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# Review and Assessment of Paratransit Models

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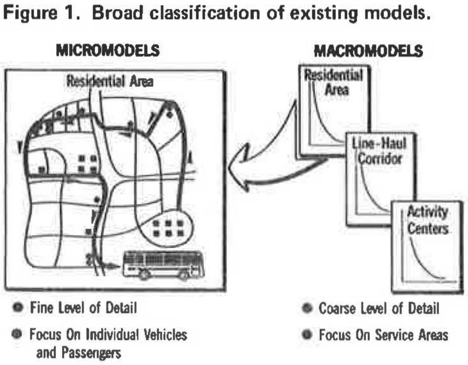
**The development of integrated paratransit systems has been accompanied by the development of a wide range of modeling and analytic activities designed to shed light on the delicate balance between supply, demand, and cost in a paratransit network. Modeling and analytic approaches have ranged from complex situations to simple rules of thumb. Of the wide range of theoretical models developed so far by academics, researchers, and consultants, relatively few have been applied in a practical planning context, and the results of these limited applications have been mixed. A comprehensive survey of the analytic procedures and tools developed to address paratransit planning and evaluation problems is presented. Modeling procedures are described and classified, the historical development of the models is traced in the context of the parallel development of paratransit systems, the performance of existing models is compared, and the attributes and application potential of several general classes of models are summarized.**

The development of integrated paratransit systems has been accompanied by the development of a wide range of modeling and analytic activities designed to shed light on the delicate balance among supply, demand, and cost in a paratransit network. Modeling and analytic approaches have ranged from complex simulations to simple rules of thumb. Of the wide range of theoretical models developed to date, relatively few have been applied in a practical planning context, and the results of these limited applications have been mixed.

**Figure 1. Broad classification of existing models.**




A comprehensive literature search, accompanied by extensive discussions with members of the paratransit community, has resulted in the identification of more than 70 references that deal with the modeling of flexibly routed transportation systems. This paper summarizes the development, classification, and application potential of the models represented in the literature. A more detailed examination of model attributes, as well as a comparison of the relative capability and ease of use of similar models, can be found elsewhere (1).

## SURVEY OF EXISTING MODELS

### General Classifications

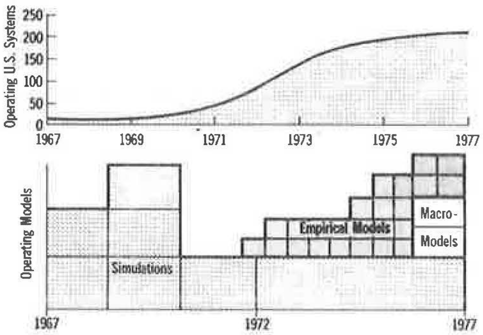
A coarse system of classification for existing models that is based on the level of model complexity and the focus of the modeling effort is shown in Figure 1. This classification system divides paratransit models into two distinct groups:

1. Micromodels, which deal with a fine level of detail and focus on the relations between individual vehicles and passengers, and
2. Macromodels, which deal with a coarser level of detail and focus on individual service areas and region-wide performance rather than on individual vehicles and passengers.

### Micromodels

Micromodels are primarily used to address analytic questions and explore detailed vehicle-passenger relations in a single service area. Detailed simulations and disaggregate supply-demand models serve as two examples of the general classification of micromodels. Current and past micromodels of paratransit systems

Figure 2. Historical development of paratransit systems and models.




include the computer simulations developed by Northwestern University (2, 3), Westinghouse, (4), General Motors (5), and Ford Motor Company (6); Princeton's generalized feeder simulation model (7); the computer-aided routing systems (CARS) simulation developed by the Massachusetts Institute of Technology (8-10) and updated in the advanced dial-a-ride (ADAR) project (11); and, on a somewhat less detailed level, the supply-demand models developed by Cambridge Systematics, Inc., and Multisystems, Inc. (12).

## Macromodels

Macromodels can range in complexity from sophisticated stochastic models to simple rules of thumb. Four levels of complexity were identified in classifying macromodels for this state-of-the-art review. These four levels are, in order of decreasing complexity, (a) stochastic models, (b) deterministic models, (c) empirical models, and (d) rules of thumb.

There are no clear lines of demarcation that separate these classifications, and the distinctions between adjacent categories tend to blur at the edges. A similar classification scheme was used by Wilson and Hendrickson (13) in reviewing paratransit supply models. The criteria to be included in each category are described in a general way below:

1. Stochastic models—Stochastic models approach micromodels in level of complexity, depth of detail, and data requirements. Relatively few stochastic models of paratransit systems have been developed thus far. Stochastic queueing models have been formulated to represent exclusive-ride taxi systems (14, 15), and Markov models of many-to-one and many-to-many paratransit services have been developed (16, 17).

2. Deterministic models—Most recent theoretical efforts to model the performance of paratransit systems can be classified as deterministic models. These models typically treat the stochastic aspects of system performance by using deterministic approximations grounded in geometric probability relations. Examples of this approach can be found in the work of Ward (18-21), the Systan SMART model (22-24), the Multisystems macromodel (25), and the descriptive supply model developed by Flusberg and Wilson (26).

3. Empirical models—Empirical models "attempt to develop simple relationships between the key attributes of system performance and design" (13), generally through regression analysis. Early empirical models (27) used simulations as a basis for generating regression relations; more recent models have reflected actual operating experience in developing relations between factors such as fleet size and demand density or ridership and population (28, 29).

4. Rules of thumb—Rules of thumb represent a distillation of conventional wisdom, operating experience, modeling results, and "quick-and-dirty" calculations reduced to single sentences that have the ring, although not necessarily the reliability, of axioms. Examples of rules of thumb are the following: "It is considered necessary to maintain the level of service such that the ratio of waiting plus travel time for a demand-responsive trip to the time required to make the same trip by automobile does not exceed 3.0" (30) or "an average of one seat per 1040 population" represents a rough cut at the total number of seats needed to start a dial-a-ride service (31).

## Model Genealogy

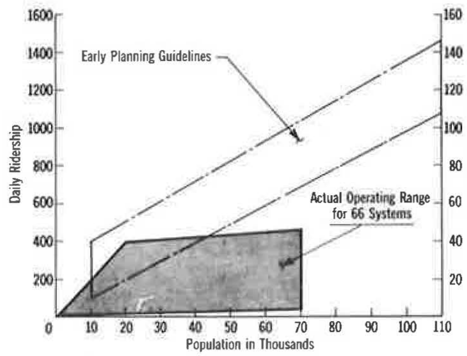
Figure 2 traces the development of paratransit models over time and relates that development to the historical introduction of paratransit systems in U.S. cities. The graph at the top of the figure charts the approximate number of operating paratransit systems in U.S. cities between 1967 and 1977. The flow diagrams beneath the graph trace the chronological development of major paratransit macromodels and micromodels over the same period and show the genealogical relations between successive modeling efforts.

Between 1967 and 1970, when there were relatively few paratransit systems operating in the United States, most efforts to model the paratransit concept took the form of complex simulations. At least four different simulations were developed during this period by Northwestern (2), Westinghouse (4), General Motors (5), and the Massachusetts Institute of Technology (M.I.T.) (9, 10, 32). As more and more paratransit systems were introduced in U.S. cities between 1972 and 1977, more and more system models were developed. But the relative complexity of the theoretical models diminished as operating experience with real systems was gained. When this paper was written, only one of the original simulations—the M.I.T. model—was known to be still in use. The most recent modeling efforts reflect regression analysis of operating systems (29, 31).

It is not surprising that elaborate simulation models should give way to simpler, empirical models as operating experience with actual systems increases. The simpler models are more accessible to planners than the simulation models, require fewer data to apply, are more easily understood, and offer results that are no less trustworthy than those of complex models for several basic planning tasks. Simulations contributed to the early understanding of demand-responsive systems by illuminating the nature of basic supply-demand relations and contributing to the education of the simulation developers, several of whom went on to help plan operating systems and develop less complex models. Although certain basic research questions remain that can best be answered through the use of detailed simulations, many practical operating decisions that relate to fleet size, service area, and operating policies can be guided just as readily by empirical models.

Early modelers of paratransit systems tended not only to develop more complex models than later analysts but also to be more optimistic. Early paratransit models were supply models that treated demand exogenously and had no internal capability for reconciling supply and demand levels. Nor was there much operating experience to provide an external reference for such a reconciliation. Modeling results were thus heavily dependent on the level of demand selected by the modeler. Early modelers typically overstated system demand and, as

Figure 3. Early planning guidelines and subsequent operating experience.




a result, overspecified system service levels. As Wilson (13) has observed, "Early studies of the economic feasibility of dial-a-ride suffered particularly from this problem, overestimating demand by between one and two orders of magnitude, leading to an overoptimistic economic assessment of the system."

The discrepancy between overly optimistic early expectations for demand-responsive systems and actual experience is reflected in Figure 3, which compares early planning guidelines developed by the Mitre Corporation (28) with later guidelines that reflect a wider range of operating experience (33). As Figure 3 shows, although the later guidelines based on operating experience with 66 systems overlap a portion of the area covered by the earlier guidelines, the ridership levels and demand density reflected by actual operating systems are but a fraction of the range anticipated in earlier theoretical work.

## MODEL PERFORMANCE

The findings of a series of comparisons made among models of a specific type and function are summarized here. In the case of microsimulations, inputs, outputs, and assumptions of different models were compared; past and potential uses of simulations in paratransit planning and analysis were reviewed; and the advantages and disadvantages of the simulation approach were itemized. In the case of macromodels, the performance of the simpler demand, supply, and cost models was compared by using sample data from a range of existing services. The details of the comparison process are discussed by Billheimer and others (1).

### Simulation Models

A simulation model is an attempt to create artificial events related to artificial objects in a manner that parallels what occurs in a real system. The interrelation of the modeled events is often complex even though the specification of the individual events and objectives may be simple. Simulation is an effective tool in developing an understanding of system behavior when the relations between model events and objects are easily understood and specified but the cumulative effect on the whole system is uncertain. The chief advantage of the simulation approach to paratransit modeling is that it enables the analyst to model those details of the interaction between passengers and vehicles that cannot be treated effectively in purely analytic models and permits the investigation of different algorithms of vehicle control.

Although the simulation approach supports the exploration of detailed system dynamics, it has several serious disadvantages. Simulation models are cumbersome, inflexible, subject to statistical sampling errors, and limited in the scope of their application. They are cumbersome because they usually have extensive data requirements, and some familiarity with computers is needed if they are to be used effectively. Since existing demand-responsive simulations usually model only one type of service, they are somewhat inflexible for analyzing alternative service types. Furthermore, extensive data requirements may make it difficult to model more than one setting. The cost of using simulation models can be high and, because of the detailed, specific nature of the input requirements, the results typically are not readily transferable to other systems and settings.

Existing simulations are incapable of addressing one of the most important problems in the analysis of demand-responsive systems, the problem of demand prediction. The analyst must use some other approach to estimate demand and then use the simulation to explore the relation between demand and such supply-related questions as fleet size or response time. In the past, this process has not led to notably accurate estimates of either supply or demand (1, 13).

Since the cited disadvantages can be severely limiting in certain applications, extreme caution should be exercised if simulations are to be used in such activities as feasibility analyses, systems design, or model calibration. Nonetheless, simulation remains the most effective tool for evaluating paratransit control algorithms and is one of the few methods currently available for obtaining disaggregate measures of system performance.

### Disaggregate Models of Supply and Demand

Few existing models treat paratransit supply and demand interactively at the disaggregate level—that is, focus on individual trip makers or socioeconomic groups rather than on entire service areas and treat the relation between supply and demand interactively. The most significant one is a model developed by Cambridge Systematics and Multisystems (12) that places a sophisticated analytic tool in the hands of the user without burdening him or her with excessive input requirements and appears to be a potentially valuable tool for analyzing systems that have reached a steady state.

### Macromodels

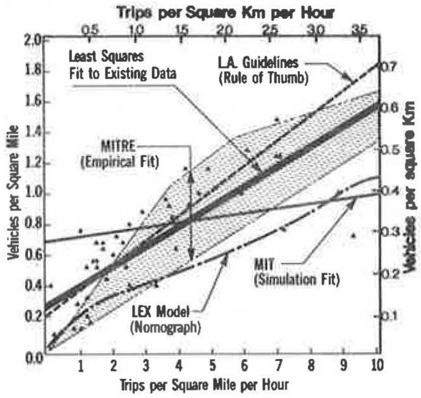
Existing macromodels of paratransit systems have addressed questions of system demand (ridership and fare elasticity), supply (fleet size), performance (level of service and response time), and cost. A hybrid class of models, designated as supply and demand models, has attempted to balance the interlocking relation between supply and demand. This relation is typically more complex in demand-responsive systems than in conventional fixed-route systems. In both types of systems, ridership is heavily dependent on service quality. In conventional systems, however, service quality is relatively independent of ridership except when the capacity of the system is approached. By way of contrast, in demand-responsive systems, service quality may suffer as ridership increases over all ranges of demand. In an attempt to reflect this interactive relation, certain supply and demand models iterate between ridership estimates and service measurements until an equilibrium point is approached. This iteration can be accomplished by computer, as in the case of the model recently developed by Cambridge Systematics and Multisystems (12), or by the successive application of nomographs, as in an

**Table 1. Analytical estimation of demand density in five test cities.**

| City | Demand Density ($trips/km^2/h$) Observed | Predicted: Empirical Fit to Population | Empirical Fit to Population Density | Lea Systems | LEX/TRAN Calculator | Los Angeles Guidelines | Mitre Nomographs |
|---|---|---|---|---|---|---|---|
| Naugatuck, Connecticut | 0.3 | 0.4 | 0.77 | 0.9 | 1.16 | 1.12 | 0.33 |
| Merrill, Wisconsin | 1.3 | 0.8 | 1 | 0.4 | 7.7 | 1.1 | 0.7 |
| Danville, Illinois | 1.2 | 0.15 | 0.31 | 0.12 | 1.54 | 0.58 | 1.5 |
| Syracuse, New York | 0.06 | 0.31 | 0.8 | 0.85 | 2.7 | 0.9 | 0.2 |
| Orange, California | 2 | 1.16 | 1.7 | 5.2 | 9.65 | 1.12 | 1.8 |

Note: $1\ km^2 = 0.386\ mile^2$.

Figure 4. Comparison of four approaches to estimating fleet size.




earlier macromodel developed by the Mitre Corporation (34).

Comparisons of Demand Models

In an effort to assess the utility of existing demand models, six of the simpler models were tested by using data from five sample dial-a-ride cities (see Table 1). The cities were chosen because, collectively, they span a spectrum of city types: small urban areas, large low-density areas, and thickly populated inner cities. None of the cities chosen was used in calibrating the six demand models tested, which are identified below:

1. Empirical fit of demand to service-area population in 43 cities that have dial-a-bus transit systems (29);
2. Empirical fit of demand density to population for the same 43 cities (29);
3. Empirical fit of demand to both population and population density on several Canadian dial-a-bus operations (35);
4. Use of nomographs that reflect both the fare and the population density of the service area (36);
5. The rule of thumb, e.g., 13.5 passenger trips/day/$km^2$ (35 passenger trips/day/$mile^2$) (31); and
6. Simultaneous estimates of demand and vehicle supply by the use of nomographs obtained by an empirical fit to dial-a-bus data for 16 cities (34).

The actual demand densities observed in each of the five test cities (in trips per square kilometer per hour) as well as values estimated by using methods 1 through 6 above are given in Table 1. Although more extensive tests should be made as additional data become available from operating systems, certain observations appear to be justified on the basis of the current analysis. It is evident in Table 1 that method 6, the Mitre nomograph technique, performed more consistently than the other methods. It seldom produced widely inaccurate estimates and sometimes gave excellent ones. The superior performance of this model can be traced jointly to the broad spectrum of city types used in its calibration and to the theoretical soundness that arises from considerations of supply-demand equilibrium. Most empirical approaches to demand prediction performed poorly in this test and, except in the case of the Mitre model, there seemed to be little overall connection between the sophistication of a model and the quality of its results.

Models of Fleet Size

Models for estimating fleet size attempt to predict the number of vehicles needed to serve a given area. Most fleet-size models require demand as an input and show approximately linear relations to demand. If demand is known, many methods of fleet-size estimation perform well in test cases; without demand estimates, most such methods fail miserably. Only the Mitre nomograph technique, because of its equilibrium structure, produced useful estimations of fleet size without accurate demand input. Figure 4 compares the fleet size (in vehicles per square kilometer) predicted by four simple models based on demand densities with a least-squares fit to data from 66 existing systems.

Performance and Cost Models

Cost models usually attempt to predict the operating costs of a new system. Because demand-responsive systems are characteristically labor intensive, labor costs typically account for between 50 and 80 percent of total system costs. In practice, system costs vary widely as a function of wage rates, work rules, and union practices. Existing models range from very simple rules of thumb to more complex, computer-based methods. The simple models are generally based on fits to one key variable, such as fleet size or labor wages. Their performance in test cases is generally adequate for purposes of preliminary planning, but they leave many variables unaccounted for and hence give the user no meaningful information on controlling costs.

Performance models attempt to estimate some variable in order to predict system performance. A variety of analytic techniques are devoted to the estimation of average wait and ride times. They perform adequately for test cases but require information on demand and fleet size. Some models attempt to analyze performance by considering system productivity. Test cases reveal, however, that these approaches have tended toward overestimation. As more and more operating data that reflect relatively low levels of productivity have become available, models have become increasingly conservative in estimating this factor. Figure 5 shows the gradual decrease of productivity estimates over time as they approach the median figure of six passengers per vehicle hour reported by a sampling of 60 general-

Figure 5. Productivity as a function of average demand density.

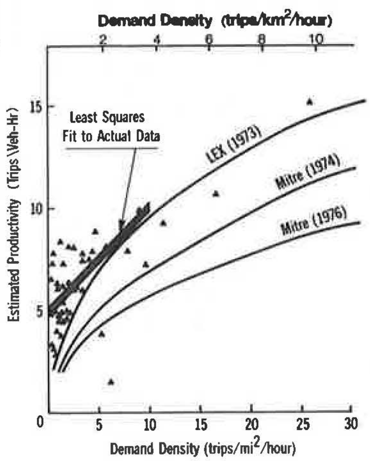
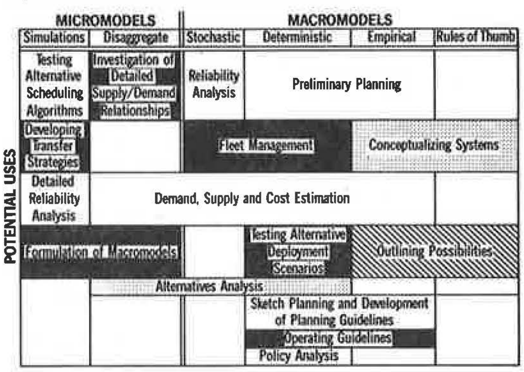



Figure 6. Potential model applications.




market dial-a-bus systems (33).

## General Observations

The failure of many models to produce accurate results in test cases can be traced to a number of factors. Chief among these are unrealistic optimism, a narrow range of calibration sites, and insufficient screening of sample data. Early demand-responsive transportation models tended to reflect an optimism about demand potential that was not borne out by operating experience. As a result, many early models produce grossly inaccurate estimates of demand, and they are usually unable to deal effectively with realistic demand levels.

Thus far, approaches that involve the use of surveys have not been effective predictors of demand. The main difficulty lies in the tendency of respondents to overestimate their potential use of a system that is still in the planning stages. In practice, advance surveys have yielded results that would promise ridership levels more than 10 times those actually experienced. Extrapolation from these very large values of "noncommitment" demand to relatively small values of real demand rarely produces accurate predictions of real demand.

The user of any model of demand-responsive transportation systems must ensure that the assumptions used in developing the model accurately reflect the situation in the area of interest. Several empirical models have been calibrated for cities that have a narrow range of demographic traits and perform poorly when applied to areas outside that range (1). Nonetheless, the relative success of certain models in predicting demand in areas similar to the calibration regions suggests that future empirical models should attempt to segregate data from different types of systems. Currently, many empirical models mix data from many-to-many services in attempting to develop relations between demand or fleet size and demographic characteristics. This practice reduces the likelihood of obtaining an acceptable fit to existing data. As more data from operating systems become available, it may be possible to stratify the samples used in calibrating empirical models by demographic characteristics and type of service so that more accuracy can be obtained.

## POTENTIAL USES

Figure 6 associates potential model applications with various levels of complexity identified in the model review process. In many cases, an application may span several levels of model complexity. In general, of course, the more complex micromodels are theoretically capable of undertaking any of the tasks designated for less complex models. However, the cost, the inflexibility, and the undependable record of these models dictate that they be considered only for tasks that cannot be handled by the simpler models. By virtue of their position in the midrange of system complexity, deterministic macromodels appear to have the widest range of potential uses. Simple enough to be used and understood by a wide range of users, they remain sufficiently detailed to provide insights into the complex relations that link supply, demand, and cost parameters.

## SUMMARY

As the first of the micromodels developed to represent paratransit systems, computer simulations have been tested in many of the applications listed for all model levels in Figure 6. These micromodels have shown themselves to be well suited for the detailed analysis necessary in the design and evaluation of scheduling and dispatching algorithms. However, Wilson, one of the early developers of the simulation approach to paratransit modeling, notes in his review of supply models (13) that "experience suggests a good deal of caution in the use of simulation models for planning new systems." Simulation models have not fared well in past planning tasks for a variety of reasons, including their dependence on exogenous demand estimates, their failure to reflect important stochastic elements, their inflexibility, the significant investment of time and cost required for their application, and their relative inaccessibility to the planning community. The planner who is designing a small demand-responsive system typically does not need the level of detail provided by a simulation model, lacks the time and sophistication necessary to adapt and apply the model, and could probably not justify the relatively high cost of analysis in light of the relatively low cost of the system itself.

Nonetheless, the simulation approach "remains the most effective tool in algorithm design and the only way to obtain disaggregate measures of system performance" (13). Existing simulations have been limited even in these applications by an inability to represent more than one control algorithm and the failure to replicate aggregate performance measures within acceptable limits of accuracy. These deficiencies in existing simulation models have led the Urban Mass Transportation Administration to fund the design and development of a more flexible microsimulation model that is capable of replicating and evaluating a wider range of service and control alternatives (37).

Although simulations have generally not served successfully as direct system-design tools, they have played an important role in contributing to the modeler's understanding of paratransit systems and have supported the development of macromodels that are appropriate for design work.

Deterministic models appear to be able to reflect many of the important aspects of system operation. If expanded to include such stochastic measures as system reliability, the most complex of these models—the Multisystems macromodel (25) and the Systan SMART model (23)—should prove useful in testing alternative deployment scenarios, evaluating trade-offs between different service combinations, and developing general guidelines that relate system design to area characteristics.

Empirical regression models are currently the most accessible tool for the system planner and offer the best means for developing rough, rapid estimates of supply, demand, and cost. As more and more operating data from different systems become available, these models should be refined to reflect the impact on supply-demand relations of such site-specific factors as climate, historical transit ridership, and automobile ownership.

## ACKNOWLEDGMENT

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# Evaluation of Interpersonal Influences in the Formation and Promotion of Carpools

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**A three-phase analysis of the role of interpersonal factors in carpooling performed at the University of Iowa is described. Phase 1 used laboratory simulation methods in which respondents rated the relative desirability of alternative carpool descriptions. The desirability of carpooling was found to decrease as the number of nonacquaintances in the pool increased, and particularly low ratings were given to carpools that consisted wholly of nonacquaintances. In phase 2, attitudinal and behavioral data from an existing industry-based carpool promotional program were analyzed by using Federal Highway Administration matching techniques. The data confirmed the importance of acquaintanceship as a factor in carpooling. Phase 3 used the findings from phases 1 and 2 to design and implement promising strategies for promoting carpooling. Strategies that stressed person-to-person contact between potential carpoolers and used existing networks of acquaintanceship to increase the number of carpools were emphasized. It is concluded that evaluation of such strategies should be useful in formulating future carpool promotional programs.**

Over the years, transportation researchers have increasingly come to realize the importance of social factors in travel decisions. In particular, the choice of a multioccupant mode, such as carpooling, for the journey to work involves interpersonal as well as economic factors. Programs designed to increase carpooling must take this into account. The goals of this paper are to advance some ideas about the role of interpersonal factors in ride sharing and to show how these ideas can be used to promote carpooling.

Hartgen (1), Horowitz and Sheth (2), Kurth and Hood (3), Levin and others (4), and Margolin and others (5) all view ride sharing as a psychosocial process. Hartgen's review of recent findings leads to four hypotheses for why ride sharing is not very common: (a) Carpoolers have unique trip and travel needs, (b) solo drivers lack the information needed to form carpools, (c) attitudes of carpoolers are different from those of solo drivers, and (d) the social processes involved in carpooling are difficult for solo drivers to overcome. Hartgen (1) reports that Margolin and Misch used decision analysis panels in the Washington, D.C., area to develop hypotheses about ride-sharing motivation and found that the factors that deter people from carpooling include a desire to maintain independence, concern over waiting for others, and personal incompatibilities with other members of the pool. Among the more interesting data in the study by Margolin and Misch on interpersonal factors were that 87 percent of their commuters wanted to meet prospective members before making any ride-sharing arrangements and 39 percent felt that they would have to know the people first. Since traditional carpool matching programs ultimately leave it to the individual participant to contact other potential ride sharers on a list, a reluctance to contact strangers can be a major problem in forming carpools.

The carpooling research program at the University of Iowa (4, 6, 7) is based on the premise that a thorough understanding of the individual decision processes and attitudes that underlie ride-sharing behavior is a prerequisite for designing and implementing effective carpooling programs. Thus, the analysis consists of three phases: (a) laboratory simulation studies of the in-influence of interpersonal factors on attitudes toward carpooling, (b) analysis of attitudinal and behavioral data from existing carpooling programs, and (c) design, implementation, and evaluation of potentially effective strategies for promoting carpooling.