 1.67 seconds. The average brake reaction times were 2.2 seconds in the simulator and 2.3 seconds on the road. Thus, on both measures the simulator provided a highly valid simulation of real driving. On the other hand performance on another related measure – the throttle release time in response to the sudden appearance of the car – was significantly faster in the simulator (0.96 seconds) than on the road (1.28 seconds).

Other studies have demonstrated that while the simulator does not replicate the effects found on the road at an absolute level there is often a strong relative validity, meaning that the same relationships observed in the simulator are observed on the road even if the absolute magnitudes are different. Thus, different studies have demonstrated the relative validity of the simulation for degraded lateral control under the influence of alcohol (Helland *et al*., 2013), the response to rumble strips (Godley*et al*., 2002), different measures of fatigue (Hallvig *et al*., 2013), and braking responses to avoid collisions (Hoffman *et al*., 2002; Donkor, Burnett, and Sharples, 2014). Recent research has even demonstrated the relative validity of driving simulators in inducing and testing the effects of emotions such as anger (Abdu *et al*., 2012; Donkor *et al*., 2014) It is important to note that these behaviors were always tested within a particular context and the degree of validity can change with the changing context, such as when tested at night versus during the day (Hallvig *et al*., 2013). Taken together, these results and many others obtained in different simulators indicate that and moderate to high levels of relative validity can be achieved (Mullen *et al*., 2011).

One study evaluated the validity of four different simulators, in different locations in the U.S. with different degrees of physical reality, on the same driving simulation task, and yielded some unexpected results. In this study by Lee *et al*. (2013) different drivers drove through the same scenarios in the NADS, in a fixed base simulator with three degrees of movement and a 240-degree horizontal field of view, in a fixed base simulator without any movement and a somewhat similar visual field, and in a mini-NADS that is a fixed base simulator with three small front screens providing a total of 132-degree horizontal visual field. The general conclusion was that all simulators had good relative fidelity for speed. More surprising was the finding that all simulators – regardless of their physical realism provided similar perception of "overall feel and similarity to driving" and similar levels of simulator sickness (a plague of driving simulation studies that seems to affect approximately 10 percent of the potential participants). It is important to note that each simulator was driven by different drivers, and thus a direct comparison of the four simulators by the same drivers was impossible. It would be puzzling (and disappointing to those who have invested so much in moving simulators) if the NADS and the mini-NADS provided the same feel of realism.

The primary objective of simulation-based studies is to predict on-road performance from simulator data. This can be accomplished without absolute validity if a transformation equation can be developed. For example, drivers in a simulator typically drive faster than on the road, probably because the optical flow in a simulator is less than in the real world. Thus, there is no absolute validity for speed. But as long as there is some mathematical, and hopefully linear, equation that relates simulator speed to road speed (as in Figure 2-5), it is easy to use simulator data to predict road behavior. Because it is less expensive to "build" new roads in a simulator, different geometries can be efficiently compared in a simulator before they are actually implemented. Finally, no one has ever died in a simulator crash so research that might be high risk on a road can still be conducted in a simulator. A good use of the simulator is demonstrated in a study by Jamson, Lai, and Jamson (2010) that compared the utility of different engineering treatments for speed abatement in a moving-base simulator. In total there were 20 different treatments including various types of peripheral hatchings of the lane markers, rumble strips, vehicle-activated electronic speed signs, and speed limit signs. Various alternative treatments were evaluated in terms of their effectiveness at speed reductions on urban (straight segments and junctions) and rural segments (straight, curved, junctions, and entry to built-up areas). The important differences between these treatments are that they affect different driver information processing and decision functions such as alerting and risk perception. Controlling all other conditions would be impossible in the real driving environment, yet easy to accomplish in the simulator. The results showed, to quote the authors that "whilst straight sections of road are difficult to treat, speed reductions can be obtained by increasing risk perception. In contrast, alerting treatments had more effect at junctions, particularly in an urban environment; drivers approaching curves demonstrated improved speed adaptation if the curve radius was highlighted (either implicitly or explicitly)" (p. 961).

The significant improvements in digital computing have brought about a change in the perception of the utility of simulators. In the U.S. driving simulators are used mostly for the evaluation of drivers' behavior in situations that would be difficult or unethical or unsafe to study on the roads, but in Europe simulators are also used as tools in roadway design. This use can range all the way from informal evaluations of alternative designs to formal experimental studies of drivers' responses to alternative designs. Informal evaluations use the simulator as a means of visualizing designs before they are implemented. Thus, in the Netherlands, highway engineers rely on the Organization for Applied Scientific Research (TNO) simulator, to view dynamic presentations of their planned designs (from the driver's perspective) before finalizing them (Keith *et al.*, 2005). Formal experimental studies have been conducted with the Norwegian Institute of Technology (SINTEF) simulator to evaluate alternative lighting designs for Europe's longest tunnel (24.5 km!). The eventual design that consists of a changing light pattern improved drivers' comfort and reduced drivers' fatigue and anxiety as they drove through this long tunnel (Lotsberg, 2001). In Florida results from a driving simulation were used to demonstrate drivers' sensitivity to the speed of opposing traffic when they had to make a left turn, and thus cross the street between the moving cars. It turned out that drivers crossed with smaller gaps (averaging 5.8 seconds) when the traffic speed was high (55 mph), and higher gaps (averaging 7.3 seconds) when the traffic speed was low (25 mph). Thus, the behavioral data cast some doubt on the U.S. federal recommendations that assume a constant minimum gap of 7.5 seconds regardless of the traffic speed (Klee, 2004).

On-the-Road Studies

On the road studies fall into two general types: experimental studies that involve some manipulation of the situation, and thus an independent variable is actually manipulated, and observational studies that simply observe behavior of unsuspecting drivers under various naturally occurring situations, and thus all variables – independent and dependent – are not under direct control of the researcher. A special and relatively new type of observational studies is the naturalistic driving studies that merit a separate discussion below.

Experimental studies

As dramatic as the results from digital simulation of the ABW were, they still did not answer two critical questions. First, do drivers in fact always brake when they release the accelerator rapidly? If they do not, then how often will the activation of the ABW create a "false alarm" – a situation when the following driver sees the rear brake lights go on despite the fact that the lead driver does not brake. Second, how often do these conditions occur in real-life? For example, are drivers always attentive to the car ahead? Both of these questions were answered in partially controlled, experimental, on-the-road studies.

To minimize the potential harm from false alarms, the ABW was designed so that the accelerator release activated the brake light for only one second – ample time to move the foot to the brake pedal (given the movement times reported above). If in that interim the driver does not brake, then the brake lights go off. To determine the potentially dangerous likelihood of false alarms, five ABWs and monitors were installed in five different vehicles that belonged to a car pool used by members of a kibbutz (a communal settlement where much of the property – such as cars – is shared). This way, the individual drivers who drove the cars were not aware that the ABWs were installed in the cars and that their driving was being monitored. All together over a period of three months these five vehicles covered a distance of nearly 62,000 kilometers, and the drivers braked approximately 95,000 times. False alarms constituted a significant 23 percent of all ABW activations, but in reality were quite rare: approximately once every 250 kilometers. Furthermore, since these false alarms appeared as 1.0 second brake lights, it was interesting to compare them to the frequency of brief braking actions lasting one second or less. It turned out that drivers actually activated their brakes for brief periods quite often: approximately 40 times for every 250 kilometers. Thus, relative to these brief actual brakes, the false alarms were nearly zero (Shinar, 1995).

The ultimate test of any safety device is its ability to prevent crashes, or reduce crash severity, or both. The problem with the evaluation of any new system – such as the ABW or the CHMSL – before it is actually implemented – is that it does not yet exist in the cars on the road, and therefore the ability to directly assess its actual safety benefit is difficult. In the case of the ABW, a "fleet study" was designed in which a fleet of cars – consisting of 764 government vehicles – were included in the study. ABWs were installed in one half of the cars, and in a matching half of the study sample no ABWs were installed. The matching consisted of making sure that for each car with an ABW, a car of identical make and model, for use in the same government department and with a similar purpose, was selected for not installing the ABW. During the study period of 23 months the cars with the ABW accumulated a total of 44.6 million (!) kilometers while the control group accumulated a total of 42.1 million kilometers. During this period the ABW-equipped cars were actually involved in slightly more rear-end collisions than the control group: 75 versus 67. After adjustments for exposure (crashes per kilometers driven) all the analyses indicated that the two groups did not differ significantly from each other in terms of their crash involvement. Thus, despite the laboratory demonstration of the time needed to move the foot to the accelerator, despite the digital simulation demonstrating a very large benefit under various hypothetical conditions, and despite the field study conducted to allay fears of excessive false alarms, the bottom line from this study was that the ABW is not a significant safety device. Why then was this field study not conducted initially? The answer is simple and pragmatic. Controlled fleet studies are very time consuming, logistically and administratively complicated, and eventually very expensive. Thus, they are typically justified only when small-scale studies looking at parts of the issue point out to a probable benefit of a system. Then a large fleet study justifies the expense.

A similar methodological approach was applied in the evaluation of the CHMSL, but the outcome was totally different as can be surmised by anyone traveling in most of the world where the CHMSL is ubiquitous. After years of various small-scale studies on different configurations, colors, and brightness levels of the rear brake lights, beginning in the late 1950s and ending with three large fleet studies (Digges, Nicholson, and Rouse, 1985, for a review of the history of the CHMSL), the U.S. National Highway Traffic Safety Administration initiated a change in the Federal Motor Vehicle Safety Codes that required all passenger cars from 1986 and onward to have a CHMSL. Then, over a period of a little more than a decade the CHMSL became standard in the rest of the world.

The “acid test” of the CHMSL’s effectiveness consisted of three independent studies, conducted on fleets of taxis and utility vehicles. In all three studies this particular configuration of the two traditional side lights plus the center high light proved to be very effective in preventing rear-end crashes. The research method was the same in all studies: a fleet of cars was identified and half of the cars in each fleet had the CHMSL installed and half did not. All cars were then tracked for their involvement in rear-end crashes for a period of approximately one year. The results of the three independent fleet studies conducted at different times and at three different sites yielded remarkably similar results: a fifty percent reduction in “relevant” rear-end collisions. The analyses in all studies involved a detailed reconstruction of every rear-end collision to determine if the CHMSL was “relevant” or not. A crash was considered “relevant” – whether or not a CHMSL was installed on the vehicles involved – if the following driver collided with a lead car that was in the process of braking or had just braked. Thus, all rear-end collisions with a parked car or with a car that has been stopped for more than a few seconds were considered irrelevant. Under these circumstances it turned out that in all three studies the CHMSL-equipped vehicles had approximately 50 percent fewer “relevant” rear-end collisions than the non-CHMSL vehicles. Since “relevant” collisions constituted approximately 65 percent of all rear-end crashes, the CHMSL was associated with an overall reduction of approximately 35 percent of all rear impact crashes (Kahane and Hertz, 1998).

A few years later, McKnight and Shinar (1992) demonstrated the effectiveness of the CHMSL in trucks and vans. In this study a research vehicle moving on the road cut in front of an unsuspecting driver. Then at a certain point, the driver of the research vehicle braked, and the time for the following driver to brake was measured. Thus, this study was similar to the laboratory study used to evaluate the brake reaction time for the ABW, but it was conducted under naturalistic conditions and the subjects were drivers who were actually responding to the real braking of a vehicle, without being aware that they were participating in a study. The independent variable of main interest in that study was the presence or absence of a CHMSL on the research vehicle. Thus, everything about the research vehicle was the same on all trials, except for the presence or absence of the CHMSL. Furthermore, the tests with and without the CHMSL were carried out on the same road, same days of the week, and same times of the day. The results indeed demonstrated a small saving of 0.06 seconds to 0.12 seconds, depending on the particular configuration of the CHMSL. With these additional data, in 1994 the NHTSA extended the requirement for a CHMSL to trucks and vans. In summary, the development and evaluation of both the ABW and the CHMSL through progressive research provide a good demonstration of the criticality of well-designed human factors research for improvements in highway safety through judicious and empirically supported changes in-vehicle design.

On-road experimental studies have also benefitted from technological innovations that enable driver monitoring to an extent never available. Instrumented vehicles can now be equipped to study driver glance behavior using in-vehicle cameras that track the eye fixations in the car and out on the road and relate these fixations to the specific devices in the car and specific objects on the road, respectively. Eye movement tracking and analysis has been applied to understanding the cognitive demands that driving places on young/novice and old drivers, hazard perception and the acquisition of hazard perception skills, distraction from in-vehicle devices, external sources, and even cognitive distraction such as using hands-free phones (Taylor *et al.*, 2013). Experimental vehicles can also be employed with devices that detect extreme behavior such as sudden acceleration or braking and sudden lane changes. Coupled with algorithms that relate these to dangerous driving, these technologies have been used to classify drivers (as aggressive or not), and feedback from such devices has been successfully used to reduce aggressive driving of young drivers (Farah *et al.*, 2014; Toledo and Lotan, 2007; Toledo, Musicant, and Lotan, 2008).

Field operational test (FOT) – A quasi-experimental method

An increasingly popular type of on-road quasi-experimental studies is that of the field operational test (FOT): a study undertaken to evaluate an existing or proposed system, under normal operating conditions, in environments typically encountered by the host vehicle(s) using quasi-experimental methods (FESTA, 2011). FOTs have been used to evaluate various driver support, information, communication, assistance, and crash avoidance systems. In FOTs volunteer participants are recruited and provided with cars that are fitted with the systems to be evaluated and with a host of (hopefully) unobtrusive sensors and recording instruments. The drivers then drive the vehicles as they would their own car: to the same places in the same times as they normally drive. Because the driving route is idiosyncratic and varies from one driver to the other, the study is not strictly experimental but quasi-experimental. The participants' driving behavior is then recorded continuously, first without the activation of the system being tested, and then with it. Any differences in behavior are then attributed to the system. The benefits of this approach – assuming that the monitoring equipment is sufficiently unobtrusive and inconspicuous – is that the systems are being evaluated under the typical conditions of everyday driving. However, as most often the vehicle is not the driver's own car, it can only be hoped that after a short period of adjustment, the participants drive these cars as they drive their own cars; for better or for worse, similarly to the way people drive rental cars. When the costs of instrumenting the vehicle are not prohibitive, the FOTs are conducted with the drivers' own personal or leased vehicle. This was effectively done in a study by Shinar and Schechtman (2002) to demonstrate the impact of a headway alerting device in changing drivers' car-following behavior. In these studies there is no control group (as there is in controlled field experiments such as the ABW fleet study), and instead each driver serves as his/her own control when the monitoring equipment is turned on but the system that is being evaluated is not. One drawback of this design is that it must assume that any change in behavior is attributed to the system being evaluated and not to any other factors such as seasonal changes or changes in driving patterns and environments that coincide with the activation of the system (i.e., potential confounding variables). However, to the extent that such changes happen they can be noted and with highly experienced drivers it is safe to assume that the typical driving style does not change throughout the duration of the study.

Several FOTs have been conducted in the U.S. in Europe, Australia, and Israel to evaluate current and emerging electronic driver assistance systems such as adaptive cruise control, forward collision warning, lane departure warning, curve speed warning, blind spot monitoring, speed limiting, and "intelligent speed adaptation" (see Chapters 8 and 19). According to Carsten, Kircher, and Jamson (2013) "FOTs provide almost the only sensible methodology for assessing long-term driver behaviour with new in-vehicle systems" (p. 165). However, their usefulness is limited because they typically focus on the effects of one or very few devices, involve small sample sizes (a bi-product of the cost of such studies), and the participants are still aware that they are in a study. Consequently, their results are often inconclusive (see Carsten *et al.*, 2013, for a review of FOTs). A research paradigm that addresses these three concerns is the Naturalistic Driving Study (NDS), a variation of the observational studies discussed below.

Observational/correlational/associational studies

Almost all of the studies described so far were experimental studies. That means that in each case an experiment was set up – whether in the laboratory or on the road – in which the independent variable was manipulated by the experimenter. In the laboratory study this was done by controlling the uncertainty of the timing of the stop light, in the road studies it was done by giving the ABW and the CHMSL to predetermined groups of drivers/cars, and *not* giving the ABW and CHMSL to a *matched* sample of control drivers/cars. In these situations the experimenter creates a difference in the manipulation of the independent variable between the groups or conditions (as in the FOTs where the study is within subjects and each driver serves as his/her own control). The effects are then observed on the dependent variables.

In many situations the experimental approach is impossible. This is most often the case in medical studies that attempt to assess the effects of various substances on humans. For example, it is ethically unthinkable of giving cigarettes to one group of people and withholding them from a matched group in order to study the effects of smoking on lung cancer. We can do it in the laboratory with mice, but when it comes to people we have to find the ones who already smoke and compare them to those who don't. Similarly it would be unthinkable to design a study in which drugs are administered to drivers who are then set loose on the road. And so, instead we resort to the epidemiological approach: we try to observe people on the road who already – of their own free will – are under the influence of drugs, and compare them to other drivers who are not. In that case the possibility of many confounding variables is very real and must be considered. Potential confounding variables that can account for differences between the two groups can be differences in the tendency for risk-taking behaviors, exercising, dieting, socio-economic class, regularity of medical check-ups, attitudes towards health and safety, and (of course) age and gender. Analysis of crash data basis is fraught with other potential random and systematic errors and a good description of these in the case of assessing drug effects on crash involvement is provided by Houwing *et al.* (2013).

In the realm of highway safety, to study the actual crash savings of the CHMSL in "real life," once it became a standard on all cars in the U.S., repeated analyses were conducted in which the U.S. National Highway Traffic Safety Administration tracked the effectiveness of the CHMSL in actually preventing rear-end collisions. The police-reported crash data from eight states were used for the data base. In each state and calendar year of data, the ratio of rear impacts to non-rear impacts for model year 1986-1989 cars (all CHMSL equipped) was compared to the corresponding ratio in 1982-1985 cars (mostly without the CHMSL). Statistical methods were used to control for the potential confounding effects of vehicle age (because it may be argued that older vehicles with older and less efficient braking systems may be involved in more rear-end crashes, regardless of the presence or absence of a CHMSL). These evaluations demonstrated a positive but diminishing contribution of the CHMSL to roadway safety. The field observational studies yielded effects that were significantly smaller than the 35 percent savings in rear-end crashes that were obtained in the early experimental studies. In 1987 the overall reduction in rear-end crashes that could be attributed to the CHMSL was 8.5 percent, and it diminished in the following two years and then stabilized at about 4.3 percent, with the last evaluation made in 1995 (Kahane and Hertz, 1998). As these vintage vehicles became older fewer of them remained on the road and it became more difficult to make meaningful comparisons to assess the effects of the CHMSL in the U.S. Nonetheless, even at the 4.3 percent savings in crashes the CHMSL was estimated by NHTSA to prevent approximately 100,000 crashes, 50,000 injuries, and over 0.5 billion dollars in property damage and associated costs across the whole U.S. on an annual basis. An extremely good return on a $15 investment in each car!

How reliable are the results obtained in the U.S.? How well do they translate to other countries? Most European countries did not implement the CHMSL as a safety standard until 1998 so its effectiveness with European drivers could not be evaluated before that time. However, in Israel the CHMSL was introduced as a mandatory standard in 1994. Bar-Gera and Schechtman (2005) evaluated its effectiveness there by comparing the crash involvement of passenger cars of model years 1994-1996 (that are all equipped with CHMSL) with the crash involvement of passenger cars of model years 1991-1993 (with almost no cars equipped with CHMSL). Their measure of effectiveness was different than that used by Kahane and Hertz (1998). It was the ratio of number of involvements as the struck vehicle in a rear-end accident relative to the number of involvements as the striking vehicle in a rear-end accident. The initial analysis indicated that the CHMSL was responsible for a seven percent decrease in police-reported accidents. However, the statistical strength of the finding was marginal and there were confounding variables (unrelated to the CHMSL) that could have accounted for the positive effect. This led the authors to conclude that "it is therefore not at all clear whether it is appropriate to attribute this specific difference to the CHMSL contribution to safety."

The history of the research on the CHMSL illustrates the importance of conducting converging operations to the study of almost any simple device, let alone any applied complex issue. Despite the overwhelming evidence in favor of the CHMSL from the early results that prompted its required installation in all cars traveling on the U.S. highways, its lasting effectiveness still remains in doubt. When the evidence must rely on observational studies there is always the fear that some confounding yet-to-be-discovered variable may actually account for the effect observed. Thus, while the results of any one study may be valid in and of themselves, the conclusions based on that study – especially an observational study – must be taken with a grain of salt.

The analyses of the actual on-the-road effectiveness of the CHMSL also illustrate another important highway safety issue. There is no single solution to the problem of highway crashes. Even a device originally estimated to be 35 percent effective in all rear-end crashes, was eventually demonstrably effective in only four percent of them, and that too only in the U.S. There are no panaceas in this area. As we add new crash prevention measures – be they through vehicle improvement, driver regulation and behavior modification, or safer and more forgiving highways – drivers adapt their behavior, and the long-term effects of any one improvement are typically much less than its initial estimated effects.

Naturalistic driving studies

An NDS is a hybrid of epidemiological and empirical methods (Dingus *et al*., 2006). In NDS volunteer drivers have their cars fitted with multiple sensing and recording instruments that typically include several video cameras that record the roadway, surrounding areas, and the vehicle's interiors that include the driver and passengers. Electronic sensors also record longitudinal and lateral vehicle movements, pedals activation, and steering wheel movements, as well as combined vehicle-road data such as lane position, and headway to a car ahead. Additional background – presumably stable – information is also collected on the drivers that may include attitude questionnaires, psycho-motor tests, and biographical details. Once instrumented, the drivers fairly quickly adapt to the instrumentation and presumably drive their cars as they normally would, while massive amounts of data are recorded continuously and then downloaded to and analyzed by a central computer. So far the NDS is very similar to the FOT. However, unlike the FOT, here the purpose is not to evaluate a particular (innovative) system, but to obtain a record of typical driving behaviors in various situations, especially near crashes, conflicts with other vehicles, and actual crashes. Because a primary goal is to understand the causes and variables associated with crashes, and because crashes are (thankfully) relatively rare events, a lot of data has to be collected in order to analyze these "needles in the haystack" of normal uneventful driving. One way to circumvent this dearth of crash data, is to examine "near crashes" – events that involve a last-minute evasive maneuver on the part of the participating driver. Near crashes are ten times as common as crashes, and arguably share the same characteristics of real crashes (Guo *et al*., 2010). In addition, "uneventful" driving data are also useful as they provide exposure data for the safety-critical events. Thus we can, for the first time, under naturalistic driving conditions study how the crash or near crash events differ from the "normal" driving in similar situations. All in all, collecting and analyzing these data make such studies quite expensive; in fact, extremely expensive.

The first large scale NDS was conducted by Virginia Tech Transportation Institute and it involved instrumenting and tracking 100 vehicles. In this "100 Car Study," as it came to be known, there were a total of 241 primary and secondary drivers who drove the cars for 12-13 months, accumulating approximately 3.2 million vehicle kilometers (two million vehicle miles) and approximately 43,000 hours of driving. The data included five channels of video recording and multiple vehicle state and kinematic variables. Yet, when all these data were examined there were a total of only 69 crashes most of them so minor as to hardly be noticed and labeled as such by the driver (Neale *et al*., 2005).

In order to increase the sample size, real crashes are often combined with near crashes and critical incidents (of which there were 761 in the 100-car study). This combination does have some validity. In fact, Guo *et al.* (2010) have argued that the combination actually underestimates the risk of contributing factors relative to looking at the crashes only. Regardless of this tendency and justification of combining real crashes with near crashes, the wealth of driving data served as an excellent proof of concept, showing that it is feasible to collect and analyze such data to arrive at conclusions concerning the involvement of various factors such as visual distraction and fatigue in crashes.

Other studies initiated since the 100-car study have selectively focused on motorcycles (McLaughlin, 2010), trucks (Dingus *et al.*, 2006; Olson *et al.*, 2009), and novice drivers (Klauer *et al.*, 2014). The NDS approach has also spread to other countries such as Japan (Uchida *et al.*, 2010), European Union countries such as The Netherlands, the United Kingdom, Sweden, Germany, Spain, and others (Twisk, Van Nes, and Haupt, 2012), and Australia (Grzebieta, 2015; Regan *et al.*, 2013). Small-scale demonstration projects of the NDS approach have also been conducted in the United Kingdom, Greece, and Spain (Valero-Mora *et al.*, 2013). The largest European study of this kind, UDRIVE, with researchers from over 20 European organizations – is being conducted right now and is scheduled for completion in 2017. It examines driving and crashes of car drivers as well as truck drivers and motorcycle riders. In addition to crash causation, risk, and driving style, the study is also focusing on the effects of distraction, and on interactions with pedestrians and bicyclists (Eenink *et al.*, 2014).

An impressive demonstration of some of the unique capabilities of the NDS approach is contained in two recent studies that evaluated the role of cell-phone based distractions in crashes and other safety-critical events (Fitch *et al.*, 2013; Klauer *et al.*, 2014). Because of the ability of these studies to collect continuous data at high rates they were able to demonstrate that safety-critical events are due primarily to visual-manual distractions, especially those associated with texting and handling of cell phone conversation. In contrast, the cognitive distraction associated with the conversation phase of the phone call was not associated with an increase in crash or near crash risk. Yet, as naturalistic as the NDS and FOT studies are, they still have their shortcomings, as they are not able to isolate the role of various individual factors, collect data that might be intrusive (such as physiological or controlled secondary task performance), thereby contaminating the naturalistic aspect of the driving and determine causal relationships (see Carsten *et al.*, 2013, for a critical review of these methods). Also, the never-before amounts of data come with a very big catch: how to analyze and make sense of it. As these data are being gathered a major effort is being dedicated to defining new algorithms for reducing tera-bytes of data into fewer manageable chunks of more comprehensible information (Dozza, Bärgman, and Lee, 2013).

A very recently completed and by far the most ambitious NDS is the U.S. congressionally mandated study known as the SHRP2 (Strategic Highway Research Program-2) NDS. This study was initiated in 2006 and by the time data collection ended in November 2013, the SHRP2 NDS had logged in-vehicle data from 3,152 consenting drivers who together drove 3,958 vehicle years, logging one million hours of driving video, in six sites across the U.S. The data base has 5.5 million trips covering approximately 35 million vehicle miles, and – most importantly – 1,541 crashes and 2,705 near-crashes. Most of the crashes were very minor, but 250 crashes were severe enough to be "police-reportable." Interestingly, there was not a single fatal crash in all the 35 million miles traveled (Figure 2-6 contains a snapshot of a combined video image from the four cameras installed in each vehicle (Council, 2013; Kidd and McCartt, 2015; Njord and Steudle, 2015). In designing the study a very serious consideration was given to what questions it can answer. Despite the huge cost of such a data collection effort, not all questions could be answered within the budget. Still over 400 research questions were defined and it is expected that over the next 10-30 years different researchers using the data will answer all of these – and some more – questions. This unprecedented effort was aptly summarized by Council (2013, p. 34) who wrote that "Never before has the science of highway safety had such a rich resource, which will not only make roads safer, but will support researchers in road safety disciplines, as well as in other disciplines related to surface transportation…" (p. 38). A few small demonstration studies based on partial SHRP2 NDS data have already been published (Hedlund, 2015), and one analysis of the role of distraction in crashes of various types and severities has already been released (Kidd and McCartt, 2015; Njord and Steudle, 2015). However, these are only the initial fruits of this huge labor, and we must now patiently wait to see how many of the anticipated benefits of this grand study will materialize.

Cost notwithstanding, NDS is often considered an ecologically attractive improvement over driving simulation studies. But contrary to the impression that may have been

Figure 2-6. Video data collected in the SHRP 2 NDS from four cameras documenting (clockwise from top left) the view of the road and traffic ahead, the driver's face and right side, the rear view, and the driver's hands and steering wheel (from Campbell, 2012. Employee demonstration, courtesy of the Virginia Tech Transportation Institute).

created in the above description of the NDS, it is not a panacea. When compared to simulated driving studies both have advantages and disadvantages that make them more complementary than competitive. Table 2-2 summarizes the differences between the two approaches along 12 dimensions. While most entries in that table are self-explanatory, one dimension needs further explanation: the representation of crashes (#5). Because real crashes are rare, as mentioned above, an NDS typically pools together near crashes,

Table 2-2. Similarities and differences between simulation studies and naturalistic driving studies along 12 dimensions (from Shinar, 2015).

	Issue	Simulation	NDS
1	Sample size	Typically small	Typically large
2	Sample representativeness	Biased toward convenience within selected groups	Biased toward safety/ research oriented drivers
3	Immersion	Partial – with by-product of simulator sickness	Practically total
4	Stimulus representation	Controlled and artificial	Uncontrolled and real
5	Response representation of crashes	Mostly surrogate measures of driver performance – not all valid predictors of safety	Surrogate and outcome measures of Safety-Critical Events – but small Ns
6	Study design	Experimental	Descriptive/associational
7	Driver demand characteristics	At forefront (based on instructions)	Over time become minimal
8	Exposure duration/ repetition	Typically one trial	Extended – over multiple trips and long periods
9	Cost	Low	Very high
10	Driver's level of control	Operational only	Strategic, tactical, and operational
11	Ecological validity	Measures performance: what drivers can do	Measures behavior: what drivers typically do
12	Impact of new technologies	Can be assessed relative to workload and risk	Difficult to assess – as only very few vehicles have them

critical events, and actual crashes. While there is a similarity in the frequency of the events that contribute to crashes and near crashes (Guo *et al.*, 2010), the few crashes that are captured by NDS are predominantly very minor property-damage crashes. Extrapolating from these to serious injury and fatal crashes is probably not warranted because minor non-injury crashes differ from serious and fatal crashes, but near crashes differ from actual crashes in even more ways. As Knipling (2015) points out, crashes are defined by their outcome, whereas near crashes are defined by the driver behaviour, two very different aspects of safety. In contrast, a significant strength of simulation is that it can create the conditions that increase the likelihood of high-impact or severe crashes (though its generalizability to real-life remains an issue).

Meta-analysis − Quantitative synthesis of the results of multiple studies

"Meta-analysis is a quantified synthesis of results of several studies that have evaluated the same road safety measure stated in the form of a weighted mean estimate of effect" (Elvik *et al.*, 2009, p. 20). With the rapid explosion of information, there is a parallel explosion of studies that evaluate various crash countermeasures; including behavioral (such as education and enforcement strategies), environmental (such as roadway illumination, signage, and delineation), and vehicular (such as in-vehicle safety technologies including forward crash avoidance, lane departure warning, and intelligent speed adaptation). Meta-analysis is a statistical technique that pools together the results of several independent studies that focus on the same issue using the same dependent variables of safety (e.g., crashes, violations) and the same independent variable (e.g., automated enforcement, cell phones) to provide a combined measure of effectiveness. An extensive compilation of meta-analyses of various safety-related measures is provided by Elvik *et al.* (2009) in their *Handbook of Road Safety Measures*. Because combining data obtained at different times, in different places, and by varying methods is fraught with pitfalls, Elvik and his associates correct for some biases by estimating a *weighted* mean effect; that is, giving more weight to recent studies, giving more weight to findings based on larger sample sizes, giving less weight the greater the dispersion of the results of a study, adjusting for skewed data points in each study, and adjusting for "publication bias" (the tendency of journals not to publish "negative" results). Following these adjustments, a mean weighted odds ratio is derived. The odds ratio is the ratio between the odds of a given independent measure (e.g., cell phone use) versus (non-use) in the crash data, divided by the odds of the same variable in the non-crash control data. When the two odds are identical the odds ratio $OR = 1.0$ and there is no significant effect of the independent variable (e.g., cell phone use) on crash risk. When the $OR > 1.0$ it means that the crash risk from the independent variable (cell phone use) is significant.

For those readers not familiar with odds ratios and relative risk, a short explanation is needed here. The odds ratio is a somewhat difficult concept to grasp. A much easier concept is that of relative risk. The similarity and difference between the two measures is demonstrated in Table 2-3 for cell-phone use.

Table 2-3. The calculation of odds ratio and relative risk.

	Crash sample	**Non-Crash sample**	**Total**
Using the phone	a	b	a + b
Not using the phone	c	d	c + d
Total	a + c	b + d	a + b + c + d

Odds ratio (OR) = (a/b)/(c/d).
Relative risk (RR) = [a/(a + b)]/[c/(c + d)].

While odds ratio compares the odds of an event relative to another, the risk compares directly by how much the risk is increased or reduced. Although the calculation is different, when the critical event (a – e.g., use of phone in crash sample and c – use of phone in the non-crash sample) is rare, the numerical values tend to become very similar. We can then get a rough estimate of the relative risk of an event (e.g., using the phone) directly from the odds ratio. Because the critical event (e.g., using the phone, taking a drug) is often confounded by other factors that are crash-related (e.g., age and gender), when data on the confounding factors is available we use an adjusted odds ratio which is the odds ratio that remains after the effects of the confounding factors are accounted for.

Some of the results of meta-analysis reported by Elvik and his associates are included in their book (in the relevant chapters), including the effects of bicycle lanes, setting speed limits, traffic controls for pedestrians, bicycle and motorcycle helmets, and public information and education. Other, meta-analyses include the evaluation of the effectiveness of graduated driver licensing programs (Vanlaar *et al.,* 2014, see Chapter 6), red light cameras (Erke, 2009, see Chapter 20), and road safety campaigns (Phillips, Ullenberg, and Vaa, 2011, see Chapter 19), and the impact of cell phones on driving behavior (Caird *et al*., 2008) and crash risk (Elvik, 2011, see Chapter 13).

As appealing as meta-analysis is, it cannot replace a focused qualitative review of the literature that it purports to summarize for the simple fact that the process of combining the results of various studies ignores the many subtle differences among them in the design, the procedure, the participants, and the techniques used to obtain the results that are eventually pooled. Thus, while meta-analysis can provide a quantitative estimate of the effect of a countermeasure or a risk factor based on results pooled from similar studies, the strength of a more qualitative literature synthesis and review is that it can provide an appreciation of the different effects from widely different studies, include insights concerning the processes underlying these effects, and include studies that do not meet the quantitative requirements of a meta-analysis (Caird *et al*., 2014).

Concluding Remarks

The study of human behavior in highway safety is challenging because it presents the researcher with many complex methodological difficulties. Because there is no single golden rule to the design and analysis of all issues, multiple methods should be considered. Though each method may have its own limitation, effects that are repeatedly obtained by multiple study designs are most likely to be ecologically valid. The two current approaches involving experimental manipulation of multiple factors with simulators, and observational naturalistic driving studies that examine actual driving in the real environment should be considered complementary approaches to common issues. Together they can provide us with reliable and valid conclusions. Also, given the limited scope and samples involved in individual studies, the best method to overcome reliability and validity issues associated with different approaches is to address each issue from a variety of perspectives, and with different research methods. Finally, as the number of studies that have examined specific issues – and especially crash countermeasures – has increased in recent years, we can now use a quantitative method – known as meta-analysis – to gain more confidence in our conclusions concerning different safety issues. Thus, in evaluating the research presented in the following chapters it would be judicious to consider the conclusions presented as strong as the number of different studies, employing different methodologies that yield the same results.

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3

Theories and Models of Driver Behavior

> "The society which scorns excellence in plumbing as a humble activity and tolerates shoddiness in philosophy because it is an exalted activity will have neither good plumbing nor good philosophy: neither its pipes nor its theories will hold water." (Gardner, 1961).

> "The increasing stress involved in motoring nowadays makes the psychological efficiency of the driver a more important factor than the mechanical efficiency of the vehicle he drives." (Parry, 1968).

The purpose of this chapter is to present some theories and conceptual models that have been offered to describe, explain, predict, and affect driver behavior. In our attempt to understand this behavior, predict it in different circumstances, and if possible control or modify it (e.g., discourage drivers from using the phone while driving, respect the speed limits, be defensive rather than aggressive), it is necessary to have some kind of a theoretical framework as a starting point. A valid theory or model of human behavior enables us not only to better understand why we behave on the road the way we do, but also to predict drivers' reactions to many potential safety measures, and to develop quantitative driver guidance systems (Donges, 1978), user-oriented highways and vehicle designs, and better driver training programs. This is because the introduction of a safety measure into the vehicle or highway – such as electronic stability control and programmable signs, respectively – not only changes the vehicle and roadway characteristics, but also changes driver behavior in response to them. Sometimes, the behavioral change may actually negate the expected benefits, and we need to understand why and when that may happen and how to avoid it.

Why We Need Driver Theories and Models

The argument for the need for theories and models of human behavior for highway safety was made very succinctly by Kantowitz *et al.* (2004): "Absent the theories, it is almost impossible to specify what new countermeasures might emerge. Thus, what is a standard operating procedure for many human factors researchers (using models) might require an act of faith from practicing highway engineers who do not normally invoke theories of human behavior. If aviation, nuclear power, and human-computer interaction can create better countermeasures through models, so can driving" (pp. 85-86).

A theory is the best practical human factors tool, because, as Kantowitz (2000) notes:

1. It fills in where data are lacking. No handbook or guideline has all the necessary data.
2. Computational theories provide quantitative predictions needed by engineers.
3. It prevents us from reinventing the wheel by allowing us to recognize similarities among problems, such as the tendency of drivers to adopt inappropriate decision criteria in many situations.
4. It is reusable. Once the investment has been made to build a model for a particular domain, the theory can be recycled inexpensively to answer many system-design questions.

The body of research that has accumulated on driving behavior is not just a collection of findings and conclusions but hopefully more like a jigsaw puzzle in which many pieces are made to fit together to form a coherent picture. That picture is our theory of driving behavior. Once we have a theory we can better direct our search at gathering additional "facts" to fill the remaining gaps. In short, the purpose of the models or theories of driver behavior are to make sense of it all.

A theory and a model are not synonymous terms. A theory is a conceptual organization of concepts, mechanisms, and processes that are involved in the operation of a system, such as the atoms in a molecule or – of greater relevance here – driver in traffic. A model is less presumptive in the sense that it does not presume that these mechanisms and processes actually exist, but only that if we posit them then we can explain human behavior. Often after a model of human behavior is developed and validated, a search is done to see if some of its mechanisms actually exist. An example of this is the formulation of the human memory in terms of two distinct mechanisms: short-term memory and long-term memory. The two different mechanisms were first defined and proposed in order to explain various phenomena associated with learning, memorizing, and forgetting. Only after their "invention," did scientists find physiological evidence for the existence of two such distinct information storage areas in the brain (in the hippocampus for short-term memory and the frontal lobes for long-term memory; Costandi, 2009). Thus, a model can often serve as a basis for a theory. In general, unless there is independent evidence for the existence of specific processes and mechanisms, it is safer to talk of models of driver behavior than theories of driver behavior.

Unlike the physical sciences, where a single model is typically the working model for all (until it is replaced by a more general, parsimonious, or valid one), in behavioral interdisciplinary sciences we often have multiple models often using the same terms inconsistently (Hughes *et al.*, 2015). Therefore, laying a unitary theoretical foundation for the discussion in the rest of the book is not practical or efficient. Instead, this chapter discusses several theories and models of driver behavior, broadly defined as theories or models of driver *performance* or driver *behavior*. The different models that are considered below can be described as belonging to one of two categories or attempts to combine both. Models designed to predict driver *performance* most often depict the driver as a limited-capacity information processor, and models designed to explain and predict the more complex real on-road *behavior* assume that actual driving behavior represents the style and strategy the driver adopts to achieve his/her goals. In the broadest sense, the models are actually complementary: the first describe *performance* – or the best the driver can do in a given situation – and the second describe *behavior* – or what a driver tends to do in the typical situation, within his or her limits of performance. Driver performance is the end product of what a driver can do, given the human limitations and given the vehicle and environmental constraints. Driver behavior is what the driver actually does given the limitations and constraints *and* given the driver's needs, motivation, and goals that can be achieved through the driving task. The foundations for the first kind of models are in cognitive and physiological psychology, whereas the foundations for the second kind of models are in theories of personality, social psychology, and organizational behavior. The performance models are used to predict the limits of maximal behavior, while the motivational models are best at predicting typical behavior.

In reality our behavior on the road is a combination of both typical behavior (most of the time we drive) and maximal performance (when we find ourselves in very demanding situations). Thus, both approaches are useful, but in slightly different contexts. This being the case, many models try to incorporate both aspects of our driving: our typical behaviors and our maximal performance or ability. Another approach to classifying models of driving behavior is to distinguish between descriptive models that focus on describing *what* the driver does in various situations, and functional models that focus on *why* the driver does what he or she does. Thus the former can serve as good prescriptive guidelines to what a driver must do to accomplish the driving task, while the latter focuses on the mechanisms and motivations that drive (no pun intended) the different behaviors. Within each class there are further distinctions based on how the different components are organized. Descriptive models can be formulated in a hierarchical fashion (as detailed below) (Michon, 1985) or in terms of feedback control loops (McRuer and Weir, 1969). Functional models are often centered on the driver's information processing system (Rasmussen, 1986) or on motivational concepts (Wilde, 1998), or both (Fuller, 2011).

Obviously, models of driver behavior should always be regarded as work in progress: they either replace one another, or supplement each other, or are updated and modified as new data on driver behavior and driver adaptation accumulate and as the driving environment and vehicles change. An excellent summary of the evolution of driver models up to the early 1990s of the last century is provided by Ranney (1994), and up to the end of the first decade of this century by Vaa (2014). The models described below were picked because they were either widely cited or because they exemplify some of the more pertinent issues that driving research addresses.

The Context of Driving: Hierarchical Decision-Making

Driving is a task that is conducted within a larger framework of mobility. The mobility task – and challenge – is to safely get from one place to another. The decisions a driver has to make in order to achieve that can be described in a hierarchical system such as the one proposed by Janssen (1979) and Michon (1985) and illustrated in Figure 3-1. The system has three levels: the top level consists of the strategic decisions, the intermediate level consists of the navigational decisions, and the lowest level consists of the operational control.

The decisions at the highest – strategic/planning – level include the decision to drive (versus to take a bus or a train or to postpone the trip), the route to choose, the time to leave, etc. The variables that moderate such decisions include the joy or distaste of driving, the need to hurry, the economy of travel mode, the time available, and the latest traffic reports. These are all issues that have to be resolved before the person gets into the car. Once a decision to drive has been made, the second-level decisions – at the tactical/navigation level – must be made. These decisions are made while driving and include how to best avoid obstacles, when and how to change lanes to gain a maneuvering advantage or in preparation for a turn, whether to slow down or speed up at a certain distance from a light that has turned yellow, etc. Finally, at the lowest – control/automatic – level the decisions are mostly unconscious and reflexive and they involve the moment-to-moment actions in response to various stimuli. These include acceleration and deceleration, signaling, changing gears, checking mirrors prior to lane changes, stopping at traffic lights and accelerating from a stop, braking and swerving response to

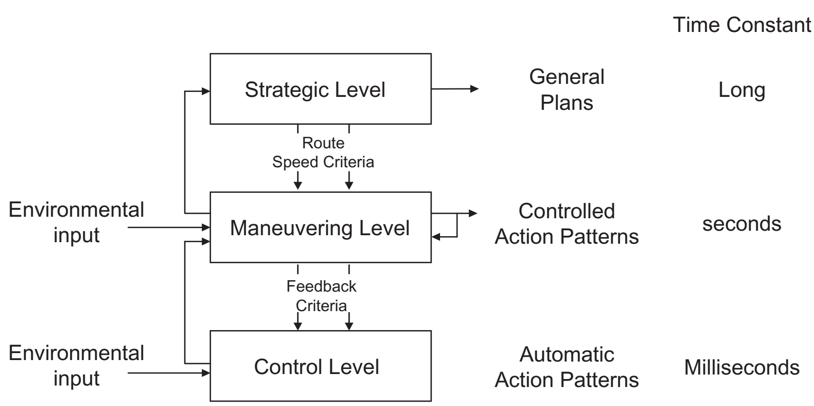

Figure 3-1. The hierarchical structure of the mobility/driving task (from Michon, 1985, based on Janssen, 1979, with kind permission of Springer Science and Business Media).

sudden emergencies, etc. Driving skills and habits play a major role in our behavior at the control level, and much of the driver instruction and initial learning is concerned with the acquisition of these skills. While these skills may not always play a role in safe driving, they often play a crucial role in the avoidance of collisions once a driver has entered a dangerous situation. The decisions a person makes at each level are very important because – among other things – when combined with the driver's specific skills and deficiencies, they directly affect his or her level of risk of being involved in a crash on a given trip (Hakamies-Blomqvist, 2006).

The decisions we make at each level of the hierarchy are based on some criteria of what we would like to achieve. Thus, if at the strategic level we wish to reach our goal with minimum time, this may imply that (1) at the strategic level we choose a certain mode of transportation (drive rather than take public transportation), (2) at the maneuvering level we decide to drive at the high-speed lane at maximum acceptable speed, and (3) at the operational level we minimize braking activities and weave between vehicles. These goals and criteria that dictate behavior then yield various performance outcomes as illustrated in Table 3-1 for a driver whose strategic goal is to reach the destination quickly.

How we perform the tasks at each level – what biases, constraints, desires, limits, and skills govern our behavior – is the subject matter of the theories and models researchers have proposed to explain on-the-road behavior. Note that our behavior does not occur in a vacuum, but has "environmental inputs." These include not only the visible and immediate inputs from the roadway, the traffic, the weather, and the lighting conditions, but also the less tangible environment consisting of traffic laws, norms of behavior, and culture that govern the way we drive. For example, it is the latter that are responsible for stereotypes of "New York drivers," "Italian drivers," "Israeli drivers," and "English drivers."

The hierarchy and time scale associated with each of the three tasks also implies a temporal sequence. When we embark on a trip, we first decide how to get there, when to leave, and by what route (strategic decisions). If we choose to drive, then once on the road we decide on a lane of travel, whether to track a car ahead or pass it (navigational decisions), and then we perform the skilled motor behaviors that govern our safe movement on a moment-to-moment basis such as accelerating, decelerating, and braking, in response to specific stimuli such as the brake lights of the car ahead (control decisions). However, note that the model has both top-to-bottom arrows and bottom-up feedback loops. Thus, repeated agitating control actions in stop-and-go traffic may make us reconsider some of the navigation decisions, and we may decide to change lanes to what appears a faster one (always the one we are not on), and eventually we may also decide to change strategies, and possibly stop for an early meal in the hope that when we resume driving the congestion will have dissipated. Thus, decisions at all levels may actually be carried out at all times, and variables that govern each level may operate at all times. This of course makes behavior quite complex to describe, and even more difficult to understand on the part of other drivers on the road. An example is a driver who suddenly cuts across our lane dangerously close to the front of our car in order to exit the motorway at the last minute.

Table 3-1. The interaction between travel related criteria, driving behaviors, and driving performance at the strategic, tactical, and operational levels of a hierarchical driver model for a driver whose goal is to reach the destination quickly (from Östlund *et al*., 2006, with permission from VTI).

	Criteria	**Behavior**	**Performance**
Strategic	1. Reach the destination quickly. 2. Stay clear of oncoming traffic and other objects.	1. Chooses a high-speed route. 2. Aims at driving fast. 3. Accepts high risks.	1. Does not reach the destination quickly enough.
Tactical	1. Drive as fast as other vehicles, the environment and the vehicle permits. 2. Overtake slow going vehicles.	1. Tailing vehicles and prone to overtake. 2. Cuts curves. 3. Drives at yellow light. 4. Drives fast.	1. Does not manage to overtake the slow vehicles as quickly as desired. 2. Tailgating.
Operational	1. Stay within accepted headway to the lead vehicle. 2. Follow the desired path of travel, e.g. when overtaking. 3. Keep vehicle within road boundaries.	1. High lateral position variation. 2. High-speed variation.	1. Occasionally less headway than accepted. 2. Occasionally departures from the desired path of travel. 3. Vehicle occasionally partly exceeds lane boundaries.

To make the hierarchical model more useful it has to be more detailed. An example of one such elaboration is provided in Figure 3-2. This model is more specific than the one in Figure 3-1 and Table 3-1, both in terms of specifying variables that can affect actions at each level and in terms of the time frame that is relevant to each level. There can be many applications of the general model, and the one in Figure 3-2 illustrates the application of the hierarchical model to evaluation of the potential impact of one of today's most heatedly debated vehicle-roadway features: telematics – an integration of wireless communications, vehicle monitoring systems and location devices (Braddy, 2006). As can be seen from Figure 3-2, the availability of on-line information transmission about the road and other traffic can initiate various types of responses at all three levels. At the strategic level, predicted levels of congestion can assist a person on deciding on what mode of transportation to take and what route to choose. At the tactical level telematics can aid a person in driving-related decisions, but they can also constitute a distraction. At the operational level, too, they can serve as an aid or as an impediment. For example,

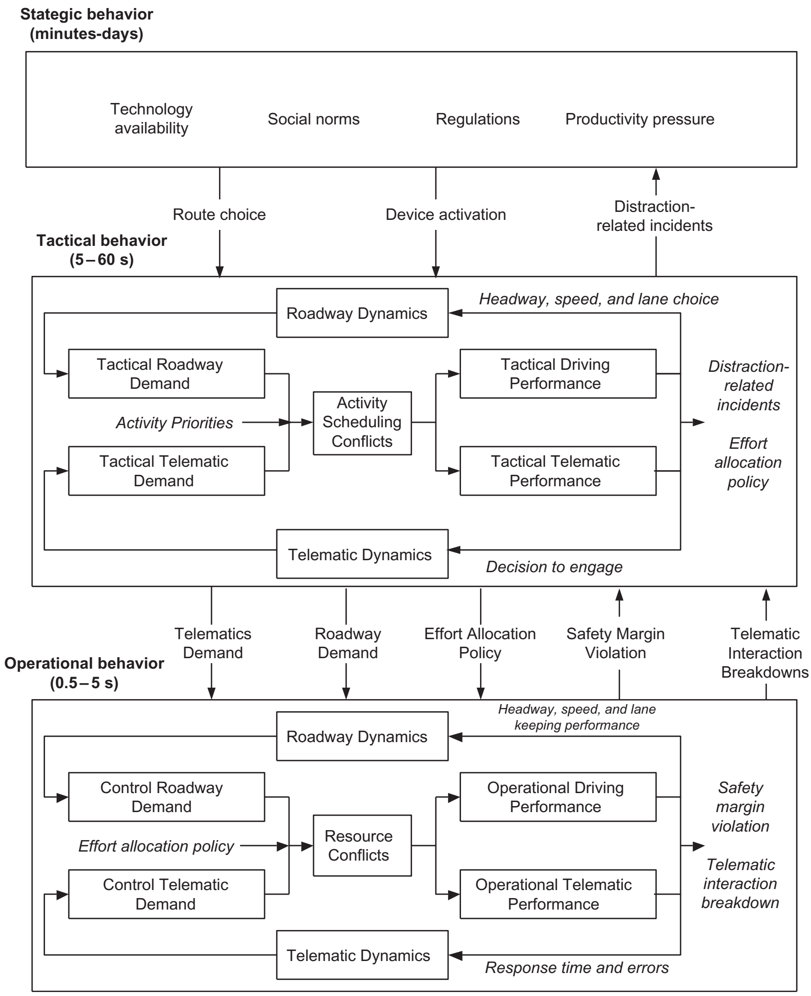

Figure 3-2. A detailed control theory-based hierarchical model of driving behavior (with application to telematics systems) (from Lee and Strayer, 2004, reprinted with permission from the Human Factors and Ergonomics Society).

consider an advance in-vehicle collision-avoidance warning system. Such systems are already installed in many new cars either as original equipment or as after-market safety devices (see e.g., http://www.mobileye.com/products/mobileye-5-series/), and their basic function is to warn a driver whenever his or her vehicle gets too close to another vehicle or object, and when the vehicle deviates from the lane. These devices can be a great aid in avoiding crashes, but reliance on an imperfect system – with some inevitable errors – can also lead to reduced attention and to crashes that would otherwise be avoided (Maltz and Shinar, 2004) or to greater risk taking due to reliance on these systems (LeBlanc *et al.*, 2013).

Still, even at the level of detail presented in Figure 3-2, the hierarchical model is insufficient to predict specific outcomes in specific situations. However, it is sufficient to demonstrate the role and potential impact of various factors in both crash prevention and crash occurrence. To be useful as a predictive model for specific situations, quantitative data has to be fed into the various functions of the model. Work in this direction has already yielded initial encouraging results that are applicable to well-defined specific situations such as the impact of forward collision warning (Barnard, Carsten, and Lai, 2014) and to specific behaviors such as visual scanning (Horrey, Wickens, and Vonsalus, 2006).

To move from the hierarchical structure of the driver task to working models of driver behavior, we now need to consider the variables that affect these decisions, the limitations placed on us as decision makers, and the needs and biases that we bring into the driving situation. That is the role of driving models: to explain and predict driver behavior in the context of the driver's environment, personal goals, and information processing limitations.

The two classes of models that are described below approach the issue from different perspectives, but they supplement each other more than conflict with each other, and both are useful for understanding driver behavior.

Attention and Information Processing Models

The common – though incorrect – notion that we cannot do more than one thing at a time is based on the fact that our capacity to process information is limited. In the context of driving, the typical limiting factor is the need to process information under severe temporal constraints. Driving is not so much a motor task – though autonomous vehicles notwithstanding we still need to employ our hands and feet to drive – as it is an information processing task in which most of the information is received through the visual channel. The typical limit on our capacity is not in the amount of information we have to see or attend to, but in the *rate* at which we can process that information. Because driving is a temporal task, we have limited *time* to identify the relevant information, attend to it, decide how to act on it, and actually perform the needed maneuver. Often the time limits for multiple driving-related tasks can be on the order of seconds, and sometimes even fractions of a second. As we drive, the roadway ahead and the traffic around us present a stream of stimuli to which we attend (or not) and respond (or not). While the total amount of information that a driver has to process between two points on the road is constant, the rate at which we have to process it varies as a function of our speed and the speed of other traffic on the road: the faster we drive, the more vehicles we have to consider, and the faster they move, the greater the rate of information flow. When critical information flows at a rate that is greater than our capacity, we experience a failure. That failure can take the form of missing some information, misperceiving information we attend to, or not considering all the information needed to make a decision. If any of these failures are critical to making the right decision at the appropriate time, then the situation can lead to a crash.

To better understand these limits on our processing capability, several information processing models have been proposed. One generally accepted model, proposed by Wickens (1992), is depicted in Figure 3-3. The model is a general one, not specific to driving behavior, but as applicable to it as to any other time-dependent task. According to this model our contact with the external world is through the sensory receptors. The amount of information that impinges on these sensors is staggering, and the first task of the human operator is to select from this array pertinent items of information. The information in the sensory receptors is there only briefly – stored in a short-term sensory storage (STSS) where it decays within a few seconds. Thus, before the infinite information is lost it must be scanned and its relevant and salient features must be extracted. This is the first stage of information filtering and selection, and it corresponds closely to attention. This means that information that we do not attend to is eternally lost to us. For all intents and purposes, transient unattended events never enter our consciousness and are as if they never happened. Events that we attend to are perceived, in the sense that we actually process them in an active manner. The perception is not an all-or-none process: we can process different items with varying degrees of attention, and consequently become aware of them at varying levels of consciousness. In routine driving much of the information that we process is done at a minimal level and consequently we are barely aware of it, despite the fact that we respond appropriately to it. This can include many of our reactions to traffic signs and signals as well as cars ahead and next to us. Most of the time – almost as soon as we pass these stimuli and they are no longer relevant – we cannot remember them. For example, several studies have demonstrated that immediately after passing a sign that was clearly unobstructed and often responded to, most drivers cannot recall what that sign was (Costa *et al.*, 2014; Martens, 2000; Milosevic and Gajic, 1986; Näätänen and Summala, 1976; Shinar and Drory, 1983), possibly because it was barely looked at or attended to begin with (Costa *et al.*, 2014).

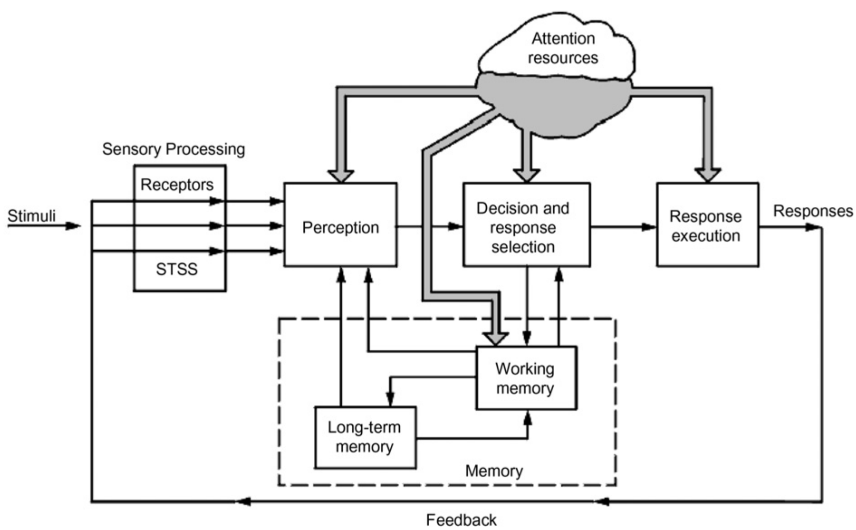

Figure 3-3. A general limited-capacity human information processing model (from Wickens, 1992).

Thus, perception is the process by which we become aware of the world around us. However, that awareness is not simply due to the stimuli impinging on our eyes, ears, nose, and proprioceptive receptors, but also due to how we interpret them with the aid of our memory of previous relevant experiences. In the model, memory is represented by two distinct storage mechanisms: short-term memory (STM) also known as working memory and long-term memory (LTM) also known as permanent storage. In many ways this distinction parallels the distinction between the working memory of a computer (RAM – random access memory) and the hard disk storage space (ROM – read only memory): the first is the one we constantly use and it is quite limited and the second is the one we occasionally refer to, in order to retrieve information, and it is bigger by several orders of magnitude. Very briefly, the two human memory systems are very different in the following respects:

1. Storage capacity: STM is extremely limited; to approximately seven unrelated pieces of information (such as the digits in an unfamiliar telephone number, and hence the typical string of digits in a phone number is seven). LTM is essentially limitless, and the implication is that we can continue to accrue new pieces of information forever, without forgetting any of the old ones.
2. Storage mechanism: Perceived information enters STM and may or may not be transferred to LTM. The transfer typically happens through rehearsal or repetition (such as recitation of a poem or a phone number, or route guidance directions), or by linking to other information by association.
3. Nature of information: The immediate information stored in STM is typically visual or acoustic in its nature while the information in LTM is typically semantic or conceptual. You tend to recall the actual words or image on a billboard off the road immediately after viewing it as they appeared, but you tend to recall – if at all – the "message" and not the specific words of the sign later on. Similarly, when we listen to a speech or try to take notes in class, our immediate memory (STM) is of the actual sounds and words. But after a short while, all we can recall is the part of the message that was transferred to LTM and not the specific words.
4. Decay of information: Information in STM can remain there indefinitely, but only as long as it is not "bumped off" by another piece of information. Thus, retention of a new phone number is lost if you are disrupted by an unrelated question. One means of preventing interference from new coming information is rehearsing it – repeating it over and over so that no other information can displace it. We often do that when we want to dial a phone number. Once we have dialed the number we allow other information to enter, only to be frustrated and needing to look the number up again if we get a busy signal. Information in LTM is practically permanent, but not always accessible or retrievable. It is analogous to a book in a library. Even if it is in the library, if it is misplaced in a wrong shelf it is as good as gone, even though physically it – and the information in it – are still in the library. Thus, the limits on LTM are mostly due to our inadequate search and retrieval. The information we are seeking may or may not be where we are searching, but it is still there "somewhere."
5. Retrieval of information: Retrieval from STM, which only contains a few items, is immediate. On the other hand, retrieval from LTM may take a long time depending on the efficiency of our search for that information.

The nature of the process so far is simple to illustrate with an example of a driver approaching and then stopping at a stop sign. The sensory information consists of a pattern of different colored dots in an octagonal shape that fall on our eyes, and our past experience helps us interpret that pattern – by retrieving the information that is already coded in LTM – as a "stop" sign. Once we obtain a match between the information that stimulates our eyes and the information retrieved from LTM, we perceive (i.e., comprehend) the image as a "stop" sign.

The next phase is the decision process. As the model shows, this phase is also heavily influenced by memory. The memory of a novice driver may be different from that of an experienced driver, and they may respond differently to the sign. To begin with, the experienced driver already has some schema (a set of experiences and relevant rules of behavior) in LTM that assist him or her in a more efficient scanning of the scene, and is therefore a priori more likely to direct the eyes toward the stop sign and detect it. This is best demonstrated when experience is actually a hindrance. For example, when a traffic sign is placed in an unexpected place, the experienced driver is less likely to detect it, while the novice driver is unaffected by the change (Borowsky, Shinar, and Parmet, 2008). Second, the experienced driver will probably know when is the best time to initiate a braking action and at what level of deceleration to do it. An experienced driver may decide to first slow down by removing the foot off the accelerator and only then brake gradually. A novice driver may continue to drive and then brake from a higher speed. An interesting example of how experience can shape behavior was provided by Routledge, Repetto-Wright, and Howarth (1976). They noted that while adults teach children to stop before they cross the street, look right-left-right (in England where cars drive on the left side of the street), and only then cross; the adults themselves do not manifest this behavior. Instead, the experienced adult pedestrian evaluates the traffic situation well before crossing the street and then adjusts the walking pace and selects the specific location of crossing so that he or she will not have to stop at all.

Once information is perceived and relevant decisions have been made, we either modify or not modify our overt response to the situation. Up to this point the process has been inferred and unobservable. The response, however, is observable and may or may not be appropriate. This is the motor aspect of behavior, and it is the one that much of the early driver training focuses on: how to brake and accelerate appropriately, how to shift gears, when to start signaling, how to negotiate a passing or turning maneuver smoothly, etc. A person can decide to make the right response, but its execution may be faulty. Because the instructor sitting next to a learner can only observe the driver's responses, it is much easier to correct the motor behavior aspects of driving than to guide the attentional and decision-making parts of the information processing sequence.

As described so far, the model is very limited. It describes the human operator as a passive information transmission channel, who performs various actions within the limits of his or her capacities. But the system has two more crucial components: the attention allocation mechanism itself and a feedback loop. The feedback loop indicates that the process we just described is a recursive ongoing one that is continuously modified in accordance with new stimuli. For example, in driving we visually perceive the rate at which we approach a car that may have stopped ahead of us, and based on that perception we modify our own braking behavior. Also, the stimuli are not limited to the road environment, the other drivers and the pedestrians, but also include our own car and the changes brought on by our own behavior. Furthermore, the stimuli to which we respond are not only visual. Our sense of proprioception – that informs us of the relative position of different parts of our body – provides us with feedback on our rate of deceleration as we stop, and if it is too abrupt we ease our foot off the brake pedal; if it is not sufficient we press harder. Our sense of proprioception is also a key factor in our speed selection and modification when we negotiate curves, and in fact is responsible for preventing us from potential rollover crashes in such circumstances (Herrin and Neuhardt, 1974), and recent research shows that it can be utilized to provide the driver with haptic steering support whenever the vehicle approaches its handling limits (Katzourakis *et al*., 2014). In short, we constantly focus on critical stimuli which we sense, perceive, analyze, and act upon in order to continue driving safely.

Arguably the most critical component of the information processing model, in the context of driving, is the attention (Klauer *et al*., 2006). Attention is the resource of psychic energy that we devote to the task at any time. It is a central capacity that is not specific to the individual senses. Thus, in a demanding driving situation – such as entering a congested highway – we often block irrelevant sensory information in order to devote all of our attention to the driving task. For example, we cease to hear the radio or a passenger sitting next to us until we relocate ourselves in the traffic stream and the lane of choice. In this case, all of our attention was diverted to the visual inputs for the driving task, and none was left to direct to the auditory inputs. Once in the lane, the rate of flow of visual information that we have to process is greatly diminished and we can once again divide our attention between the auditory and visual channels. We may then direct our gaze toward the road ahead of us, while being oblivious to many of the non-essential stimuli there.

Attentional capacity and distribution of attention

There are two critical aspects to the allocation of attention: the total amount of attentional capacity that we have at any one time and the distribution of that amount among various driving and non-driving tasks. The amount is finite, but it is not constant, and the distribution of attention is possible, but within limits.

From our own experience we know that we can be and generally are more attentive after a good night sleep than at the end of a long working day. But our level of available attention to the driving task varies even more dramatically from moment to moment as we divert resources from one task to another. Here, we have good and bad news. The good news is that we can allocate the total capacity that we have to different tasks at the same time. The bad news is that we don't always do it appropriately. Two advantages of a skilled and experienced driver over a novice one is that the skilled driver is both much more adaptive in the allocation of attention, and requires less attention for the driving task. The ability to adapt the allocation of attention is achieved by the experienced driver through the complementary processes of focusing attention on selected sources of information and dividing attention among several sources of interest. The efficiency is achieved through reliance on automated rather than controlled processes (discussed below).

Let us first consider the use of focused and divided attention. Much of the time that we drive we divide our attention between the driving task and various non-driving tasks. For example, while driving home from work, we may be preoccupied at processing some events from a meeting we just ended (diverting much of our attentional resources to decision-making and memory that is not related to the driving task), and only minimally paying attention to the visual stimuli from the road and traffic – but enough to manage the drive on most days most of the time. Similarly, we may be almost totally absorbed in a phone conversation or a radio broadcast while driving and unequally dividing our attention between the two tasks. Extensive research in cognitive psychology has revealed that although the process of dividing attention itself requires some attentional resources, we are generally quite good in the allocation of attention to various simultaneous tasks (Wickens and Hollands, 2000).

An interesting aspect of our ability to divide attention among multiple sources of information is that this ability is not constant but depends on the amount of resources the multiple tasks demand and extent to which these demands are placed on the same or different dimensions of the information processing resources. In a well validated model known as the "Theory of Multiple Resources" Wickens (1984) showed that these different dimensions include (1) the stages of processing (perception + memory versus response selection + execution), (2) the input modalities (visual versus auditory, though there could be more), and (3) the response modalities (manual/spatial versus verbal/auditory). In experiments designed to validate the model, Wickens and his colleagues (Horrey *et al*., 2006) noted that within the perceptual dimension, inputs to the peripheral and focal system do not conflict with each other and so the model was modified to include these as independent inputs. An example of such non-interfering dual processing is the management of the car position within the lane by relying on peripheral stimulation of lane markers while focusing on objects ahead that could turn into safety-critical events such as a change in the signal light. The model predicts that multiple tasks that load on different components of the three dimensions interfere less with each other than multiple tasks that load on the same ones. This makes the model extremely important for predicting the impact of various tasks and for designing various in-vehicle systems. For example, it predicts that texting while driving should be much more demanding and detrimental to driving than talking on the phone while driving, as the former competes for the same inputs and responses as the driving (visual and manual) while the latter employs different inputs (auditory) and responses (verbal). Recent research in this area provides strong support for this prediction (Fitch *et al*., 2013; Klauer *et al*., 2013; see Chapter 13 for a detailed discussion of the distraction issue).

In a complementary process to multi-tasking or the division of attention, we can also focus our attention on selected sources of information and ignore irrelevant stimuli (that constitute noise). This is classically demonstrated by the "cocktail party phenomenon" where we are able to maintain a conversation with one person while ignoring the many other conversations going on around us, even if their volume levels exceed ours (Cherry, 1953). In general, division of attention is more difficult than focusing attention. We are much less efficient in our attempts to simultaneously attend to multiple sources (divided attention) than in our attempts to focus on specific stimuli while ignoring others (selective or focused attention).

The limits of attention are one of the primary reasons for accidents, as illustrated in Figure 3-4, which is based on an early cognitive model of driving proposed by Blumenthal (1968). In this simplistic and intuitively appealing model the X-axis represents travel time and the Y-axis represents the attentional energy allocated to and required by the driving task. The two curves represent the moment-to-moment variations in the attention demanded by the road and the traffic (dashed line) and the energy, or attentional resources, allocated by the driver to the road and the traffic (continuous line). If we think of the demands in terms of the rate of information that the road and traffic present to us, then it is easy to accept that this rate varies greatly. It is very low when we drive slowly down a deserted rural road. It increases as we increase our speed; it increases further as more traffic joins the road; and it can become quite high in specific situations such as high-speed merging maneuvers on motorways. Fortunately, most of the time we can anticipate the attentional requirements and the energy we allocate to the driving task is above the level that is required. We manage to do this because part of the driving skill that we have all acquired is good situation awareness (SA) (discussed below): the rapid comprehension of the driving situation and the ability to predict events. For example, we know that a light that has just turned red will typically stay that way for the next 20-40 seconds and we can relax our attention while we wait for it to change – to the point of quickly reading some newspaper

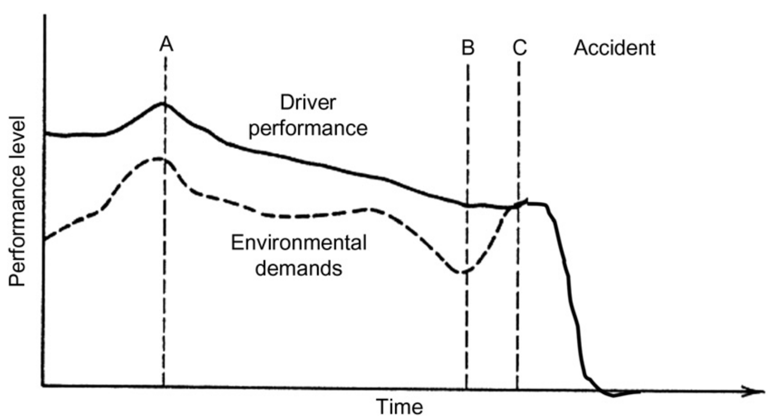

Figure 3-4. A simple model depicting the relationship between the temporal changes in the attention demands of the drive and the attention levels allocated by the driver. A is a typical situation when the amount allocated is greater than the amount needed. B is a situation with a sudden increase in demand that is not perceived by the driver. C is the situation when the demand exceeds the attention allocated and a crash results (adapted from Blumenthal, 1968).

headlines. We also know that at the end of the green phase, a brief (typically 3 seconds in Israel) yellow phase will be followed by a red light. So when approaching a green light we have to allocate more attention in order to analyze our situation and take an immediate action (to speed or to brake) if the green phase ends. However, every once in a while – fortunately quite rarely – the demand suddenly and unexpectedly increases to a level beyond the level of allocated attention – while we are distracted by a pedestrian on the curb or by a phone conversation – as when the car ahead suddenly stops. It is then that we have a crash!

The distinction between controlled and automated processes was first defined and studied by Schneider and Shiffrin (1977). In a series of laboratory studies they demonstrated that the process by which we learn to deal with complex situations involves the "automation" of various sequences of behavior. Prior to automation each component in that behavior is controlled through monitoring and feedback. This process is relatively slow, requires much attention, and prevents us from doing other tasks simultaneously. As we repeatedly perform some of these sequences, the process becomes automated, in the sense that once it is initiated, the sequence of actions is hardly monitored, requires minimal attention, and is performed more or less unconsciously. Changing manual gears has often been used as an example of a controlled process that through repeated experience becomes automated (Shinar, Meir, and Ben-Shoham, 1998). The concepts of controlled and automated processes are discussed in more details in Chapter 5 on Information Processing.

A driver information processing model

We can now consider Wickens' model in light of Blumenthal's focus on the importance of allocating attentional resources, and apply both to a driver information processing model, such as the one described in Figure 3-5. I proposed this model nearly 40 years ago (Shinar, 1978), and it is sufficiently general that it is still valid today. In fact, a similar model is one of the models currently used to guide the human factors research on driving safety at the Netherlands' Organization for Applied Scientific Research (TNO) (Keith *et al*., 2005). This model presents the driver as a limited-capacity controlling element in the driver-vehicle-roadway system. This limited capacity is used to perceive the driving-related (and distracting) cues, make instantaneous decisions, and act on them through the vehicle controls. Because the central processing capacity is quite limited, the first step the driver must take is to filter much of the stimulation that impinges on his or her senses. This includes visual inputs from other drivers, pedestrians, traffic signs and signals, and his or her vehicle's own displays such as the speedometer and the mirrors. There are also auditory inputs from other vehicles, other drivers and pedestrians, the driver's own car and proprioceptive inputs from the driver's own body when he or she accelerates, decelerates, or turns a corner. And these are only the driving-relevant stimuli. In addition there are irrelevant stimuli such as billboards (including dynamic electronic billboards) and scenery outside the car as well as in-vehicle distractions from stereo systems, cellular phones, navigation systems, and passengers; distractions that can be auditory, visual, or both. All of these can have a significant impact on the driver's allocation of attention, behavior, and crash rates, as described in the following chapters.

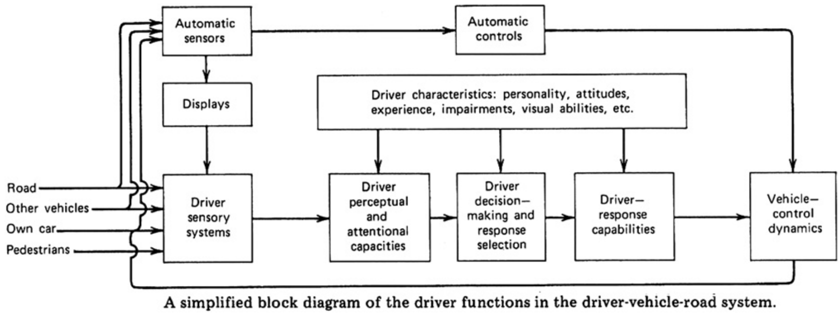

Figure 3-5. A limited-capacity model of driver information processing (from Shinar, 1978).

To alleviate some of the demands on the driver's limited information processing capabilities, a plethora of driver aids have been proposed, tested, and in some cases implemented in many new vehicles. These have included automatic sensing devices that act to either alert drivers to impending crashes (such as in-vehicle crash avoidance warnings – IVCAW; Maltz and Shinar, 2004; Wege, Will, and Victor, 2013) or actually intervene in the vehicle control (such as adaptive cruise control systems, anti-lock braking systems, and electronic stability control; often referred to as ACC, ABS, and ESC, respectively; see Chapter 19).

The efficiency and appropriateness of the selection of the information and its processing depend on many factors too. They are listed in Figure 3-5 under the general heading of driver characteristics. Although most of these factors are unobservable, they are very real: they include the driver's level of fatigue, possible intoxication, amount of experience, familiarity with the vehicle and the road, and various motivations and needs that govern the way the driver drives. By any criterion this is indeed a complex process. Given that complexity, it is actually amazing that most of the time, most of the drivers manage to drive within inches of each other (in parallel and opposing lanes) at speeds that are definitely greater than those for which humans were designed (i.e., walking and running speeds), without repeatedly colliding with each other.

Blumenthal's, Shinar's, and Wickens' models leave a most important issue unanswered: what determines the driver's attention allocation strategy? Once we can answer this question, we can design effective countermeasures to increase and properly direct the driver's attention to the relevant sources of information; and also – in some situations – redesign the environment so that its attentional demands will not overwhelm the drivers. This issue is addressed by motivational models described later in this chapter.

Measuring mental task load

Given the predominance of the information processing approach to assessing driver behavior, it is worthwhile to briefly describe the main methods that have been developed to measure it. In general three approaches have been used to assess mental task load: performance based measures using a secondary task, physiological measures of stress, and subjective evaluations of mental load.

Performance on a secondary task

The use of a secondary task derives directly from the information processing model. If a primary task – such as driving – does not require all of our processing capacities, then when another task – such as a phone conversation – is added, it is difficult to assess the added load that it imposes. One way to solve this problem is to give the driver an additional task that is difficult enough so that the driver cannot perform it perfectly. With two tasks – the driving task and the secondary task – the driver is then already overloaded in the sense that despite all the attentional capacity allocated, performance falls short of perfect. We then introduce the task whose demands we would like to assess, such as a distracting phone task, and measure by how much the secondary task performance is degraded. The rationale for this approach is illustrated in Figure 3-6. We can illustrate the application of this model to driver behavior with a study conducted by Patten *et al.* (2004) on the effects of a cell phone task on driving. Consider driving without talking on the phone the easy primary task in Figure 3-6, and driving while talking on the phone the more difficult task. Because in both situations the driver's maximum capacity is not exceeded, it is impossible to tell how taxing the added phone task is. To assess the mental load imposed by the cell phone task, we now add a "secondary task" (though it is already a third task, after driving and talking on the phone) – such as detecting visual targets presented in the peripheral visual field.

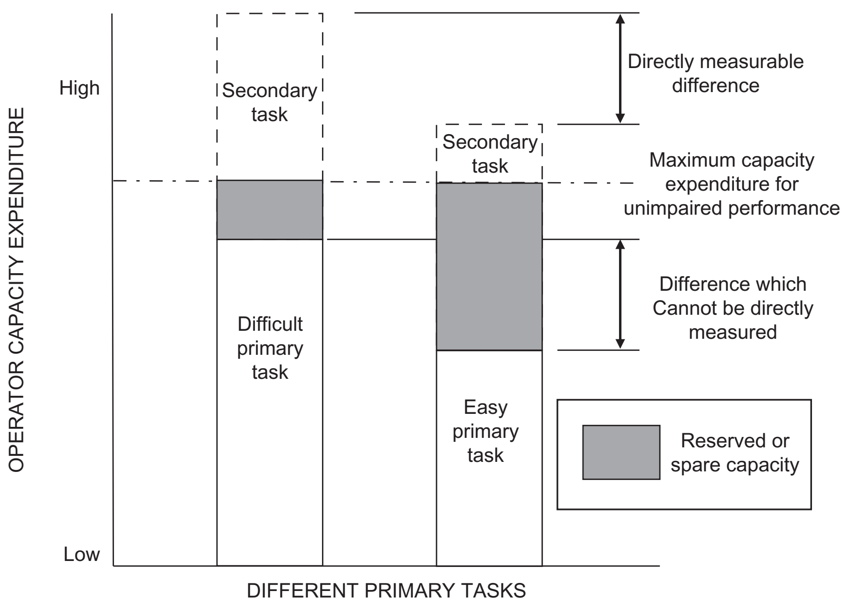

Figure 3-6. The subsidiary task paradigm (from O'Donnel and Eggemeier, 1986, with permission from Wiley-Liss, Inc., a subsidiary of John Wiley & Sons, Inc.).

With this additional task, we now exceed the driver's maximum capacity as indicated in Figure 3-6. The difference in performance on the detection task between the driving task alone and the driving task while talking on the phone can now be estimated directly from the difference in the performance on the target detection task. The secondary task method has also been used to demonstrate that novice drivers experience a much greater mental load than experienced drivers even when they drive in the same environments (Patten *et al.*, 2004).

Physiological indicators of stress

There are various physiological indicators of stress that are used to measure mental task load. One of the more popular measures that have been related to driver task load in particular is heart rate variability (HRV – the variability around the mean heart rate). While the mean level of heart rate is primarily sensitive to physical – and not mental – stress, the variability of the heart rate around the mean level is sensitive to mental load. During rest, the heart rate is quite variable. As the level of stress or mental task load increases, the HRV decreases, and the relative change from a relaxed or resting position can then serve as a reliable indicator of stress and workload (Brookhuis and de Waard, 1993; 2001). Average heart rate is much more sensitive to physical workload, but it too has been used to measure mental stress or task load (Liu and Lee, 2006). Other measures include electrical evoked brain potentials (Gopher and Donchin, 1986) and pupil diameter (the larger the pupil the greater the load – Kahneman and Beatty 1966; Kahneman, Beatty, and Pollack 1967).

Subjective scales of mental load

The most direct way of assessing mental load is simply asking people how loaded they feel. Because "mental load" may be a multi-dimensional concept, different indices have been developed in which people are asked to rate their level of load on different dimensions. Perhaps the most popular of all subjective mental task load indices is the one developed by the U.S. National Aeronautical and Space Administration: the NASA-TLX. This measure is based on questions pertaining to six self-reported different dimensions of stress: mental demands, physical demands, temporal demands, performance (the perceived task accomplishment), effort exerted, and frustration felt. A composite measure based on all dimensions is also calculated to give the total task load index. Other measures of subjective task load have also been used, including a multi-dimensional scale known as Subjective Workload Assessment Scale (SWAT), and even a simple one-question of "overall task load experienced." Interestingly, in a study that compared the scores people gave to the same tasks with the different scales, the correlations among all subjective ratings were quite high, indicating that for a single one-dimensional assessment of workload the single "overall workload" question may be just as good as the more complicated tests (Hill *et al.*, 1992). The NASA-TLX has been extensively used to assess the workload imposed by the use of in-vehicle technologies, such as cell phones, on driving (see Chapter 13).

Endsley's situation awareness model and efficient information processing

Responding to all the inputs in a timely manner while driving at high speeds would be close to impossible if in fact we had no way of streamlining the information processing task. Automatic processing goes a long way toward that goal, but not enough. There are simply too many stimuli to attend to, too many alternatives to consider, and not enough time to make proper rational decisions based on unbounded knowledge of all the relevant information. So we have to devise a method of making rational decisions that are limited to or "bounded" by our past experience. We do that through a process known as Situation Awareness (SA).

SA has been studied extensively by researchers of human behavior in complex systems. It refers to an ability of an operator to effectively filter information in a data-rich environment. Driving, being a very rich environment, easily lends itself to this need to filter information, and so the issue becomes one of how to filter the information effectively. Endsley, one of the leading researchers in this area, defines SA as "the perception of the elements in the environment within a volume of time and space, the comprehension of their meaning, and the projection of their status to the near future" (Endsley, 1995, p. 36). Thus, the concept involves three hierarchical levels: perception, comprehension of meaning, and projection to the future. Applied to the driving environment, at the perceptual level the driver would have to perceive among other things, the roadway geometry, other vehicles and road users, their relation relative to his or her vehicle, and the speed and acceleration of all vehicles, including the driver's own. At the comprehension level the driver has to understand the "significance of those elements in light of (his or her) goals." To do so, the driver has to create a "holistic picture of the environment comprehending the significance of objects and events" (Endsley, 1995, p. 37). Finally, at the highest level the driver must perceive the implications of this pattern of events and objects for the near and the immediate future in order to take the most appropriate action. For example, an experienced driver approaching a traffic signal that has just turned green will typically also observe the behavior of the cross traffic, and project the slowing down or speeding up of a crossing car to the next few seconds, in order to decide if to slow down to accommodate it or to ignore it and accelerate into the intersection.

In layman's terms, Endsley suggests that SA basically means "knowing what is going on." She also distinguishes among three mechanisms involved in SA: (1) short-term sensory storage, (2) working memory that includes perception, interpretation of the situation, and projection from it to the future, decision-making, and action guidance – all of which are affected by attention allocation, and (3) long-term memory that includes various schemata – experience-based frameworks for understanding various patterns of elements and events; and scripts – schemata for sequences of appropriate actions – that guide the operator's decisions and actions. The model, presented in Figure 3-7, has many similarities to Wickens' and Shinar's models of information processing. This is not by chance. SA builds on the information processing model, and attempts to define how we actually use these mechanisms in the process of highly learned, but complex, skills like driving. In such situations with information overload from high rate of information presentation and the need to rapidly make complex decisions and perform multiple tasks, the needed capacity can easily exceed that of the driver, and unless the driver can adjust the rate of information input (e.g., by slowing down), an accident can occur. This in fact is a relatively rare occasion because in the course of gaining experience we learn

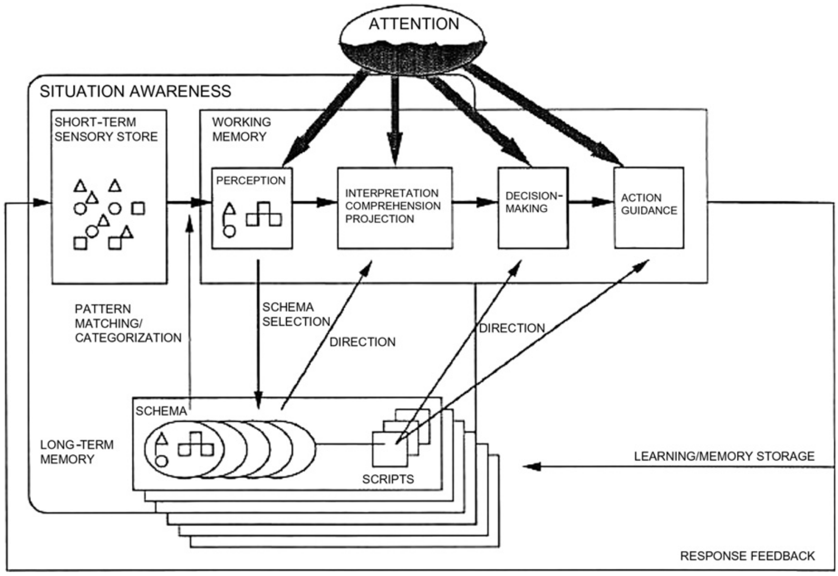

Figure 3-7. The mechanisms involved in situation awareness (from Endsley, 1995, reprinted with permission from the Human Factors and Ergonomics Society).

to select cues from our environment more efficiently, perceive the relevant ones more quickly, utilize various remembrances (schemas) in long-term memory, to identify their implications, and to retrieve effective appropriate action plans (scripts) in a timely fashion to deal with the situation.

To illustrate the relevance of SA for driving, let us consider the case of hazard perception and hazard avoidance for a novice and an experienced driver. Hazard perception is a critical skill that correlates with crash involvement (Horswill, Hill, and Wetton, 2015) and distinguishes skilled drivers from novice drivers (Horswill and McKenna, 2004). To develop the three levels of SA – perceive, comprehend, and project – for any given situation, a novice driver must, under the time constraints of driving, be able to quickly select the cues that are indicative of a hazard, integrate them into holistic patterns, comprehend their implications, project how the situation may evolve into a potential accident, and select the necessary action from his or her repertoire of driving behaviors. The more experience a driver has, the greater the repertoire of situations and schemata he or she has in long-term memory. Thus, with experience the driver learns to effectively select the cues to attend to, quickly perceive their meanings, and on the basis of these cues quickly identify the situation and project its implications into the immediate future (Borowsky, Shinar, and Oron-Gilad, 2010; 2012; Lim, Sheppard, and Crundall, 2014). Using scripts built through past experience this driver then controls the vehicle in a very effective manner. This mode of driving is very effective because behaviors are guided by partial information that has been previously organized into complete situations which in turn are linked to pre-established behavior sequences. Thus, much of the driving can be automated, and when a totally unexpected hazard (e.g., one never encountered before) is encountered the driver still has spare capacity to deal with it. The novice driver, in contrast, does not have all of these benefits of experience and therefore must attend to more stimuli, which necessitate slower driving in environments that are not as complex in order to build up the necessary skills and repertoire of experiences. As this driver accumulates experience, more and more of the driving scene is recognized through schemata and more and more of the behavior is automated; allowing the driver to better attend to other driving tasks, or to time-share the driving with non-driving tasks (such as talking on the phone). This in fact is the rationale behind the controlled gradual exposure in the graduated driving licensing paradigm (see Chapter 6). Results of driver eye movement research support this model and show that novice drivers are less efficient in their visual scanning (Borowsky *et al*., 2010; Konstantopoulos, Chapman, and Crundall, 2010; Mourant and Rockwell, 1972); that experienced drivers adapt their scanning to the various environments more readily than novice drivers (Crundall, Underwood, and Chapman, 1998); that older drivers are better than novice drivers at detecting far hazards (Brown, 1982) and can be trained to improve that skill (Horswill *et al*., 2010); and that advance police training in hazardous driving leads to both faster hazard perception reaction times (McKenna and Crick, 1994), and more appropriate speed adjustments in hazardous situations (McKenna, Horswill, and Alexander, 2006).

Automation is also involved in driving on familiar roads. Charlton and Starkey (2013) had drivers drive the same route for 20 sessions over a period of three months in a driving simulator. While the road geometry remained the same, there were occasional slight variations in the scenery and occasional targets that had to be detected. As expected, they found that driving effort declined over the repeated exposure and people started to describe the experience as "driving without thinking about it" or "going on autopilot." However, when familiar landmarks or critical driving cues (such as lane markers) were removed the rated difficulty increased. Thus, even when driving without awareness, changes in the scenery caught the drivers' attention and resulted in a shift from mostly automated driving to largely controlled driving.

The concepts of SA, schemata, and scripts all have uses in understanding driver behavior, and in developing driver education and training programs to make driving safe and efficient. Drivers can be trained to develop schematas and scripts that can help them recognize and respond appropriately to hazards. Knowledge of schematas and scripts that drivers have can enable us to estimate what we can and cannot expect from drivers with particular levels and types of experience in particular environments. This knowledge can also serve highway and vehicle designers in their quest for reducing the driver information load. In all of these respects the SA theory is a very good theory: it is practical.

Rational Decision-Making Models

Many of us like to think that we behave in a rational manner. This is not always the case, and economists often use the "rational man" model only as a straw man, to demonstrate and understand biases in the actual behavior of people, especially in their purchasing decisions. Our decisions are biased in many ways, and only recently have some of the psychological biases been understood (Kahneman, 2013; Tversky and Kahneman, 1992). Still, there is reason to our behavior; at least on many occasions and at least within limits of the information available to us. The challenge to the rational model of driver behavior is to allow for all our limitations and biases. Conceptual approaches to explaining and predicting driver behavior in the context of a process of "rational" decisions have been offered by Sivak (2002), Fuller (2005), and Parker and her associates (1992).

Application of "bounded rationality" to driver behavior

In the context of driving, Sivak (2002) and Elvik (2016) suggest that we consider the economic concepts of "bounded" and "unbounded" rationality as tools to understand driver and pedestrian behavior. Decisions based on unbounded rationality consider all of the alternative options, the use of all the information needed to select among them, unlimited processing capabilities to analyze them, and no restriction of time. Obviously, in driving when decisions often have to be made almost instantaneously this is not the case. Bounded rationality is what we use when we do not have all the information, processing capacity, and time to consider all of the options. Our rationality is then "bounded" or restricted by some limits of knowledge and time, and our decisions are further biased by needs and misperceptions. Thus, bounded rationality is a form of experience-based behavior modification. This is the typical situation we have in driving. Sivak (2002) provides an example of a driver waiting at a stop sign to cross the street. Unbounded rationality would suggest that the driver first calculate the temporal gap needed to cross the street and then observe the opposing traffic for the first opportunity of such a gap based on the speed and distance between cars in the crossing traffic. With bounded rationality, we set a criterion gap that we consider safe, based on our past experience (which may or may not be totally safe), and then observe the traffic for such a gap. However, our estimates of the gaps are actually flawed, and the longer we wait, the greater the risk we might assume by adding other considerations, such as an expectation that a crossing driver will slow down once he or she sees us entering his or her path. By simply observing the behavior of a driver stopped at an intersection we cannot know how flawed the bounded rationality of the driver is until we observe a collision – something that would never occur with unbounded rationality, because no driver would voluntarily enter the intersection knowing that a collision would result. If we now add the limits of bounded rationality to the hierarchical models in Figures 3-1 and 3-2, we can see how the bounded rationality can affect all three decision levels of this hierarchy, leading to potentially very dangerous behaviors on the road. For example, bounded rationality can account for a driver's speed choice between the two alternatives of speeding up and slowing down. If the goal is to arrive at the destination as quickly as possible without being in a crash or being stopped for speeding then the past experiences in these domains can account for the speed chosen (Schmidt-Daffy, 2014). Elvik (2016) argues that within limits the theory of bounded rationality can account for the success of some safety communication campaigns, and can serve as a guide to better campaigns that can affect road users' bounded rationality.

Ajzen's theory of planned behavior (TPB)

The theory of planned behavior (TPB), proposed by Ajzen, is an attempt to explain behavior in a social context. It was derived from an earlier formulation of a social behavior model – that of reasoned behavior – proposed approximately 40 years ago by Fishbein and Ajzen (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975). According to the theory of reasoned behavior, when people are in full control of their behavior, it can be easily tracked to their intentions, which in turn are based on their attitudes and subjective (internalized) norms. In short, we are responsible for our actions and we supposedly behave as we planned. In reality, in most social contexts we do not have full control of our behavior. In that respect, driving definitely occurs in a social context much of the time (even when other drivers are not present we stop at a stop light because we have internalized the prevailing social norm – or, in some parts of the world – such as New York City at 3 am – some drivers do *not* stop for the same reason). To account for this, Ajzen (1991) proposed the TPB that is schematically illustrated in Figure 3-8. This figure illustrates how we formulate our intentions to commit any behavior (e.g., speeding) on the basis of the attitude we have toward that behavior (e.g., we enjoy speed, believe it is safe, and tend to do it in the absence of constraints), the subjective norm we embrace (e.g., all of our friends do it, except for the "sissies" and the "nerds"), and the perceived

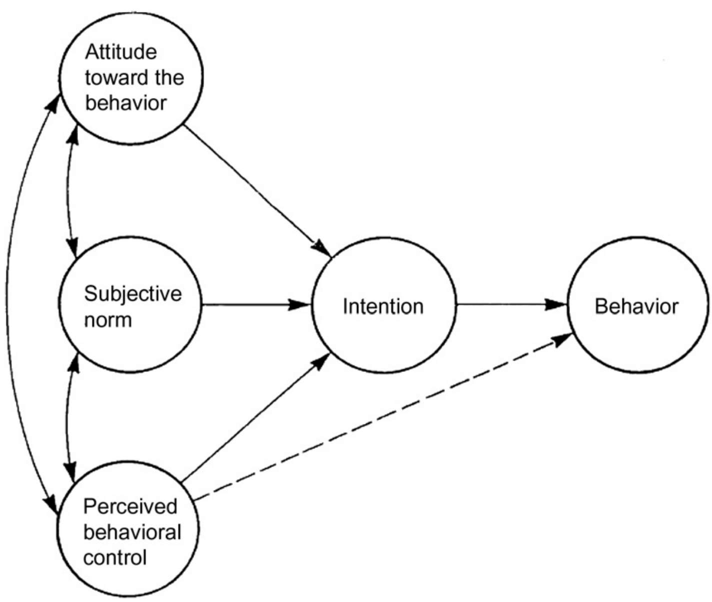

Figure 3-8. Schematic representation of Ajzen's theory of planned behavior (from Ajzen, 1991, with permission from Elsevier).

control on this behavior (e.g., there is a speed camera immediately up the road or the road is straight and empty and there is no enforcement in sight). The three factors may provide us with consistent information (e.g., there is no enforcement in sight) in which case the intention and the behavior follow in a very predictable manner (we intend to and we speed). But often the information from the three sources is not consistent (e.g., there is a speed camera ahead), and then the resulting behavior is a resolution of the relative risks involved in the alternative behaviors (e.g., we might restrain ourselves from speeding or we might take a risk and speed in the hope that the camera is inoperative).

Ajzen's TPB has been extremely fertile in spawning hypotheses and predicting multiple aspects of health-related behaviors (McEachan *et al.*, 2011). In the context of driving, it has been successfully applied to explain and predict risky driving that involves conscious violations (rather than unintended errors) (Parker *et al.*, 1992), aggressive driving (Efrat and Shoham, 2013; Özkan and Lajunen, 2005), driver education programs for young drivers (Brijs *et al.*, 2014), effects of peer pressure on young drivers (Møller and Haustein, 2014), speeding in general (Elliott and Armitage, 2009) and of young drivers in particular (Cestac, Paran, Delhomme, 2011; 2014); pedestrians' street-crossing behavior (Holland and Hill, 2007; Zhou and Horrey, 2010); mobile phone use (Waddell and Wiener, 2014; Zhou *et al.*, 2012), and drinking and driving (Castanier and Woodman, 2013; Elias *et al.*, 2016; Johnson and Voas, 2004).

To illustrate, how the theory is useful we can consider the study by Iversen and Rundmo (2004). They demonstrated the utility of the model in a survey of the attitudes of a nationally representative sample of Norwegian drivers. In their study they examined the correlation between drivers' self-reported attitudes and near accidents and their accidents and violations history. The results, reproduced in part in Figure 3-9 demonstrate how attitudes toward violations and speeding, careless driving, and drinking and driving related to risky driving behaviors, and how the latter are significantly associated with crash involvement. In this schematic representation, attitudes were based on the drivers' tendencies to violate traffic rules and to speed, including the overtaking of others even when they keep appropriate speed, and ignoring and breaking traffic rules to proceed

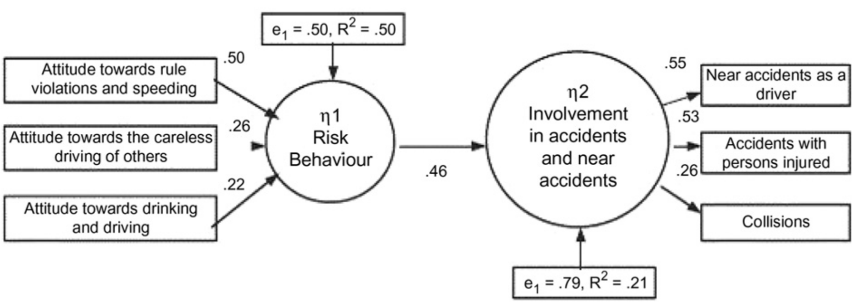

Figure 3-9. The associations between attitudes toward safe driving behaviors, risky behaviors, and accident involvement (from Iversen and Rundmo, 2004, with permission from Taylor and Francis, Ltd. http://www.informaworld.com).

faster. Reckless driving attitudes included driving too close to the car in front, creating dangerous situations caused by lack of attention, and driving without any or enough safety margins. Drinking and driving included attitudes toward driving after drinking more than one glass of beer or wine, and attitudes toward riding with someone who the respondent knows has been drinking too much. Together, these variables accounted for 50 percent of the variance in the respondents' inclinations toward engaging in risky behaviors. These behavioral inclinations, in turn, correlated quite highly with the combined measure of accident involvement. In assessing the predictive power of the TPB, it is important to note that the predictive power cannot be higher than the reliability of the predicting measures. This is a serious limitation because questionnaire-based assessments of attitudes, subjective norms, and perceived behavioral control rarely exceed $r = 0.80$ (Ajzen, 2011). In addition, the strength of the predictive power is moderated by the time interval between the stated intentions and the measured behaviors (McEachan *et al.*, 2011), and this is often a significant interval.

Fuller's task-capability interface (TCI) model and risk allostasis theory (RAT) of driving behavior

How is attention allocated within the maximal performance limits of each function specified in Wickens' model (Figure 3-3)? The answer is that it depends on a variety of things. Fortunately, we are fairly flexible in our allocation, and seem to be able to change allocation of attention fairly quickly. The change is determined by multiple factors – both endogenous (such as an individual driver's experience, skills, attitudes, etc.), and exogenous (such as the road, weather, and traffic conditions). An attempt to address that issue is made in a model that focuses on the relationship between the driving demands and the driver's capacities to handle them. The Task-Capability interface model was first proposed by Fuller in 2005, who later revised it slightly and renamed it risk allostasis theory (Fuller, 2011). The schematic representation of the earlier model is depicted in Figure 3-10.

In this model the main diagonal line represents the crossover point from a non-collision situation (control) to one involving a collision. Whenever the task demands (denoted as D) exceed the driver's capabilities (denoted as C) we enter the situation of "loss of control" which may turn into a collision or – when we are lucky because other drivers compensate for our mistakes or a forgiving highway is there for us – a "lucky escape." The added value of this model to that of Blumenthal's (1968) is in the additional boxes that specify the sources of the task demands on the one hand and the limits on the driver's capabilities – the "human factors" – on the other hand. The shortcoming of this model is that it does not address the time-dependent contingencies that are so critical to driving and that are a focus of attention in the previous models.

An interesting concept that ties this model to Blumenthal's early model is "task difficulty." Task difficulty is the driver's subjective appraisal of the disparity between the capabilities allocated to the task of driving and the demands placed on performing the task successfully. When the capabilities allocated greatly exceed the demands the task is

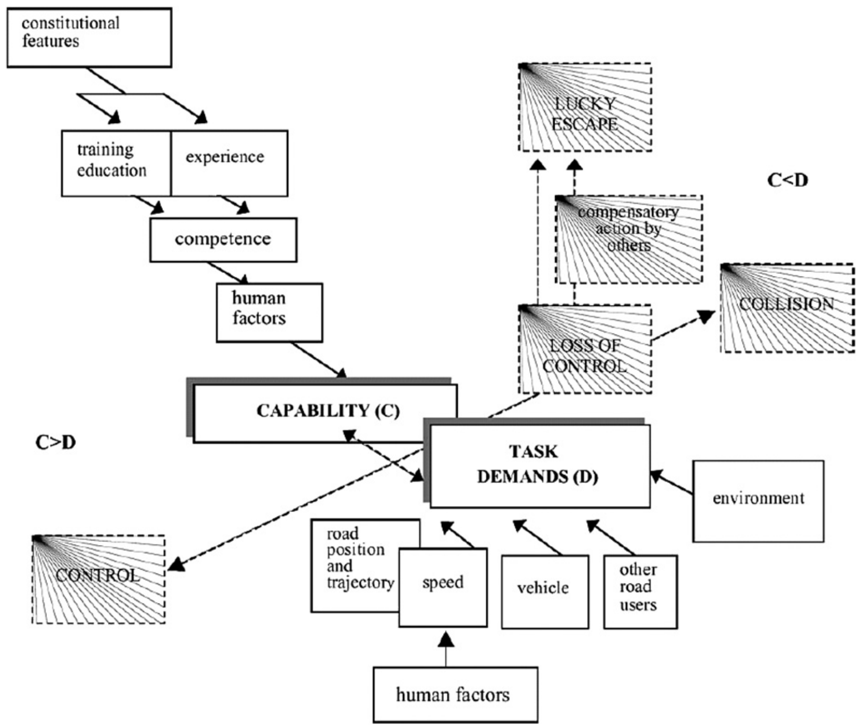

Figure 3-10. Driver capacity versus driving demands model (reprinted from Fuller, 2005, with permission from Elsevier).

easy. When the capabilities allocated match the demands the task, the safe control of the vehicle is maintained but the task is perceived as difficult. However, when the demands exceed the capabilities, the driver loses control, and – depending on the forgiveness of the roadway and compensation by other road users – may or may not have an accident. Loss of control may be limited to forgoing some safe behaviors and not necessarily to total loss of control. For example, an experienced driver would check the rear-view mirror before braking abruptly to verify that he or she is not being tailgated. However, in a very demanding situation – such as the unexpected and abrupt braking of a car ahead – this precautionary behavior may be omitted. A rear end collision is then avoided only if there are no cars immediately behind the driver. Chain collisions on motorways are typical of such situations when all the drivers are proceeding at high speed and short headways, assuming that no one will brake suddenly. Once the first driver violates this assumption, the drivers behind often lose control in the sense that they cannot reallocate their attention and respond appropriately in sufficient time given the short headways and long stopping distances.

In Fuller's model, the driving demands are quite easy to assess and quantify. They consist of the vehicle dynamics and characteristics (e.g., acceleration, field of view), the roadway characteristics (e.g., shoulders, lane markings, potholes, signs, and signals), and other road users (e.g., other drivers and pedestrians). Fuller also includes speed as a demand. This is because once a driver selects a speed – although it is a "human factor" that we can select to fit our capabilities, it becomes part of the driving conditions, with implications for the task demands. For example, to respond to a change in a traffic signal light when the driver is at a given distance from the intersection, the faster a driver is driving the faster he or she must respond to the changing light. This makes driving very different from externally paced tasks (such as working on a production line). Because driving most often is self-paced, we have a significant control over the task demands. This is an essential characteristic of driving that complicates much of the research in this area. For example, elderly drivers (see Chapter 8) whose driving skills are often impaired, control their safety by driving at low speeds and in low risk situations. Similar speed compensations have also been noted for drivers under the influence of marijuana (see Chapter 12) and drivers talking on their cell phones (see Chapter 13).

On the driver capabilities side of the equation, Fuller notes that our long-term capabilities are based on the competence that we bring to the driving situation. This, in turn, is based on our experience, driver education, and training, which are discussed in detail in Chapter 6. Beyond these human factors, the model also acknowledges the driver's "constitutional features." These include various personality attributes, attitudes, and cognitive style that are discussed in Chapter 9. They also include various states of consciousness that can reduce overall capabilities such as alcohol impairment, drug impairment, distraction, and fatigue (discussed in Chapters 11-14, respectively). The inclusion of the constitutional features is a significant addition to Blumenthal's and Wickens' models, because it acknowledges motivational factors that affect our driving style, with implications for our information processing capabilities that affect our driving performance.

Given all these human factors, we can now see that the task difficulty varies not only as a function of the changing road demands, but also as a function of fluctuating capabilities allocated to the driving task. How then does the driver adjust the gap between the two? According to Fuller, "drivers are motivated to maintain a preferred level of task difficulty," and "speed choice is the primary solution to the problem of keeping task difficulty within selected boundaries" (2005, p. 467).

In its revised version, as Risk Allostasis Theory (RAT), Fuller notes that two emotions that drive speed choice are fear (when it is perceived as too high) and frustration (when it is perceived as too low) (Fuller, 2011). The concept of allostasis implies that the risk the driver selects is not a statistical constant but an equilibrium that is sought in a constantly changing driving situation. Furthermore, the notion of risk here is a subjective one – the feeling of risk – rather than an objective risk tied to empirical data (as in Wilde's theory below). To illustrate, if we perceive the driving task demands as low (such as when driving within a posted low speed limit zone on a deserted rural road), then rather than increase the gap between demands and capabilities, we instead reduce the capabilities allocated to the task and end up with "spare" capacity that may be allocated to non-driving tasks such as talking on the phone or listening to the radio. In a corresponding manner, if for some reason we decide to allocate some of our attention to a non-driving task (such as talking on the phone), we can maintain the desired task difficulty or risk by reducing the task demands through a reduction in speed (Lansdown, Brook-Carter, and Kersloot, 2004; Shinar, Tractinsky, and Compton, 2005) or an increase in headways (Jamson *et al.*, 2004). This, in fact, has been demonstrated in controlled studies where people were required to share the driving with phone tasks (Brookhuis, De Vries, and de Waard, 1991; Recarte and Nunes, 2003; Shinar *et al.*, 2005 – see Chapter 13).

The hypothesized desire to maintain a constant level of task difficulty has two critical implications: The first is that when the demands are perceived as low and the attention allocated is correspondingly low, we may not have enough time to adjust to a sudden increase in the demands (as illustrated in Point C in Blumenthal's model in Figure 3-4). The second implication is that as highway and automotive engineers design safer roads and vehicles, we adjust to that by allowing ourselves to devote less and less of our capacity to the task, and thus the overall safety is not improved. This brings forth the issue of motivation. What motives play a part in the way we transport ourselves from one place to another? Do we strive to maximize safety (obviously not)? Minimize time (not always)? Maximize pleasure or comfort (sometimes)? Are there other motives that come into play? The obvious answer is that we try to do it all. This is where motivational models come into play.

Motivational Models

Motivational models of driver behavior are labeled as such because they emphasize the driver motivations – rather than the driver capacity – as a key determinant of the driving style and safety. Fuller's model incorporates the motivational aspect through the driver's "constitutional features" but certainly does not make that the heart of the model. Motivational models assume that most of the time we do not allocate all of our attentional capacities to the safe negotiation of our car. Safety is just one motive, and – judging by the marketing strategies of the automotive industry (Ferguson, Hardy, and Williams, 2003; Schonfeld, Sheehan, and Steinhardt, 2005; Shin *et al.*, 2005), with some exceptions such as Volvo's – is not even an important one. Based on content analyses of new car advertisements in Australia (Schonfeld *et al.*, 2005), and in North America (Ferguson *et al.*, 2003; Shin *et al.*, 2005), marketing gurus believe that the primary motives behind the choice of the car we buy are related to the car's performance (including high-risk speeding) and looks. This is despite the fact that at least according to one survey, 40 percent of the U.S. drivers rate "safety" as the single most important feature that they look for in a car. However, in the same survey significant numbers of drivers rated economic/fuel efficiency as the most important feature is selecting a car (31 percent), or seating and cargo space (13 percent), or speed/performance (8 percent), or appearance (6 percent) (Mason-Dixon, 2005). Nonetheless, much of the automobile industry's advertising focuses on vehicle performance, and – when targeting the younger consumers – speed (Donovan *et al.*, 2011) and aggressive driving (Shin *et al.*, 2005). Once we drive the car we bought, we also try to satisfy various needs and