# Analysis of Bus Transit Accidents: Empirical, Methodological, and Policy Issues

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Reports of approximately 1,800 accidents between 1982 and 1984 were analyzed to identify factors contributing to accidents involving mass transit buses. Data were provided by Pace, the suburban bus agency in the Chicago metropolitan area. Tactics that would enable Pace and similar agencies across the United States to do an even more effective job of safety management are identified. For the entire data set, 89 percent of the accidents involved collision with another object or person, and the remaining 11 percent involved passenger injuries while boarding, alighting, or moving about the bus. Severity levels were generally low; most accidents involved property damage only. Drivers of the other vehicle involved in the accident were much more likely to be injured than the bus driver: 10 percent of collision accidents involved automobile driver injuries, whereas bus drivers were injured in only 2 percent of the collisions. Despite the relative rareness of occurrence, clear patterns of injury have been identified. When the bus is in motion, 40 percent of automobile and bus driver injuries occur because of rear-end collisions. When the bus is stationary, 80 percent of the automobile occupant injuries occurred when the automobile rear-ended the bus. The analysis of bus drivers' attributes indicated that gender does not contribute to accident occurrence. Age appears to have a negative impact on accident involvement when experience is accounted for. Experience with the transit agency was strongly associated with accident occurrence (i.e., drivers with 3 to 6 years of experience at Pace were significantly overrepresented in accidents).

Vehicular safety is an important attribute of public transportation from the perspectives of both the operator and the passenger. To the operator, excessive vehicle accidents inflate costs in an industry already squeezed between limited revenues and high costs. The costs of accidents are multidimensional and may not always be apparent in a carrier's budget. Data from a 1973 study (*1*) suggest that safety costs are approximately 5 percent of agency operating costs. Components of those costs are not clearly described, however. Obvious costs are reflected in insurance premium rates and claims set-asides for partially self-insured carriers. Other costs, such as repair of vehicles damaged in accidents, excessive vehicle downtime, shortened vehicle life, road calls related to accidents, employee medical cost, and absenteeism, may be buried in a carrier's operating budget. In addition, transit accidents may affect ridership because of fears generated in potential users. This cost is measured in lost ridership and revenue.

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Accident statistics suggest that public transit, in general, is safe compared with other modes. Data from the National Safety Council (*2*) indicate that fatality rates for bus transit (per 100 million passenger miles) varied between 0.15 and 0.17 from 1974 to 1980. During the same period, automobile passenger rates varied from 1.40 to 1.30 and railroad passenger rates from 0.13 to 0.04.

These statistics indicate that, on a passenger-mile basis, bus travel has relatively low risk. Furthermore, as many as 63 percent of bus transit accidents involve no collision (*1*). These noncollision accidents have no parallel outcome for automobile accidents. If someone is injured while moving into or out of an automobile, the injury will not appear in a formal transportation accident report. These injuries are reported for transit, however, increasing apparent accident rates.

The key to improved understanding of accident causality lies in the careful analysis of past accident experience, in terms of both detailed attributes of samples of accidents and appropriate exposure measures for determining rates. A fundamental exploration of bus accident data is needed to understand the scope of bus accident experience. This paper focuses on a detailed examination of accident data in an effort to develop a set of testable hypotheses concerning accident causality.

## OBJECTIVES

The objectives of this research are to develop refined measures of transit accident rates and to define a set of hypotheses concerning accident causation in public transportation. Refinement of measures of accident rates is essential to understanding where the industry stands today. It is also useful to explore the implications of conducting the analyses at different levels. Broad indicators of safety performance at the system level may be useful for some analyses. For others, route-level safety studies may be required. The search for causality in transit accidents, therefore, is likely to involve analyses at several levels. This paper reports on findings from such analyses.

When accident data bases are derived from accident reports collected in the field, they may be prepared for reasons only weakly linked to operations management and the assurance of a safe transit system. For example, police accident reports tend to focus on simple explanations of causality in an attempt to assign unitary fault. A pilot study of child pedestrian accidents (*3*) determined that causal factors extend far beyond the immediate actions of the children or drivers involved; for example, environmental characteristics, neighborhood social patterns, family and life-style attributes, and physical and emotional states of the children appear to play major roles in the process. It is important to recognize the limitations of self-reported data when conducting any analysis.

Each time a vehicular collision or other type of accident occurs that results in a personal injury, fatality, or property damage, the transit operator completes an accident/incident report. The report typically contains a description of conditions at the accident scene, vehicle identification, driver attributes, and details of the event, including collision type and bus activity at time of incident. It is useful to consider this information in the broader context of a conceptual structure for accident causation.

To meet these objectives, we undertook a moderate-scale but detailed examination of the accident experience of a major bus transit carrier. Working closely with representatives of the carrier, we examined internal (and normally unpublished) accident records to formulate and conduct preliminary tests on a series of hypotheses concerning accident patterns and causation. We paid particular attention to the limitations imposed by available data and to alternative ways to collect more useful data.

## RESEARCH APPROACII

The usefulness of this research was closely linked to the connection we were able to make with transit operators and their data bases. Otherwise, we would have faced the risk of using only published data, which is of a summary nature, and of developing hypotheses that may not lead transit managers to practical solutions to safety problems. Therefore, we established contact with Pace, a major public suburban bus operator that operates and contracts for services in a wide variety of communities in the Chicago region, ranging from extremely low-density hinterlands to routes penetrating the Chicago central business district (CBD). Pace managers expressed a willingness to cooperate with us in this effort, permitted us to use their accident records, and counseled us on directions for our work.

One of the most sensitive issues in bus transit safety research is a strong desire of transit agencies to protect the confidentiality of their accident records. In the course of eliciting support for this research project, the question of confidentiality recurred. Transit agencies appear to be concerned that

1. Analysis of safety (and accidents) may affect litigation on existing or future claims;
2. Analysis of safety data will be used to evaluate the agency's safety program (perhaps negatively);
3. Acknowledgment of the existence of transit safety data will ultimately lead to charges (whether rational or not) that the agency is not doing enough to correct safety deficiencies (these charges may influence litigation and public opinion); and
4. The identity of individuals involved in accidents and incidents be protected.

Whether these fears are real or imagined, it is clear that most transit agencies experience them. Rather than ignore this issue we dealt with it directly. During the analyses, we identified where, when, and how confidentiality questions arise. We discussed these issues in our interactions with participating transit managers and have identified how they may have limited our ability to analyze safety data and develop ameliorative policies.

## CONCEPTUAL STRUCTURE

It is traditional to view the occurrence of a highway traffic accident as the result of the interaction of the driver, vehicle, roadway, and environment (*4*). This framework is useful because it provides the analyst with a structure to use in studying the causes of accidents. Urban bus accidents certainly fit within this framework with the additional complication that the risk of an accident is affected by characteristics of the transit service and agency policies (e.g., route design, driver safety incentives, etc.). Furthermore, bus operators are concerned with a significant number of noncollision passenger injury accidents (frequently called incidents). The outcomes of noncollision events have no parallel structure in the traditional highway safety field.

Potential interactions between some possible causative factors, accident risk, and accident outcomes are shown in Figure 1. The four traditional factors as well as transit service characteristics and agency policies interact to define a particular level of accident risk. This level results in a certain probability of having an accident; when combined with exposure to risk, this yields a certain number of accidents. If an accident occurs, it will either be a noncollision passenger accident or a collision accident of a particular type resulting in property damage, personal injury, fatality, or some combination of the three.

Certain boundaries were set for our safety investigations. Specifically, property damage or injuries resulting from crimes and acts of vandalism were excluded. These are deliberate acts of destruction and do not have the same etiology as "accidents" in a traditional sense. Unsubstantiated claims of injury or property damage were also excluded. Whereas a substantial number of these claims are processed by transit operators (*5*), there is considerable doubt concerning the occurrence of these events. To avoid this uncertainty, we decided to focus our attention only on accidents reported by transit agency personnel.

It is best to consider the conceptual framework in the light of what is already known about highway and transit safety. Driver characteristics and their contribution to accident occurrence have been broadly studied in the highway safety field (*4*), but findings that apply directly to the transit industry are limited. Reports from other metropolitan areas (*6*) identify the age and experience of accident-involved drivers but do not compare them with distributions of characteristics for the entire transit driver population. Studies of age and experience of drivers involved in accidents are of limited utility if such a

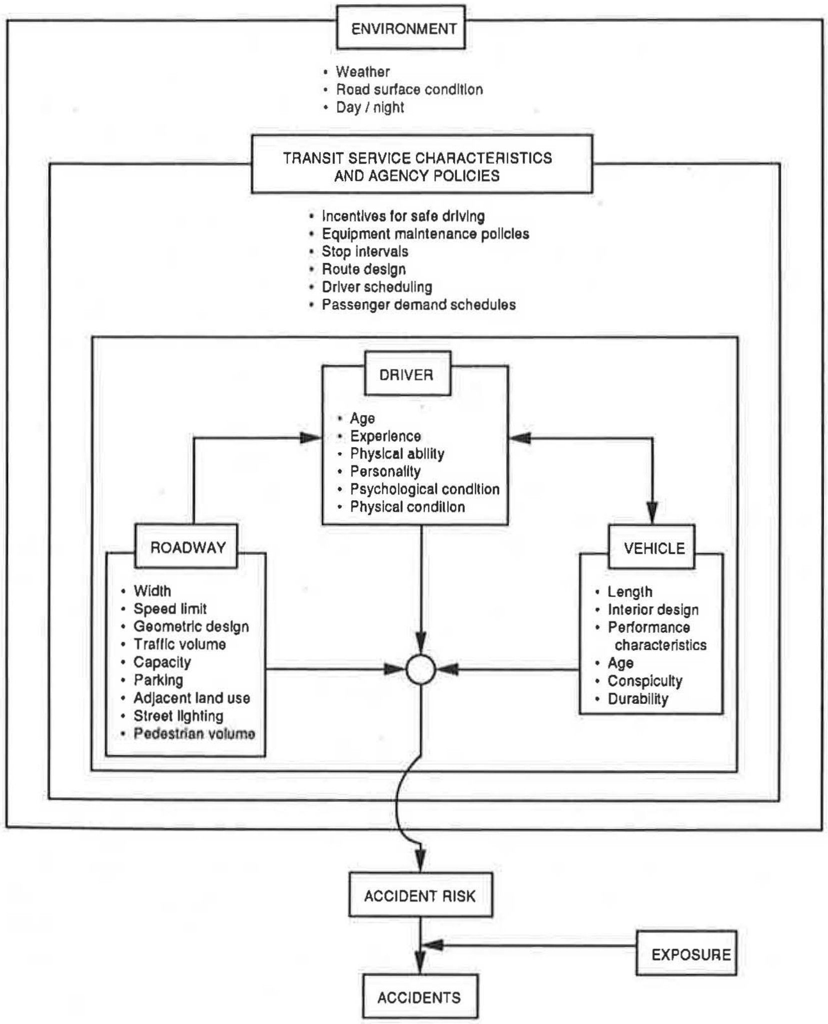


**FIGURE 1 Conceptual structure of bus transit safety research.**

comparison is not made. For example, a study of truck accidents for several national carriers (*7*) indicated that drivers with less than 1 year of experience are involved in six times the number of accidents that one would expect on the basis of their proportion in the population.

Conversations revealed a belief among transit industry officials that accident rates are highest for first-year drivers, drop for second- through fifth-year drivers, and then rise again. We tested the validity of this belief by comparing the experience of accident-involved drivers with the population of transit drivers. Age can act as a surrogate for physical ability, so we included comparisons of the age of the driving population with the ages of drivers involved in accidents.

Personality, psychological condition, and physical condition at the time of the accident (e.g., drug or alcohol impairment) are difficult to assess without special studies. These factors are discussed in the broad highway safety literature (*8*), although there are no findings that relate them directly to the transit industry. We recognize that these factors are important in accident occurrence, but they are beyond the scope and resources of this study.

Vehicle attributes affect accident occurrence in two ways. First, the handling attributes of the bus affect the driver's ability to take corrective or evasive action when presented with a threatening situation. Vehicle age may affect handling characteristics, and they may vary for different types of buses (e.g., articulated and standard coach). Vehicle-handling characteristics may be particularly important in restricted geometries, heavy traffic, inclement weather, or combinations of these conditions. Second, vehicle attributes affect other drivers, passengers, and pedestrians. Vehicle conspicuity to drivers and pedestrians may affect accident occurrence, particularly at night. Bus interior design may affect the probability (and severity) of noncollision passenger accidents.

Roadway characteristics affect the occurrence of potential accident situations as well as the ability of the driver to maneuver to avoid the collision. Roadway and lane width, geometric design, traffic volume, and parking represent factors that can increase the risk of an accident by increasing opportunities for collisions and reducing opportunities for avoidance. The character and activity level of adjacent land uses determine the amount of pedestrian traffic, which could conflict with bus operations. Driveways and cross streets intersecting the bus route also represent opportunities for collisions. Street lighting levels could affect accident risk. The speed limit may affect accident risk by reducing the reaction time available to the driver.

Environmental conditions, including weather (*9*), road surface (*9*), and lighting conditions (*10*) are significant factors in accident causation. Weather conditions may have a smaller effect on bus accidents than automobile accidents because the bus driver is a professional who should be better able to cope with adverse driving conditions. Studies of truck accidents (*11*) tend to support this contention.

In the identification of accident causes (and, eventually, countermeasures), it is useful to separate the four traditional factors mentioned previously from those largely controlled by the transit agency. The existence of a variety of incentives may influence driver behavior and thus accident risk: bonuses, salary increases, and even promotions tied to a good safety record may act as positive reinforcement for safe driving. Driver scheduling may interact strongly with experience, because the most experienced drivers have priority in their choice of runs; they may choose runs that are shorter or less prone to risk. Equipment failure is one cause of vehicular accidents that is directly influenced by an agency's maintenance policies. There may be an indirect effect on driver attitudes if buses are not clean and well maintained. Route design and layout may influence accident risk.

In exploring the factors that may cause bus accidents, it is useful to keep in mind the opportunities for intervention in the accident causation process. These opportunities should be the focus of the inquiry, because several safety studies make it clear that some factors will be outside the control of policy makers, managers, and operators.

## DATA COLLECTION AND CODING

Pace is a public agency that both operates direct bus services and contracts for services with carriers and municipalities. Services are provided by Pace for the Chicago metropolitan area, excluding the city of Chicago. Services include collector-distributor hauls to fixed rapid transit and commuter rail stations, local community and intercommunity services, and some express runs from the suburbs to Chicago's business district. Until 1983 Pace was a suburban bus division of the Regional Transportation Authority (RTA). Since that time Pace has become a separate entity subsidized by RTA.

We used data from four contractors of Pace: (*a*) Nortran, which serves the northwest suburbs, (*b*) West Towns, which serves the near-west suburbs, (*c*) Oak Lawn, which serves the near-southwest suburbs, and (*d*) Harvey, which serves the south and far-south suburbs.

Our data from Pace come from two sources: accident/incident reports and descriptions of individual bus routes. From the first source we collected all the information pertaining to an accident or incident occurrence. To shield the identity of individuals from our research team, RTA required that personal information, such as names, addresses, and telephone numbers, be concealed during photocopying of accident reports. Because this information is not essential to the analysis of broad accident trends, it did not hinder our subsequent activities.

The second source provides information about route service that is important in identifying the contribution of route characteristics to accident occurrence. From Pace's *Bus Route Descriptions* (*12*), we were able to get useful operational profiles for each route. Information included route length, duration of trip, revenue miles, bus requirements (peak and off-peak), number of trips, and average headways. Some of these pieces of information were useful in creating exposure measures.

For the collection of data concerning the road and roadside characteristics, we used a computer printout detailing the name of the street each bus route follows as well as the streets intersecting the route. We drove each route and collected information block by block for each of 10 routes served by Nortran. Further details of this data collection and coding are contained in the project final report (*13*). Data from a variety of sources were required to conduct this research study. Whereas some were provided by Pace, important engineering data concerning the routes were almost completely lacking. Data from the service provider must be integrated with roadway and environmental data from other public agencies for a comprehensive analysis of bus accident causality.

## DATA ANALYSIS

### Overview

The approach we adopted for conducting our empirical analysis was to explore available data from several perspectives, using qualitative (graphical) analysis, correlation, regression, and, where appropriate, more sophisticated modeling.

At the system level we used all the accident/incident report data collected from Pace and conducted an in-depth analysis aimed at the identification of the distribution and effects of various factors. The distribution of accidents with respect to time, the distribution of the types of accidents (alone or conditional), the driver's characteristics, and the effect of environmental factors such as weather, type of traffic control, and so forth were identified.

At the route level, we tried to identify the effect of route-specific operational characteristics, such as ridership, type of area (i.e., CBD or suburban) the route crosses, headway, trip frequency, annual revenue miles, and so forth. Finally, we analyzed the accident propensity of bus drivers. This was based on the hypothesis that the ability of a driver to avoid accidents follows a learning curve.

### System-Level Analyses

This section presents the results of the analysis of the accident data at the system level. The data base contains information on the accidents that occurred during the 3-year study period (1982–1984) among the four Pace subsidiary companies (Harvey, Nortran, Oak Lawn, and West Towns). After screening out unreliable or questionable accident reports and verifying the completeness of data contained in the reports, we developed a data base of approximately 1,800 accidents. Of these accidents, 1,600 (89 percent) were collision accidents, and the rest (11 percent) were noncollision passenger accidents. The percentages are approximately the same as those reported in a British study (*14*).

### *Overview of Accident Characteristics*

Figure 2 shows the yearly occurrence of collision accidents for the 3 years. It does not show any distinct trend of accident frequency during the period, but it shows a dramatic decrease in noncollision passenger accidents in 1984. However, this appears to be due to a lack of reporting of noncollision accidents for the last 2 months of 1984. We have been unable to obtain the additional reports, but it is unlikely that they would change our interpretation of the data.

Figure 3 shows the monthly occurrence of collision accidents by year. Accident frequency may be hypothesized to be correlated with weather conditions and thus display an annual cycle, but such a hypothesis is not supported by the data.

Figure 4 shows the distribution of accident occurrence by time of day for each type of accident. Both distributions have four peaks: two high peaks at morning and evening rush hours (6:00–8:30 a.m. and 3:30–7:00 p.m.) and two low peaks occurring around 10:00 a.m. and 2:00 p.m. The peak periods in the morning and evening rush hours for noncollision passenger accidents are narrower than those for collision accidents, displaying higher concentration of the occurrences, which is probably connected with ridership levels. The spikes at 11:00 a.m. and 2:00 p.m. coincide with shift change times for drivers. Limitations in data precluded further analysis of this phenomenon, but it would be of interest to see whether the accidents were more common for drivers who had recently changed shifts.

Analysis of accident locations indicates that, not surprisingly, 70 percent of the collision accidents occur at intersections, whereas 30 percent occur at some other location; the corresponding percentages are 80 and 20, respectively, for noncollision passenger accidents. The observation that a high concentration of noncollision passenger accidents occurs in

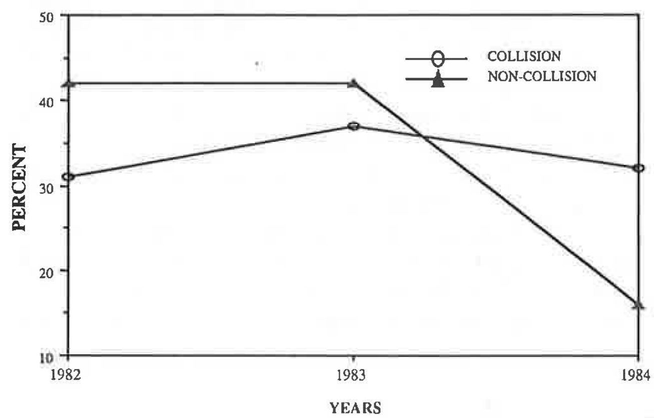


**FIGURE 2 Collision and noncollision accidents.**

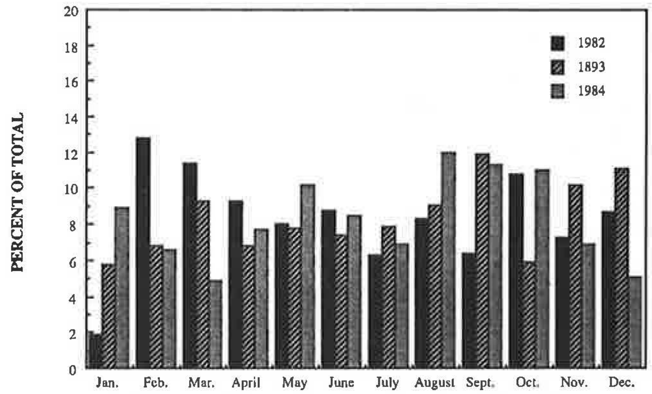


**FIGURE 3 Monthly distribution of collision accidents.**

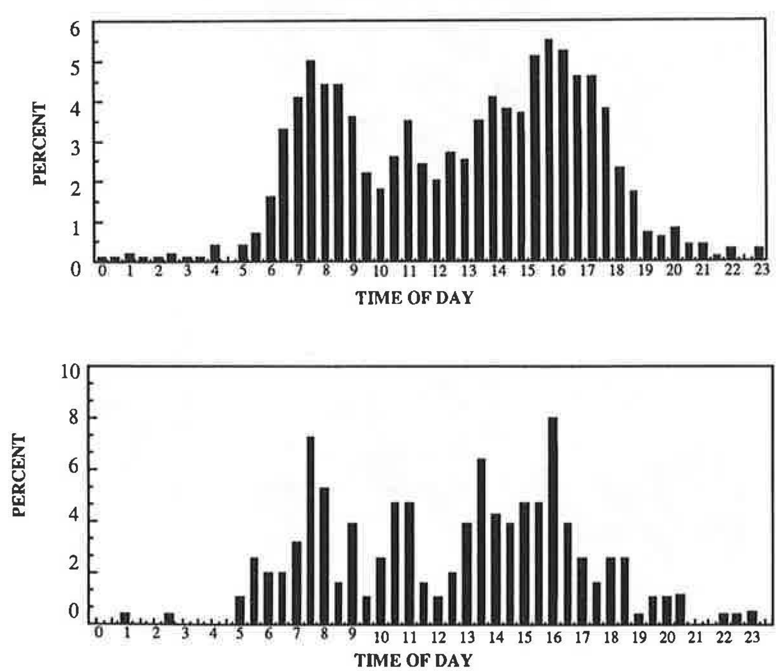


**FIGURE 4 Hourly distribution of accidents: *top*, collision; *bottom*, noncollision.**

the vicinity of intersections is consistent with the fact that 55 percent of passenger accidents occurred when passengers were either boarding or alighting buses (Figure 5).

Figure 6 shows the proportion of collision accidents by type of occurrence. The two most common collision types are sideswipe (34 percent) and rear end (25 percent). These are followed by right angle (10.5 percent), passenger injury (9 percent), and left angle (7.5 percent).

*Driver Characteristics*

Figure 7 (top) shows the age distribution for RTA drivers involved in each type of accident. If this age distribution is representative of the driver population for the 3-year study period, the figure indicates the following: drivers in their 20s are only slightly (approximately 2 percent) overrepresented in accidents compared with the population distribution, and drivers in their 50s are slightly (2 percent) underrepresented. Furthermore, bus drivers in their 30s are overrepresented in accidents with other motor vehicles; bus drivers in their 40s and 50s are slightly underrepresented in these collision accidents. Because the distribution in Figure 7 is not adjusted by relevant exposure measures (e.g., route or vehicle miles), these findings are tentative. However, the comparison between these two distributions indicates an age-related difference between proneness to collision accidents and noncollision passenger accidents.

Figure 7 (bottom) shows the sex distribution of RTA drivers who were involved in each type of accident. Both distributions have 90 percent male and 10 percent female drivers, so there appears to be no sex-related difference in accident rate.

Figure 8 compares the seniority distributions for drivers from the four RTA subsidiaries with those involved in each type of accident. The comparison indicates that drivers with 3 to 6 years of service are substantially overrepresented in accident involvement. The opposite is true for drivers with 9 to 11 years of service. Drivers with more than 18 years of experience are moderately underrepresented in the accident involvement population. Caution must be exercised in interpreting these findings, because the seniority distribution for all drivers is not adjusted by appropriate exposure measures.

These findings are particularly interesting because they appear to substantiate the perception of Pace safety officers that the group of drivers with 3 to 5 years of experience is particularly prone to accidents. Targeted driver retraining and education activities may reduce this apparent overrepresentation.

The incidence of injuries in bus crashes is very low. Only a small proportion of RTA drivers (less than 5 percent) are injured in collisions; the percentage is virtually zero while the bus is stationary. Automobile drivers are injured in only 10 percent of the accidents and more often (relatively) when the bus is in motion. We can speculate that this is due to the large difference in mass between a bus and a car.

Despite their comparative rareness, we sought to develop a better understanding of the etiology of injury accidents. Figure 9 shows that, for both RTA drivers and other drivers, more than 40 percent of driver injuries in collision accidents that involved RTA buses are caused by rear-end collisions. Automobile drivers are also slightly more likely to be injured

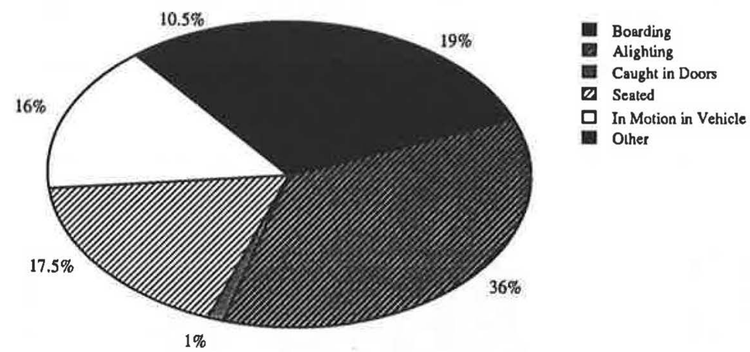


**FIGURE 5 Passenger's action (noncollision accidents).**

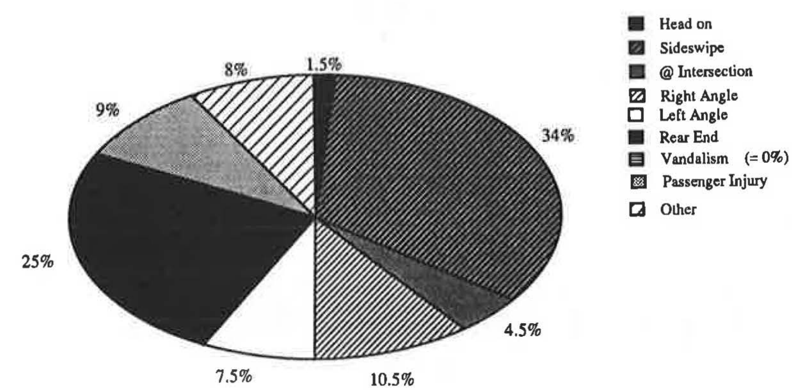


**FIGURE 6 Proportion of collision accident types.**

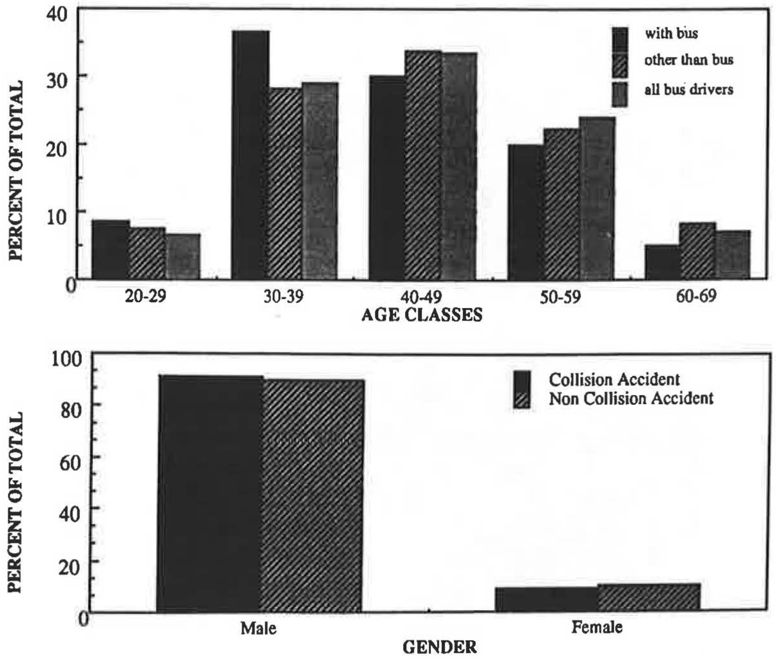


**FIGURE 7** ***Top*: Age distribution of RTA drivers involved in accidents. *Bottom*: Sex distribution of RTA drivers involved in each type of accident.**

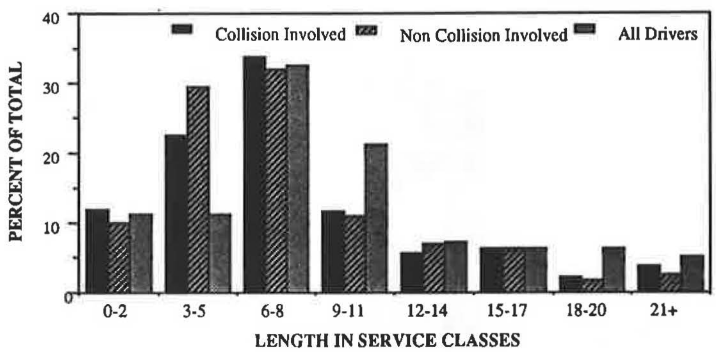


**FIGURE 8 Seniority distributions of drivers.**

in a sideswipe accident. Figure 10 shows, however, that for collision accidents occurring when RTA buses were stationary, this figure is more than 80 percent for both RTA and other drivers. Thus, the severity is much higher for both bus and automobile occupants in rear-ending a bus compared with the severity of being rear-ended by a bus.

Figure 11 shows that more than 80 percent of the accidents involving buses occur near intersections with either no control or traffic signals in the direction of the bus. It is notable that more noncollision passenger accidents than collision accidents occur at stop signs. This suggests that it may be useful for drivers to warn passengers before buses stop at a stop sign or to slow down more gradually when approaching a stop sign.

The data also indicate that more than 75 percent of accidents occur in clear weather, more than 65 percent on clear roads, and 80 percent during daylight. Thus weather, though important in some accidents, is not a contributing factor in a large percentage of our bus accidents.

**Route-Level Analysis**

To explore the effect of route characteristics on accident frequencies, an analysis file was created that contains the data on accident frequency by route as well as various descriptors of route characteristics. Accident frequency of a route (ACCYR) is the average number of accidents that occurred on the route per year obtained by compiling the RTA accident/incident report data file. Because some bus routes have shorter service periods than the analysis period (January 1982 through December 1984), appropriate adjustment was made when the average frequencies were computed. Bus route descriptor data were compiled from Pace's *Bus Route Descriptions* (*12*) for 65 separate routes.

As a preliminary step in the analysis, pairwise correlations of a large number of variables were examined using scatter plots. The major findings of this analysis are as follows:

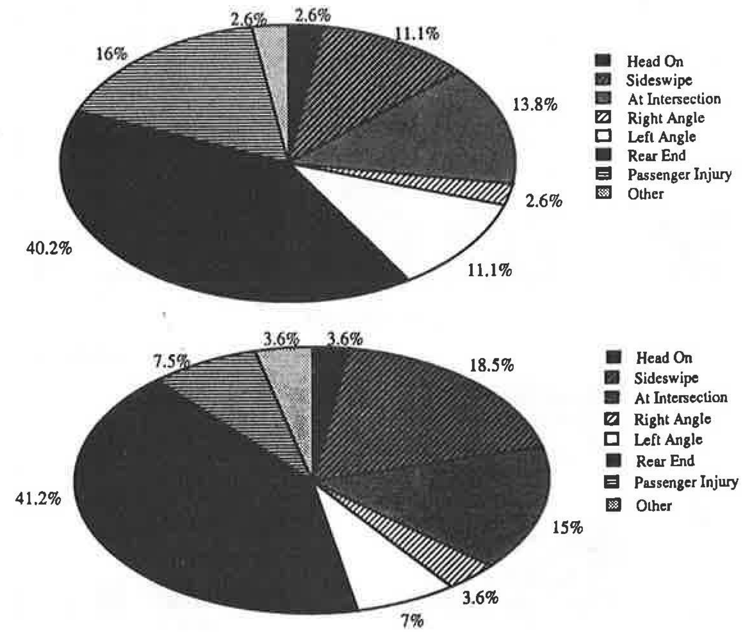


**FIGURE 9 Proportion of collision accident types. *Top*: Bus driver was injured and bus was moving. *Bottom*: Other driver was injured and bus was moving.**

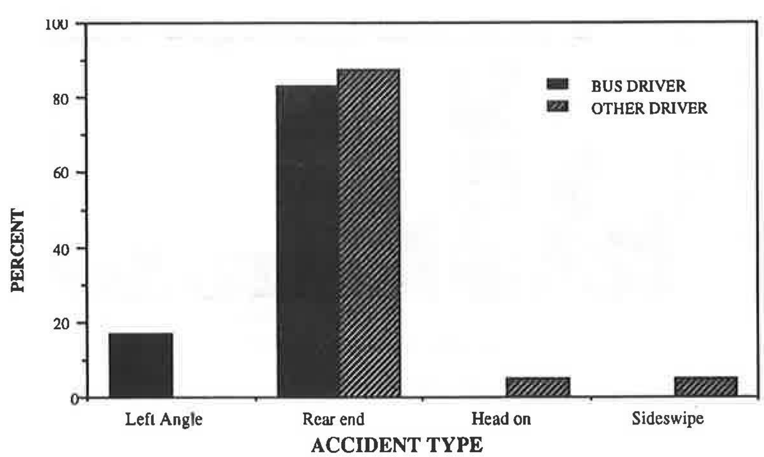


**FIGURE 10 Type of accident—driver or drivers injured and bus stationary.**

1. Only a small number of routes exist that belong to route categories O (outlying suburban route) and F (feeder service to rail stations); most routes belong to the category I (inner suburban route). Thus, separate analyses by route category are not feasible.
2. Revenue miles, revenue hours, ridership, and number of weekly bus trips have a strongly positive correlation with each other.
3. Morning headways have a moderately negative correlation with all of the preceding variables.
4. Average base headway and speed have a slightly negative correlation with revenue hours, ridership, and number of trips and a slightly positive correlation with morning headways.
5. On the basis of these observations, major variables appear to fall into four groups: revenue miles; revenue hours, riders, and number of trips; morning headways; and base headways and speed.

Revenue miles, ridership, morning headway, and speed were chosen to represent each of these groups. Regression analyses were conducted to estimate models that relate accident frequencies to these variables. Estimation results for log-linear models are summarized in Table 1. They are estimated with reasonable $R^2$ values ranging from 0.73 to 0.75; all parameters in all models are estimated with signs consistent with the preceding discussion. The third model, which is the

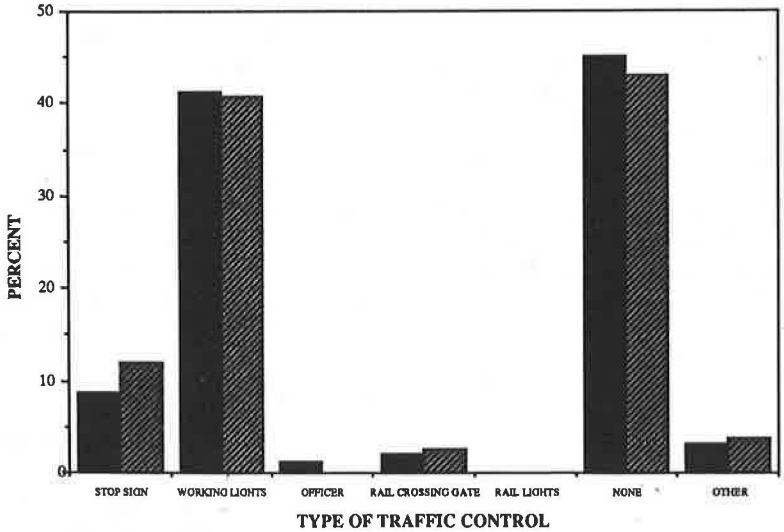


**FIGURE 11 Accidents by type of traffic control.**

TABLE 1 LOG-LINEAR REGRESSION MODEL OF ACCIDENT FREQUENCY

$\ln(ACCYR) = a + b_1 \cdot \ln(RMYR) + b_2 \cdot \ln(RIDER) + b_3 \cdot \ln(HWAM) + b_4 \cdot \ln(SPEED)$

| | a | $b_1$ | $b_2$ | $b_3$ | $b_4$ | |
|---|---|---|---|---|---|---|
| **Model 1** | 2.32 | 0.70 | 0.30 | -0.42 | | ---> $R^2 = 0.74$ |
| (t) | (1.8) | (5.0) | (2.8) | (2.4) | | |
| **Model 2** | 2.96 | 0.82 | 0.28 | | -0.53 | ---> $R^2 = 0.73$ |
| (t) | (1.1) | (4.3) | (1.7) | | (1.1) | |
| **Model 3** | 7.60 | 1.03 | | -0.43 | -0.86 | ---> $R^2 = 0.74$ |
| (t) | (7.6) | (11.1) | | (2.5) | (2.5) | |
| **Model 4** | 4.13 | 0.80 | 0.22 | -0.40 | -0.38 | ---> $R^2 = 0.75$ |
| (t) | (1.8) | (5.0) | (2.8) | (2.4) | (0.8) | |

where,
RIDER = weekday average ridership,
HWAM = average weekday morning headway (inter-departure time),
RMYR = annual revenue miles,
RHRYR = annual revenue hours,
SPEED = RMYR/RHRYR.

preferred one in the light of the high *t*-statistics of all parameters, implies that accident frequency is almost linearly proportional to revenue miles and inversely proportional to morning headways and speed raised to the powers of 0.43 and 0.86, respectively.

Speed has a negative relationship to the number of accidents, largely because lower average speed reflects traffic-congested routes along narrow streets, whereas higher average speed reflects routes along high design arterials with moderate traffic volumes.

Although the variables appearing in the models are considered to represent various route characteristics affecting accident frequencies, the models should not be interpreted as directly indicating the causality of bus accidents. Thus, it is unrealistic to expect to reduce the number of accidents by increasing bus speeds while keeping other variables constant. Rather, the models should be interpreted as indicating that the number of accidents would decrease if the determinants of bus speed, such as traffic volume, land use, number of bus stops, road geometry, and so forth, were different. The models may be used to predict the number of accidents expected on new routes. They may also be useful in identifying routes of unusually high or low accident rates, which may provide clues to measures for reducing the number of accidents.

The models presented have been derived using data from a specific area. Model calibration for use in other areas may be necessary for representative results (i.e., avoidance of transferability errors).

### Analysis of Accident Propensity of Bus Drivers

The ability of a bus driver to avoid accidents is hypothesized as developed according to some learning curve. The level of this ability, denoted by $m$, $0 \leq m \leq 1$, may be represented mathematically as follows:

$$m = 1 - 2/(1 + e^{\alpha t}) \quad (1)$$

In this generic learning curve, $t$ is the time elapsed since the start of learning, and $\alpha$ is the parameter that determines the curvature.

We further hypothesize that each driver has a certain basic accident propensity and that a certain portion of accidents are unavoidable even after the driver attains the maximum level of learning. Thus

$$P = P_0(1 - \beta m) \quad (2)$$

where

$P$ = the accident propensity of a driver,
$P_0$ = the basic accident propensity,
$m$ = the level of learning defined by Equation 1, and
$\beta$ = the maximum reduction in accident propensity by learning.

To estimate the parameters of the model and test the reasonableness of this hypothesis, an analysis file was created that contained the ratios of the number of drivers who had accidents during the analysis period and those employed as of spring 1985. This file was created by compiling the Pace accident/incident report data file and the seniority lists provided by Pace operators.

If accident propensities of drivers belonging to age and seniority groups are assumed to be these ratios, the model in Equations 1 and 2 can be estimated with this data file. In the estimation, we assumed that parameters and ß were constants that did not depend on age and seniority. However, we assumed that the basic accident propensity depended linearly on the age of drivers. Thus, the model to be estimated has the following form:

$$P(y,t) = P_0(1 - \beta m) \tag{3}$$

or

$$P(y,t) = (a + by)\left[1 - \beta\left(1 - \frac{2}{1 + e^{\alpha t}}\right)\right] \tag{4}$$

where

$P(y,t)$ = the accident propensity of drivers in age and seniority group $(y,t)$,
$y$ = int(driver age/10),
$t$ = int(driver seniority/3), and
int = the integer part of the resulting value.

Noting the difference in the number of drivers in age and seniority groups in the data, we used the weighted nonlinear regression procedure of SAS to estimate Model 4 with the number of drivers employed in each age and seniority group as weights. The $R^2$ value for the model was 0.82, which indicates a good fit of the model with the data. This estimated model, in a form similar to Model 4, is

$$P = (7.44 - 0.833y)\left[1 - 0.611\left(1 - \frac{2}{1 + e^{0.472t}}\right)\right] \tag{5}$$

($t$-scores
4.7 2.2 1.7 1.0)

This result suggests that the learning curve hypothesis is reasonable; as indicated by the estimate of parameter $\beta$, the maximum reduction in accident propensity due to learning is as large as 61 percent. As indicated by the negative estimate of parameter $b$, the basic accident propensity appears to decrease with driver age.

### Summary

The objectives of the empirical analyses were to obtain substantive information about the safety performance of the case study transit system and to explore the use of a variety of statistical methods to analyze bus safety data. Rather than a single analysis technique, a broader-based approach appeared more appropriate to the exploratory nature of the research. A multilevel approach was used to guide the empirical studies. First, system safety performance was assessed by analyzing data that reflected systemwide accident experience. The primary techniques used to conduct these studies were cross-classification analysis and simple graphical plots.

Additional studies were conducted at the route level to obtain a more detailed understanding of factors that contribute to accident occurrence. Use of the transit route as the analysis unit allowed the infusion of a number of useful exposure variables; the principal analytic technique was nonlinear regression. Finally, several studies were undertaken at the disaggregate or individual level. Driver age and experience were used to estimate a learning curve model.

## CONCLUSIONS

Reports of approximately 1,800 accidents occurring over a 3-year period (1982–1984) were analyzed to identify factors contributing to bus accident occurrence. Data were provided by Pace, the suburban bus agency of the Regional Transit Authority in the Chicago, Illinois, metropolitan area. For the entire data set, 89 percent of the accidents involved a collision with another object or person, and the remaining 11 percent involved passenger injuries while boarding, alighting, or moving about the bus.

Severity levels were generally low; most accidents caused only property damage. Drivers of the other vehicle were much more likely to be injured than the bus driver: automobile drivers were injured in 10 percent of collision accidents, whereas bus drivers were injured in only 2 percent of the crashes. Despite their relatively rare occurrence, clear patterns of injury have been identified. When the bus was in motion, 40 percent of automobile and bus driver injuries occurred because of rear-end collisions. When the bus was stationary, 80 percent of automobile occupant injuries occurred when the automobile rear-ended the bus. The findings suggest that stationary buses (for example, buses stopped for a queue of vehicles or to process passengers) pose the greatest risk to automobile occupants. Data limitations did not permit the determination of how many crashes occurred because buses were stopped to process passengers while the nearby traffic signal displayed a green light. The unexpected stop under this condition could surprise the automobile driver and lead to an accident. Because of the relatively high severity of rear-end accidents, serious consideration should be given to expanding the use of bus bays (adjacent to the general roadway) so that buses do not impede through traffic. This is particularly important along high-speed (e.g., 40-mph speed limit) roads with long bus headways.

Trends in total accident occurrence or the separate occurrence of collision and noncollision accidents could not be identified from examination of monthly accident totals. Weather was clearly a contributing factor in some accidents but not a major overall factor, because 75 percent of the accidents occurred during clear weather with dry pavement. These findings are similar to those reported for trucks (*11*). Bus accidents do not appear to be more frequent during darkness. Accident occurrence drops dramatically during night hours, reflecting both changes in service frequency and lowering of automobile traffic flows.

The analysis of bus drivers' attributes indicated that gender does not appear to contribute to accident occurrence; the observed accident frequencies are similar to what would be expected given the proportion of each sex in the bus driver population as a whole. Age, on the other hand, appears to have a negative effect on accident involvement, when experience on the job is accounted for. Experience with the transit agency, however, was strongly associated with accident occurrence. Drivers with 3 to 6 years of experience at Pace were significantly overrepresented in accident occurrence and are the only category of experience that is overrepresented. These findings are consistent with the qualitative expectations of Pace safety officials. The results are pronounced but difficult to explain. Some Pace officials speculate that drivers become overconfident and more ready to take risks after 1 to 2 years of relatively safe driving. The increase in risk taking, presumably, results in more accidents. Though plausible, the theoretical foundations of this hypothesis could not be established. Again, recent findings in the motor carrier industry indicate increased risk of accidents both at the beginning and end of a driver's duty cycle (*15*).

Whereas plots of accident frequency by time of day generally tracked urban congestion patterns (i.e., on morning and evening peaks), there were also smaller peaks around 10:00 to 11:00 a.m. and at 2:00 p.m. These correspond to shift change times for transit drivers. Data limitations precluded further study, but it would be of interest to identify whether the increases in occurrence are associated with drivers just beginning or ending a shift.

At the level of individual routes, regression analyses yielded results that were consistent with expectations. The expected number of accidents on a route was virtually linear with route miles operated and of strong statistical significance ($t = 11$). Mean accident frequency was also negatively associated with vehicle headway and with speed along a route. Whereas the models explained a significant amount of the variance in the data ($R^2 = 0.73$ to 0.75), they did not directly relate accident occurrence to causal factors. For example, the negative association with speed is interpreted to represent lower accident occurrence on high-speed roads, which are more likely to be well designed, carry smaller traffic flows, and have fewer stops. Good design, low volumes, and infrequent stops would result in lower accident risk, but it is not sensible to argue that transit routes should be located exclusively by these criteria; routes must serve markets (i.e., patrons) where they are located. If transit planners have a routing choice, these results imply that routes that may be characterized as yielding higher speeds, because of the combination of these three factors, are preferred for safety purposes.

## RECOMMENDATIONS FOR FUTURE RESEARCH

Lack of comprehensive information about drivers involved in accidents (both bus and other vehicle drivers) limited the research team's ability to identify driver factors that may have contributed to accidents. It would be of interest to examine the driving records (citations and accidents) of bus drivers to determine whether their service records with the agency are similar to their driving records with private vehicles. Evidence from the trucking industry indicates that professional drivers with poor driving records in their private cars are more likely to have poor professional driving records as well. Union agreements and other legal considerations may prohibit actions against currently employed drivers, but it may be possible to use an individual's driving record as a screening device for new hires. It would also be useful to conduct a study of automobile drivers involved in bus accidents, and in particular to compare them with the population of all drivers and the population of drivers involved in automobile accidents. This would provide additional insight into whether particular segments of society (e.g., the elderly) are overrepresented among victims of bus accidents. Safety programs targeted at these groups could then be developed. Confidentiality concerns may limit these studies, but they should be explored.

There is a need for a focused study of the potential effect of driver shift changes on accident occurrence. The lack of driver shift changes data in this study meant that it remains unclear whether accidents are more likely at the beginning of a shift (e.g., a "warmup" phenomenon) or at the end of a shift (e.g., driver fatigue). Evidence from the trucking industry is that both occur (*15*). Noncollision accidents appear to be particularly clustered near the shift changes, indicating that bus drivers may be having difficulty with fine vehicle control. Empirical studies should include analysis of driver performance on actual routes. Particular caution should be exercised in controlling for effects of driver experience that may result from the minimum guarantee.

There is a need to improve data collection tools for noncollision accidents. Use of a data collection tool oriented to road accidents leads to collection of insufficient information to identify countermeasures. It is not possible to identify events antecedent to or the contribution of detailed interior design features to a passenger's fall in a bus. Countermeasures involving changes in vehicle design will thus be based more on belief than on solid evidence.

Whereas aggregate systemwide analysis of accident data is useful in identifying general trends in accident characteristics, more sophisticated techniques are needed to obtain greater insight into accident causality. Two recent studies of motor carrier accidents (*16,17*) use disaggregate trips at the individual level. This structure allows a more accurate assessment of the driver, roadway, route, environment, and agency policy characteristics that contribute to accident occurrence. Accident data are generally available in this form. The utility of these disaggregate approaches depends on the availability of individual nonaccident data for comparisons. These data are more likely to be available and complete as information systems become more common in the industry.

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## REFERENCES

1. J. A. Matcyka. Cause and Prevention of On-Board Accidents. *Nation Safety Congress Transactions*, Chicago, Ill., 1975.
2. *Accident Facts*. National Safety Council, Chicago, Ill., 1982.

3. K. Christoffel, J. L. Schofer, P. P. Jovanis, et al. Multidisciplinary Staffing for Etiologic Analysis of Child Pedestrian Injury: Pilot Study of Methodology. *Society of Automotive Engineers Child Restraint and Injury Conference Proceedings*, Society of Automotive Engineers, 1983, pp. 125–136.
4. W. Homburger (ed.). *Transportation and Traffic Engineering Handbook* (2nd ed.). Institute of Transportation Engineers, Prentice-Hall, Inc., Englewood Cliffs, N.J., 1982.
5. R. J. Pawlak. *Annotated Bibliography of Rail Transit Safety, 1975–1980, with Emphasis on Safety Research and Development*. Transportation Systems Center, 1981.
6. *An Analytical Safety and Security Program for Public Transportation in Southeast Michigan*. Public Safety Division, Southeastern Michigan Council of Governments, Detroit, 1985, 65 pp.
7. P. P. Jovanis. *Synopsis of Research Activities: Identification of Motor Carrier Accident Causality*. The Transportation Center, Northwestern University, Evanston, Ill., 1985.
8. D. Shinar. *Psychology on the Road: The Human Factor in Traffic Safety New York*. John Wiley and Sons, Inc., New York, 1978.
9. D. L. Ivey. Predicting Wet Weather Accidents. *Accident Analysis and Prevention*, Vol. 13, No. 2, June 1981, pp. 83–99.
10. B. E. Sabey. Road Accidents in Darkness. *Transport and Road Research Laboratory Report*, Vol. 536. Crowthorne, Berkshire, England, 1973.
11. P. P. Jovanis and J. Delleur. Exposure-Based Analysis of Motor Vehicle Accidents. In *Transportation Research Record 910*, TRB, National Research Council, Washington, D.C., 1983, pp. 1–7.
12. Pace. *Bus Route Descriptions*. Regional Transit Authority, Chicago, Ill., 1985.
13. P. P. Jovanis, J. L. Schofer, P. D. Prevedouros, and K. Tsunokawa. *Analysis of Bus Transit Accidents: Empirical, Methodological and Policy Issues*. Final Report, Project Il-11-0031. Transportation Center, Northwestern University; UMTA, U.S. Department of Transportation, 1989.
14. Passenger Problems on Moving Buses. *TRRL Supplementary Report*, Vol. 520. Transport and Road Research Laboratory, Crowthorne, Berkshire, England, 1980.
15. T. Kaneko and P. P. Jovanis. *Multiday Driving Patterns and Motor Carrier Accident Risk: A Disaggregate Analysis*. Transportation Research Group Research Report UCD-TRG-RR-90-9. Department of Civil Engineering, University of California at Davis, Davis, 1990, 32 pp.
16. H. S. Stein and I. S. Jones. Crash Involvement of Large Trucks by Configuration: A Case-Control Study. *American Journal of Public Health*, Vol. 78, 1988, pp. 491–498.
17. P. P. Jovanis and H. L. Chang. A Disaggregate Model of Accident Occurrence Using Survival Theory. *Accident Analysis and Prevention*, Vol. 21, No. 5, 1989, pp. 445–458.


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