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Development of Guidance for a Vehicle Occupancy Rate Data Collection Program

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16. Abstract:

Transportation planning practices increasingly require knowing the number of occupants per vehicle. Except for manual observations, Virginia has two data sources for obtaining occupancy: the American Community Survey and the National Household Travel Survey, neither of which provides corridor-specific values. This study developed an approach for estimating occupancy based on crash records data—now feasible because Virginia routinely collects, for each crash, the total number of occupants regardless of injury status. This occupancy is not widely available because of privacy concerns but can be obtained through a special tabulation performed by VDOT's Traffic Engineering Division.

Having crash data is not a panacea: as the area of interest shrinks from a district to a roadway segment, the likelihood that crashes alone provide a biased estimate of occupancy increases. Accordingly, the recommended approach for detecting occupancy contains two additional steps beyond extracting crash data: (1) at the jurisdiction level, test whether this bias exists by performing an eta-squared test; if appropriate, perform Type 1 bias correction by ensuring all occupancy groups (e.g., three occupants per vehicle) are synthesized in the crash data set; and (2) at the corridor level, perform Type 2 bias correction by building a correction model incorporating field observations. Yet bias is not necessarily a fatal flaw. At the corridor level, the mean average absolute difference between occupancy based on uncorrected crash data and occupancy collected from field observations was 0.06; use of the Type 2 bias correction model showed a difference of 0.05 between field observations and corrected data when the model was used on a set of data not used to build the model. At the jurisdiction level, the difference between uncorrected occupancies and Type 1 bias correction was never above 0.02 as long as at least 200 vehicles are observed in crashes.

This method allows Virginia to estimate occupancies by time period, day type, and functional class. Crash data for VDOT's Hampton Roads District showed statistically significant differences in occupancies ranging from 1.18 to 1.30 (midweek vs. weekend); 1.15 to 1.22 (AM peak vs. off-peak); and 1.16 to 1.26 (variation among seven functional classes).

The study recommends that VDOT establish an occupancy data collection program in one district based on two elements: (1) the extraction of occupancies from crash reports, and (2) an adjustment of these occupancies based on the two bias correction methods studied. These two recommendations need not preclude the possibility of using new technologies, some of which were examined in this study, but the approaches highlighted in this report have been successfully tested on a case study basis in Virginia.

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FINAL REPORT

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EXECUTIVE SUMMARY

Introduction: Vehicle Occupancy Is Not Widely Available

Congestion management strategies, travel demand models, federally required performance measures, and project prioritization approaches increasingly concern person movements, which typically are the product of vehicle movement and occupancy, i.e., the number of persons per vehicle. Except for manual observations, Virginia has two data sources for obtaining occupancy: (1) the U.S. Census Bureau's American Community Survey (ACS), and (2) the Federal Highway Administration's (FHWA) National Household Travel Survey (NHTS). Buchanan (2022) showed that the former provides occupancies for only one trip purpose (the work trip) and is updated every 1 to 5 years depending on the jurisdiction's population. Rates vary from 1.10 (Chesterfield County, Virginia) to 1.27 (Stafford County, Virginia). The latter provides occupancies by trip purpose, density, and other variables but is updated only every 5 to 7 years. For instance, extraction of NHTS data (FHWA, 2019) by the research team showed Virginia rates of 1.18 (work-based trips) and 1.66 (shopping trips). Neither source provides corridor-specific occupancies.

Virginia is not alone in not having detailed occupancy data. A 2021 survey of state departments of transportation (DOTs) conducted by the research team showed that of 20 responding state DOTs, only 4 collected vehicle occupancy data. South Carolina and Vermont used the NHTS where states can purchase additional NHTS add-on samples that then allow them to estimate occupancy for a smaller geographic area than an entire state; Virginia did this in 2009 but not in 2017. Michigan used a household travel survey, and Montana used field data: each quarter, DOT personnel collected occupancy data for 2 hours to sample each roadway functional class. These four respondents generally collected these data to calibrate travel demand models. A separate survey of the Virginia Department of Transportation's (VDOT's) nine districts showed that of the eight responding districts, vehicle occupancy data were routinely collected to support high occupancy vehicle monitoring in just a few locations in the Northern Virginia and Hampton Roads districts to satisfy federal requirements.

Problem: Why Occupancy Matters, and Then How to Get it, Is Not Fully Understood

Conceptually, occupancy matters because the capacity of transportation infrastructure should be measured from a "people-moving perspective" (Meyer and Miller, 2020) rather than solely a vehicle perspective—a perspective espoused by national performance measure requirements. In practice, the extent to which having more detailed corridor occupancies would affect planning practice relative to the use of national or statewide defaults is not known. Thus, the problem facing Virginia is twofold: (1) there is no known way to obtain vehicle occupancy on a routine basis except through surveys, and (2) except for anecdotes, the utility of such vehicle occupancies on planning decisions has not been quantified.

Purpose and Scope

The purpose of this study was to develop a method to estimate passenger vehicle occupancy and quantify the potential impact of more detailed occupancies on one key planning practice: evaluation of candidate transportation investments.

This study first quantified the potential impact of having more detailed occupancies on the evaluation of candidate transportation investments. The study then examined candidate approaches for estimating passenger vehicle occupancy, refining one of them for VDOT's Hampton Roads District, and examined the extent to which occupancy varied by time of day, type of day, and roadway functional class.

Methods

Five major tasks were undertaken to accomplish the study objectives:

1. Quantify the importance of vehicle occupancy.
2. Identify approaches for estimating vehicle occupancy.
3. Collect Virginia-specific vehicle occupancy data.
4. Develop a repeatable procedure for obtaining occupancy in Virginia.
5. Determine the variation in occupancy by site characteristics.

To quantify the importance of vehicle occupancy, Task 1 examined how deviations in occupancy from a perfectly accurate value could affect the prioritization of projects if it were the case that Virginia used jurisdiction-specific occupancies rather than a single statewide occupancy. SMART SCALE is Virginia's project prioritization scheme, and presently, Virginia uses the same passenger vehicle occupancy for all projects in this process [Jackson, 2022]. An experiment investigated what would happen if this scheme were altered so that different projects could have different occupancies by jurisdiction. This experiment used SMART SCALE rankings for 38 candidate projects in the Hampton Roads District. As an example, if the projects that were ranked 1, 3, 5, …37 had their occupancies reduced by 0.05 persons per vehicle, how many rankings would change?

To identify ways to estimate vehicle occupancy, Task 2 reviewed different approaches for obtaining occupancy. These approaches may be categorized as image processing (e.g., the proprietary Invision Video Occupancy Detection System); non-visual (e.g., the StreetLight InSight platform to which VDOT has a subscription, and the use of Bluetooth detectors); manual observation (e.g., the carousel method, which entails a slow-moving vehicle carrying a data collector who records occupancies of passing vehicles); and the use of crash data. In some cases, it was possible to test directly a given approach; in other cases, the research team relied on interviews with experts.

To collect Virginia-specific vehicle occupancy data, Task 3 synthesized data from three key sources: field data collected by the research team in 2021-2022; field data provided by The Traffic Group as part of this project; and historical occupancy data provided by VDOT staff for 2019. Task 4 developed a repeatable procedure for obtaining occupancy in Virginia; the most promising method was refined using these Virginia-specific data. Task 4 comprised the bulk of the research team's effort. Task 5 used these data to determine how occupancy varied by site characteristics such as time of day, day of week, and roadway functional class.

Key Results

Occupancy clearly had an impact on project prioritization but was not the sole determinant. Based on the results for 38 projects in the Hampton Roads District, a change in occupancy of 0.10 from a particular baseline could alter the rankings for 4 to 11 of the projects—i.e., it could affect between 11% and 29% of all project rankings. A change in rankings would mean, for example, that a change in occupancy for the project currently ranked 14th caused it to become the 15th ranked project. By contrast, a deviation of 0.05 might affect at most (roughly) 10% of rankings. In the past, jurisdictions in the Hampton Roads District showed an average occupancy of 1.14 based on ACS data (Buchanan, 2022). The 1.14 was tabulated by the research team and was used as the basis for a case study. The fact that this quantity is larger than 1.0 means that the impact of a change in occupancy alone would be slightly less than the impact of a change in the link volume, such that a change in occupancy of 0.05 would correspond to a change in link volume of 4.4%.

Two technologies tested—StreetLight InSight and Bluetooth detectors—cannot provide occupancy data at this time. One technology examined on a pilot basis—the Wejo platform—may have the potential to help collect vehicle occupancies in the future. However, Wejo provides information only for the front seat (hence, occupancy is either 1 or 2). Further, there is the potential for VDOT to purchase, on a pilot basis, a portable image-based processing system; the cost is estimated to be $30,000 to $50,000. The use of data from Virginia police crash reports appears feasible because Virginia routinely collects, for each crash, the total number of occupants regardless of injury status. This method was further explored as a way of routinely obtaining occupancy data throughout Virginia.

The report outlines a way of extracting occupancy data so that vehicle occupancies can be linked to a specific roadway. These data must be obtained through a special tabulation performed by staff of VDOT's Traffic Engineering Division—they are not publicly available, in contrast to many other crash data elements. One concern, however, is that occupancies based on vehicles involved in a crash may not reflect occupancies based on all roadway vehicles. Accordingly, this report discusses two additional methods beyond extracting crash data for using crash-based vehicle occupancies.

1. *Type 1 bias correction*. At the jurisdiction level, one may test whether this bias exists by performing an eta-squared test; if appropriate, Type 1 bias correction may be performed by ensuring all occupancy groups (e.g., three occupants per vehicle) are synthesized in the crash data set. This Type 1 bias correction is not labor intensive because it does not require the collection of field data. Type 1 bias correction is not critical for larger jurisdictions: at the jurisdiction level, the difference between uncorrected data and data with Type 1 bias correction was never above 0.02 (as long as at least 200 vehicles were observed in crashes) or 0.05 (as long as at least 100 vehicles were observed in crashes).

2. *Type 2 bias correction*. For the corridor level, this method is considerably more labor intensive than Type 1 bias correction because it requires the collection of occupancies from field data and then the construction of a bias correction model. Further, the variable identification process, used to determine variables for the bias correction model, is fairly detailed, requiring both the aforementioned eta-squared test and a rule-based Apriori test. Type 2 bias correction is helpful but not essential: at the corridor level, the mean average absolute difference between occupancy based on uncorrected crash data and occupancy collected from field observations was 0.06. Then, after the model was built and applied at locations not used to build the model, the Type 2 bias correction model showed a difference of 0.05 between field observations and corrected data.

These differences attributable to crash bias appear roughly comparable to differences in field data collection methods. For example, at five sites where the carousel method was used with at least two data collection teams, the differences in teams was, on average 0.04. At the same five sites a different method of manual data collection, known as the windshield method, was applied: a third data collection team sat in a stationary vehicle near the roadside and recorded the number of occupants in passing vehicles. The difference in results between the carousel method and the windshield method was on average 0.07, although part of this difference was possibly attributable to variation because of site characteristics between the two methods with regard to which vehicles were identified.

By using the crash data, it was possible to estimate occupancies by time of day, type of day, and functional class. The Hampton Roads District crash data showed statistically significant differences in occupancies ranging from 1.18 to 1.30 (midweek vs. weekend); 1.15 to 1.22 (morning peak vs. off-peak); and 1.16 to 1.26 (variation among seven functional classes).

Table ES1 summarizes occupancies determined using three different methods for some cities in the Hampton Roads District.

Table ES1. Comparison of Occupancies From Three Different Methods[a]

Jurisdiction	NHTS (Weekday AM)	ACS (Work Trips)	Crash[b]	Range
Chesapeake	1.36	1.13	1.15	0.22[a]
Hampton	1.32	1.13	1.20	0.19
Newport News	1.36	1.20	1.08	0.28
Norfolk	1.20	1.14	1.14[b]	0.06
Portsmouth	1.60	1.15	1.12[b]	0.48
Suffolk	1.24	1.12	1.11[b]	0.13
Virginia Beach	1.31	1.13	1.14	0.17
Mean	1.34	1.14	1.13	0.22

NHTS = National Household Travel Survey; ACS = American Community Survey; Crash = crash data with bias correction.
[a] All values are rounded to two decimal places.
[b] Without correction for crash bias, the occupancy would be 0.01 lower than what is shown (Norfolk and Portsmouth) or 0.02 lower than what is shown (Suffolk).

The occupancies for NHTS data refer to the weekday AM trip, and the ACS data refer to the work trip; Buchanan (2022) provided both data sets. The ACS data were obtained for year 2016, and the NHTS data refer to the 2009 NHTS for which Virginia purchased add-on samples. The crash data refer to the AM peak period crash data extracted for 2016 weekdays (Tuesday, Wednesday, and Thursday) for the entire year. Thus, these occupancies will differ not only because different methods were used but also because they measure different phenomena. For example, ACS captures only work trip occupancy, which usually, but not always, occurs during the AM peak; by contrast, crash data denote all trip types, not just work trips, and are always for the AM peak.

Key Conclusions

- *Link-specific occupancies have modest potential to affect project prioritization if future prioritization processes are modified to use such occupancies.* A change in occupancy of 0.05 affected between 5% and 11% of project rankings. For example, if 0.05 occupancy was added to every other project (e.g., those ranked second, fourth, sixth, and so forth), for most projects, rankings would not change. However, for a small portion of those projects (5% to 11%), the change in occupancy would be enough to change the rank of a project by at least one spot (e.g., after its occupancy was increased by 0.05, the eighth ranked project would become the seventh ranked project).

- *The use of crash data is a feasible way at present to estimate occupancy.* Virginia records the total number of occupants in all crashes regardless of injury status, which yields a larger sample size than would be the case if only injury crashes were available. For example, in the Hampton Roads District, when just the fall and spring periods were considered, a single year yielded more than 49,000 vehicle occupancies based on 22,545 crashes. Because field data are helpful but not required, this method could be useful for obtaining occupancies over a large area.

- *Crash data may benefit from some type of bias correction depending on the geographic scope of the analysis and the number of vehicles.* Type 1 bias correction, which entails synthesizing missing vehicle occupancies, is useful for smaller jurisdictions and does not require field data. Type 2 bias correction is more labor intensive and offers a moderate benefit for corridor-level occupancy estimation.

- *Occupancy varies by 0.12 or less when time of day, midweek vs. weekend, and functional class are considered.*

Recommendations

The report describes in detail two recommendations for a pilot study in one VDOT district. The district should ideally have urban and rural areas, and tentatively the Richmond District is a candidate location. The recommendations are that VDOT's Transportation and Mobility Planning Division (1) extract occupancies from crash reports for a 3-year period in the selected district and document fully the steps required to do so, and (2) adjust these occupancies to account for potential crash bias. Although these two methods have been used in one district, the pilot study should partially automate this process to a greater degree than is currently the case.

Implementing the two recommendations would allow VDOT to move forward with a pilot program that is feasible at the present time. It would not eliminate the possibility of testing new technologies for determining occupancy, some of which were examined in this study. However, the approach for investigating new technologies is likely to evolve after the publication of this report, and thus no specific recommendation for how to evaluate new technologies is provided.

TABLE OF CONTENTS

FINAL REPORT

DEVELOPMENT OF GUIDANCE FOR A VEHICLE OCCUPANCY RATE DATA COLLECTION PROGRAM

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INTRODUCTION

Transportation planning initiatives, such as project prioritization, travel demand modeling, economic impacts, and the placement of park and ride lots, require some estimate of the number of occupants per vehicle. The Albany (New York) Metropolitan Planning Organization (MPO) uses person-hours of delay (based on vehicle delay coupled with an estimate of occupancy) as one input in the consideration of transportation investments (Federal Highway Administration [FHWA], 2009). In travel demand models, occupancy is used to relate person trips to vehicle trips (FHWA, 2010; Ohstrom and Stopher, 1984): If a forecast of the number of person trips is generated by an area, one can divide by a vehicle occupancy to forecast vehicle trips; alternatively, if forecasting the benefits of widening a facility, one can multiply the new vehicular capacity by occupancy to forecast person trips that will be accommodated. One model used in Seattle differentiates between vehicles with one, two, and three occupants (Meyer and Miller, 2020). Occupancy helps quantify the impacts of congestion by time of day: a custom tabulation based on Appendix A of Lasley (2017) showed occupancy changing from 1.52 (6 AM-10 AM) to 1.78 (10 AM-3 PM). Liu (2007) reported that vehicle occupancy is the key element for determining the necessary number of parking spots for “fixed seat facilities” such as a park and ride lot serving a heavy rail station.

The Virginia Experience

The limited data sets specific to Virginia confirm the relevance of vehicle occupancy for transportation planning, partly because occupancy varies by trip purpose and location and partly because occupancy influences the evaluation of investments and project prioritization.

Occupancy is clearly variable in Virginia based on the limited data obtained by the research team. Extraction of FHWA’s National Household Travel Survey (NHTS) data (FHWA, 2019) showed that Virginia’s lowest population density locations (less than 100 people per square mile) yield an occupancy of 1.36 (for sedans and SUVs) compared to an occupancy of 1.52 for trips from the highest population density locations (more than 25,000 people per square mile). Occupancies also varied by purpose: the same data set showed occupancies of 1.18 (work), 1.45 (recreation), and 1.66 (shopping). A more defined trip purpose resulted in additional variation in occupancy. Execution of the Charlottesville-Albemarle [Virginia] Regional Travel Model by the research team for one particular scenario revealed an auto occupancy of 1.06 for trips made directly between home and work whereas an occupancy of 1.15 reflected home-work trips that included an intermediate stop (RSG and Whitman, Requart & Associates, LLP, 2019).

The aforementioned numbers are known as trip-based vehicle occupancy as they reflect the number of passengers plus the driver in a vehicle during an entire trip. By contrast, a link-based occupancy, also known as an "average vehicle occupancy" (AVO) (Spillar, 1997), denotes the average occupants per vehicle for all vehicles on a particular road or set of roadways. This latter definition also is used in transportation planning, especially for evaluating the effectiveness of investments. Martin et al. (2005) suggested that the efficacy of high occupancy vehicle (HOV) lanes, compared to general purpose (GP) lanes, may be evaluated by comparing the number of persons served (rather than the number of vehicles served). Occupancy is essential for this evaluation; in fact, application of this method to one site in the Hampton Roads District (Table 1) revealed that in contrast to the findings of Martin et al. (2005), the hourly per-lane HOV throughput (2,248 persons) was substantially less than the hourly per lane GP throughput (3,295 persons). However, there was no barrier separation between the HOV and GP lanes. Thus, an alternative explanation particular to the site reflected in Table 1 is that GP Lane 3 reflects higher occupant vehicles switching between this leftmost lane and the adjacent HOV lane, in which case per-lane throughput for these two lanes indeed is higher than that of the rightmost two GP lanes.

Virginia's SMART SCALE project prioritization scheme uses a single estimate of statewide passenger vehicle occupancy to convert vehicle delay to person delay. Buchanan (2022) provided several sources of data that have been considered in the past. For example, data from the 2009 NHTS showed weekday AM and PM peak occupancies for Albemarle County as 1.32 and 1.41, respectively, lower than a weekend occupancy of 1.67. American Community Survey (ACS) data are available by year but only for commuters; for 2014-2016, the same jurisdiction has considerably lower occupancies of 1.09, 1.10, and 1.12 for 2014, 2015, and 2016, respectively. The collection of field data by the research team further suggested that even within a jurisdiction, occupancy varies by direction at a location. At one site in Albemarle County (Route 20) near the border with Charlottesville during the PM peak period (4 PM-6 PM), field data showed an average occupancy of 1.29 (southbound) and 1.18 (northbound).

Table 1. Comparison of Person Throughput at One Site in the Hampton Roads District

Lane Type	Lane No.	Vehicles	Persons	Average Vehicle Occupancy
High Occupancy Vehicle	1	1,761	2,248	1.28
General Purpose	1 (far right)	2,142	2,562	1.20
	2 (middle)	2,253	2,586	1.15
	3 (far left)	3,701	4,738	1.28
	Total	8,096	9,886	1.22
	Average per lane	2,699	3,295	

Data were collected in the eastbound direction, 3-5 PM, on July 18, 2019, on I-64 near Indian River Road.

The Problem: A Lack of Detailed Occupancy Data

Outside Virginia, others have articulated a need for understanding variation in vehicle occupancies. Tomer (2011) noted that public ridesharing facilities should ideally be located to areas that have concentrated carless households. Mitra and Saphores (2018) stated that NHTS data are not sufficient for such an analysis because they do not provide details about how these occupancies vary by location or trip. At the national level, the Moving Ahead for Progress in the 21st Century Act (MAP-21) fosters congestion management and mobility initiatives, many of which emphasize person movement in contrast to vehicle movement. Because vehicle occupancy varies by location and purpose, vehicle occupancy data are critical for evaluating the impact of these initiatives.

Currently, Virginia relies mostly on two data sources for estimating occupancy. The NHTS (which started as the National Personal Transportation Survey in 1969) has been conducted every 5 to 7 years: 1977, 1983, 1990, 1995, 2001, 2009, and most recently in 2017). Although the NHTS provides point values for occupancy, it is also possible to obtain a 95% confidence interval whose breadth is inversely proportional to the sample size. Unless the state purchases additional samples (which Virginia did in 2009 but not in 2017; these additional samples can support the determination of occupancy in some jurisdictions), these data generally can provide only a statewide figure (e.g., examination of 2017 NHTS data showed slightly fewer than 300 households reporting at least one home-based work trip). The only other routine source of occupancy, the ACS, pertains solely to work trips: it is updated every year, 3 years, or 5 years (depending on the size of the jurisdiction) and provides occupancy by city or county.

Otherwise, Virginia has no other routine sources of occupancy except special studies. Field data collection is routinely performed in just two of the Virginia Department of Transportation's (VDOT's) nine districts—and at only a small number of sites within these districts. Most other states are similar to Virginia in that although they have reported sporadic studies, they have no routine updates to occupancy except the NHTS (which, without an add-on, gives only a state-level occupancy) or the ACS (which gives occupancies by city or county but for work trips only). Yet planning initiatives (e.g., project prioritization, equity analyses, and an efficiency evaluation of managed lanes as shown in Table 1) can be strengthened with more detailed estimates of auto occupancy.

As a consequence, in order to conform more accurately to MAP-21 performance measure requirements and to support various planning efforts, VDOT needs guidance for developing a corridor level occupancy rate data collection program. This guidance should consider the use of new technologies and existing resources, and because any data collection program has a cost, this guidance should quantify the benefit of the program relative to using current statewide or national default values.

Research Need Summary

Meyer and Miller (2020) stated that the capacity of transportation infrastructure should be measured from a "people-moving perspective" rather than solely from a vehicle perspective—a perspective reflected in national performance measure requirements and Virginia project prioritization methods. In theory, such data are needed at the corridor level—not just the state level—and for all trips—not just for the commute to work. In practice, the extent to which more detailed corridor occupancies would affect planning practice relative to the use of national or statewide defaults is not known. Thus, the problem facing Virginia is twofold: there is no known way to obtain vehicle occupancy on a routine basis except through surveys or manual observations, and except for anecdotes, the utility of such vehicle occupancies in planning decisions has not been quantified.

PURPOSE AND SCOPE

The purpose of this study was to develop a method to estimate passenger vehicle occupancy and quantify the potential impact of more detailed occupancies on one key planning practice: evaluation of candidate transportation investments.

First, the study sought to determine the utility of more detailed occupancy estimates (compared to default values from existing sources). Second, the study identified a wide range of approaches that could be used routinely to provide occupancy; for an approach that appeared promising, the study demonstrated that approach for one VDOT district. Third, the study used the results of that approach, which yielded a large number of vehicle occupancies that previously had not been available, to determine the extent to which occupancy varied by time of day (peak vs. off-peak), type of day (weekday vs. weekend), roadway functional class, and field data collection method.

METHODS

Five major tasks were undertaken to accomplish the study objectives:

1. Quantify the importance of vehicle occupancy.
2. Identify approaches for estimating vehicle occupancy.
3. Collect Virginia-specific vehicle occupancy data.
4. Develop a repeatable procedure for obtaining occupancy in Virginia.
5. Determine the variation in occupancy by site characteristics.

Quantify the Importance of Vehicle Occupancy

For computing travel time reliability measures and peak hour excessive delay metrics, 23 CFR 490.509(d) and 23 CFR 490.709(e) of the Code of Federal Regulations require AVO factors. The data needed to calculate the measures must come from the most recently available data tables published by FHWA or state DOT estimates that are more specific than FHWA data. Table 2 shows recent AVO factors for car, bus, and truck vehicle types in the Atlanta, Georgia; Columbus, Ohio; and Washington, D.C., metropolitan areas (the last includes portions of Virginia and Maryland).

Table 2. Annual Average Vehicle Occupancy Factors for Cars, Buses, and Trucks

Vehicle Type	Applicable Area	Average Vehicle Occupancy Factor
Cars	All	1.7
Buses	Atlanta, Georgia	10.3
	Columbus, Ohio	5.7
	Washington, D.C., Virginia, Maryland	8.9
Trucks	All	1.0

Source: FHWA (2018).

FHWA (2018) indicated that these factors are derived from 2017 NHTS data for deriving AVO factor for cars; 2016 National Transit Database for deriving AVO factor for buses; the third national performance management measures final rule for trucks; and 2016 Highway Statistics for aggregating AVOs for cars, buses and trucks to estimate an AVO factor for all vehicles.

Vehicle occupancy estimates affect the estimation of project benefits if they are based on person movements rather than only vehicle movements and if occupancy varies by project. Presently, Virginia's SMART SCALE prioritization process uses a single statewide estimate of passenger vehicle occupancy. This task examined how occupancy could affect project prioritization if project specific occupancies, rather than a single statewide occupancy, were used.

SMART SCALE evaluates candidate investments through six benefits: safety, congestion mitigation, accessibility, environment, economic development, and land use and transportation coordination. For most projects in VDOT's Northern Virginia and Hampton Roads districts, which account for more than one-half (50.3%) of Virginia's total population (Bhairavabhatla et al., 2020), congestion mitigation is weighted to account for 45% of these benefits (Commonwealth Transportation Board [CTB], 2021e). There are a few exceptions such as projects on the rural Eastern Shore where congestion has a weight of just 10% rather than 45%. Congestion mitigation is based on how a project improves two performance measures: (1) additional peak period person throughput, determined by multiplying vehicle throughput by the AVO rate, and (2) reduction in peak period person delay, which is the product of reduction in vehicle delay and the AVO rate. Details are provided by CTB (2021e), but for the purposes of explaining the case study, the research team summarized Virginia's process as five computational steps:

1. Identify from all Virginia projects—not just those in the case study area—the single project with the best performance measure for person throughput and the single project with the best performance measure for delay.

2. For each of the 38 case study projects and for each of the two performance measures, compute the ratio of the project's performance to the best project's performance from Step 1.

3. Multiply each of the ratios from Step 2 by 50% to obtain a total congestion score and then multiply the total congestion score by 45% to obtain a total congestion mitigation score.

4. Repeat a similar process (i.e., Steps 1, 2, and 3) for the other five categories (safety, accessibility, environment, economic development, and land use and transportation coordination) to obtain scores in those five categories.

5. Sum the six scores, divide by the money requested by the project sponsor in units of tens of millions of dollars, and then rank the projects based on the score/cost ratio.

The research team investigated how variations in occupancy could affect project rankings by first ensuring Virginia's SMART SCALE steps could be replicated and second by examining the sensitivity of the rankings to changes in project-specific occupancy.

Ensure Replication of SMART SCALE Steps

The research team replicated this process such that the results matched those used in SMART SCALE (CTB, 2021a-d), for instance, considering Project 6690 (an improvement on Holland Road in Virginia Beach). Table 3 (Columns 1 and 2) forecasts that this project will increase person throughput by 348.27 and reduce person-hours of delay by 121.5 (CTB, 2021b-d) during the peak period. Then, for roadway-specific projects, the changes in vehicle throughput were multiplied by an AVO rate in order to determine a change in person throughput.

The best project with regard to these two performance measures in Virginia was Project 6641 in Loudoun County, forecast to increase person throughput by 1862.33 and to reduce delay by 610.1 person-hours. Steps 1 through 3 showed that the congestion score for Project 6690 (Eq. 1) was 8.69 (Table 3, Column 3). For the performance measures of safety, accessibility, environment, economic development, and land use / transportation coordination, scores were determined in a similar manner (albeit with different factors, weights, and single best projects in those respective measures), and case study data (CTB, 2021b) showed 10.37 (Column 4). The total benefit, based on summing all six scores, was 8.69 + 10.37 = 19.06 (Column 5). The funds sought for this project by the sponsor (Virginia Beach City) were $16.8 million (Column 6). The final score (calculated by 19.06/1.68) was 11.35. This Holland Road project received a higher final score than the next highest project, which was Project 6692 (11.22).

$$\text{Congestion score} = (50\%*348.27/1862.33 *100+50\%*121.5/610.1*100) *0.45 \qquad \text{[Eq. 1]}$$

Table 3. Impact of Reducing Holland Road Project Occupancy on Project Rankings

Situation	Project	Increase in Person Throughput (1)	Delay Reduction in Person-Hours (2)	Congestion Score (3)	Other PM Scores (4)	Total Benefit Score (5)	Requested Cost in $10 Million (6)	SMART SCALE Score (7)
Holland occupancy unchanged[a]	Holland (6690)	348.27	121.50	8.688	10.37	19.06	$1.68	11.35
	6692	110.76	24.55	2.244	8.75	11.00	$0.98	11.22
Holland occupancy drops by 0.04[b]	Holland (6690)	337.47	117.73	8.419	10.37	18.79	$1.68	11.18

PM = Performance measure.
[a] The data in Rows 1 and 2 match those available from Commonwealth Transportation Board (2021a-d).
[b] The data in Row 3 were determined by the research team based on a presumed occupancy of 1.29 that then drops to 1.25, with the benefits computed as the ratio of 1.25/1.29.

Examine the Sensitivity of Rankings to Changes in Occupancy

The research team then examined how changes in occupancy affected the rankings. One may hypothesize that the true occupancy at Holland Road is 1.29—a value recorded by the research team at another location in central Virginia on April 20, 2021. A spreadsheet was created that, based on this occupancy and other project data elements, computes the score of 11.35. Then, one may suppose that the Holland occupancy falls by 0.04. This reduces the person throughput and person-hours of delay shown in the last row of Table 3. Because of this reduction, the project now ranked below Project 6692.

A more systematic way to ascertain the importance of occupancy is to determine how many of the 38 Hampton Roads District projects would change rankings if, for each project, the occupancy for the next highest or next lowest project were to change by a particular amount. Accordingly, three separate experiments were undertaken.

In Experiment 1, the research team defined each of the 38 projects based on their initial rank as even (ranked 2nd, 4th, …38th) or odd (ranked 1st, 3rd, … 37th). Then, the occupancies for the odd projects were reduced from a presumed baseline of 1.29 to 1.24 (a deviation of -0.05). The number of projects whose rankings changed was determined. Then, this step was repeated by changing occupancies only with the even projects (again with a deviation of -0.05); this repetition avoided project selection bias. Then, this entire process was continued for other occupancy deviations (e.g., +0.05, -0.10, +0.10, stopping at -0.25 and +0.25). Experiment 1 was performed twice—once with a baseline occupancy of 1.29 and once with a baseline occupancy of 1.14 (the mean vehicle occupancy for ACS Census data for commuting to work in the region).

In Experiment 2, since all project factors, not just those related to occupancy, are subject to some uncertainty, Experiment 1 was repeated such that for each project, 45% of the score based on congestion mitigation (which is influenced by occupancy) was left unchanged but the remaining five factors of safety, accessibility, environment, economic development, and coordination were allowed to vary. The impact of this variation on project ranking was compared to that in Experiment 1.

At the conclusion of Experiment 2, new rankings were developed. In Experiment 3, the approach of Experiment 1 was repeated with these new rankings: change occupancy (for odd projects and then even projects in deviations of +0.05, -0.05, …+0.25, -0.25).

Identify Methods for Estimating Vehicle Occupancy

After transportation agencies were surveyed to identify approaches used to estimate vehicle occupancy, four categories of approaches for estimating occupancy were examined: (1) image processing, (2) non-visual approaches, (3) human observations, and (4) crash data. For each category, the most pressing research question was identified and a method for answering that question was developed.

Survey of Transportation Agencies

To determine methods currently in use for determining occupancy, two entities were surveyed: VDOT districts and other state DOTs.

Survey of VDOT Districts

Staff of VDOT's Traffic Engineering Division (TED) (Jones, 2021) explained that VDOT's Highway Performance Monitoring System (HPMS) PM3 submittal is assembled each year via a contract with the Regional Integrated Transportation Information System (RITIS) housed in the University of Maryland's Center for Advanced Transportation Technology Laboratory (University of Maryland, 2022). In RITIS' National Performance Management Research Data Set Analytics dashboard, the MAP-21 link enables DOTs to create a PM3 report, which contains 31 attributes for each roadway in HPMS. Table 4 shows select attributes for one roadway as excerpted from VDOT's 2019 PM3 report submission to the HPMS portal.

Table 4 shows that VDOT does not report a value for the OCC_FAC field. DOTs have the option to report a value in the AVO field or leave the field blank. If the field is left blank, it indicates that the default values provided by FHWA are to be used. For Virginia, the default values (as indicated in Table 2) are 1.7 (passenger cars), 8.9 (buses), and 1.0 (heavy trucks).

To determine if, in contrast to Table 4, any VDOT districts nonetheless collect their own occupancies (and the reason for doing so), a survey (Figure A1 in the Appendix) was distributed to district planners in each of VDOT's nine districts: Bristol, Culpeper, Fredericksburg, Hampton Roads, Lynchburg, Northern Virginia, Richmond, Salem, and Staunton.

Table 4. Excerpt of VDOT's HMPS Submittal for 2019

Attribute	Example for one roadway
Year_Record	2019
State_Code	51
Travel_Time_Code (input is Traffic Message Channel)	110-04120
F_System (Freeway System)	1
Urban_Code	92242
Facility_Type	2
NHS (National Highway System)	1
Segment_Length	0.212
Directionality	2
DIR_AADT (AADT by direction)	107446
LOTTR_AM (level of travel time reliability for the AM peak)	1.06
TT_AMP50PCT (50th percentile travel time in AM peak)	14
OCC_FAC (occupancy factor)	
METRIC_SOURCE	1

HMPS = Highway Performance Monitoring System. In the submittal, data such as those shown are provided for each roadway. Not all attributes are shown.

Survey of State DOTs

To determine how DOTs are reporting AVO factors in accordance with the CFR requirements, an email-based questionnaire was developed (Figure A2 in the Appendix) and distributed to all 50 state DOTs, targeting staff affiliated with traffic monitoring data and analyses. Of particular interest was whether states were using the supplied FHWA factors (such as those shown in Table 2) or their own more specific factor estimates, in which case respondents were asked about methods used to collect the data and the purpose those data served.

Automated Image Processing Approaches

Background

Automated image-based occupancy detection (Chan et al., 2011) uses an automated system to capture vehicle images and tabulate occupancy. Until recently, these systems were not generally deployed to detect occupancy owing to challenges with either accuracy or system costs.

When implementing a process to collect vehicle occupancy data, Chan et al. (2011) found that their existing "dtect" camera system could not detect vehicle occupancy accurately; further, their method required an appropriate sample size. In their evaluation of the dtect system, Chan et al. (2011) conducted a variety of field tests where they reported that if an occupant was successfully detected, this was reported as a "pass"; otherwise, this was reported as a "failure." The authors reported that "overall testing results showed very low accuracy or pass rates of the dtect system output." For example, for one subset of tests where the authors examined different age groups (child, teenager, or adult) and different positions within the vehicle (e.g., back seat driver side and front seat passenger side), the system detected roughly 20% of the occupants.

More recently, a discussion with Transurban staff on May 14, 2021, revealed that during the period 2017-2021, Transurban has developed an occupancy detection system to monitor six sites along the 95/395/495 express lanes. These sites are located on I-495 near Route 50, I-395 near Glebe Road, and I-95 near the Fairfax County Parkway, with each site capturing one direction of travel. The existing system is fixed and is designed to detect only whether a vehicle meets the occupancy threshold of three or more persons per vehicle. Thus, a vehicle is given one of two classifications: low occupancy or high occupancy. Transurban representatives noted they have had conversations with other state DOTs, such as California, regarding the potential development of a portable system that uses sidefire cameras (L. Pinelis and C. Salmon, personal communication, May 14, 2021).

Research Question and Method of Resolution

The key research question was whether an image processing system such as that deployed by Transurban is economically feasible. Thus, an interview with a provider of such a system, InVision, was held on May 3, 2022, where the focus was the InVision Video Occupancy Detection (iVOD) system.

Non-Visual Approaches

The research team also considered three technologies that do not rely on visual observations and were available to VDOT staff at the time of the study. One technology was the cloud-based StreetLight InSight platform, which obtains data, in part, from "anonymized location records" from connected vehicles and smartphones and then combines these with other data sources such as a representation of roadway networks (StreetLight InSight, 2022). A second technology was Wejo's "driver events" stream, which was made available to VDOT ON a 2-week basis with limited functionality (VDOT has since decided to subscribe to this data set in the future.) A third technology was the use of Bluetooth detectors owned by VDOT that can presently obtain a small percentage of media access control addresses from vehicles and electronic devices owned by passengers such as cell phones and thus potentially give a surrogate for vehicle occupancy.

StreetLight InSight (Background)

The research team initially hypothesized that StreetLight InSight might be useful for estimating auto occupancy based on a hypothetical example (Rea, 2020) that explained that this platform provides different types of output, such that in theory one might be able to acquire both the number of vehicle trips and the number of occupants:

> As stated earlier, devices on buses will create trips in the "All Vehicles" mode of travel, but your choice of output will determine how all the trips the devices on the bus are reported. For example, imagine a bus with five people in our sample, each with a device. Each of those five devices will create a trip, making five trips in total. Those five trips are all repo[r]ted in your metrics based on your output type.

This difference in metrics is available in the form of two different StreetLight InSight output types.

1. *StreetLight Sample Trip Counts (Device Trips)* is the total number of trips as recorded by devices (e.g., if three people are traveling in a vehicle and each has a cell phone turned on, that value would theoretically be 3).

2. *StreetLight Volume* is the number of vehicle trips (e.g., three persons traveling in one vehicle would theoretically yield a value of 1). This variable is sometimes abbreviated as "STL Volume."

The research team hypothesized that at sites with higher occupancies, such as HOV or high occupancy toll (HOT) lanes, one would tend to see a higher ratio of the first variable to the second variable (e.g., 3 device trips / 1 vehicle trip = 3.0) than on GP lanes (e.g., 1 device trip / 1 vehicle = 1.0). Accordingly, two initial experiments were conducted with the StreetLight InSight platform at sites in the Hampton Roads District in October 2020 and on I-66 in the Northern Virginia District in January 2021, where the team sought to obtain both outputs and results were shared with StreetLight staff.

Insights from these staff were essential for two critical reasons. First, the research team learned that until February 2021, the second metric StreetLight Sample Trip Counts (Device Trips) was not available to Virginia. In response, StreetLight InSight asked for information about this study (Shepard, 2021a) and then made this metric available (Shepard, 2021b). Second, White (2021ab) pointed out that because of changes in data suppliers, it was possible for penetration rates, and hence one's estimate of occupancy, to change. It thus appeared unlikely that one could derive occupancy directly from StreetLight InSight.

StreetLight InSight (Research Question and Method of Resolution)

Although StreetLight does not give occupancy directly, the research team wondered if it might be possible to use this platform simply to determine if one site has higher occupancy than another site, where both were examined at the same time. To increase the likelihood of detecting a difference between a site with higher occupancy and a site with lower occupancy, the research team used a site located on I-66 east of I-495, which on weekdays varies from being GP lanes to HOT lanes depending on time of day and direction of travel. At this site, StreetLight Volume, StreetLight Sample Trip Counts (Device Trips), and StreetLight Index (Device Trips) were obtained. This analysis was performed in October 2021 to determine if one could possibly use different types of metrics to determine differences in occupancy.

Wejo (Background)

A 2-week sample of probe-based data was made available from a private vendor, and these data were extracted for 23 zip codes that encompassed Henrico County (U.S. Department of Housing and Urban Development Office of Policy Development and Research, 2022). The data were provided in two formats: one focused explicitly on seat occupancy (e.g., driver seat occupied, passenger seat unoccupied), and one focused on belt use (e.g., front passenger belt is not latched, front driver belt is latched). For each format, the number of samples was reported in two ways: as a "journey" and as a "datapoint" (e.g., between 7 AM and 8 AM at the zip codes in Henrico County over this 2-week period, there were 2,242 datapoints where the driver seat was occupied and 1,723 journeys where the driver seat was occupied); the former is always greater than the latter. A review of Wollet and Eaton (2021) suggested that a datapoint is an observation from a specific instant in time, whereas a journey refers to information gathered about a vehicle trip.

Wejo (Research Question and Method of Resolution)

In April, the research team used the data to estimate AVO (based solely on the front seat) and shared the analysis with VDOT's Central Office staff who forwarded the material to Wejo staff for review. Wejo staff provided comments, and then the Virginia Transportation Research Council (VTRC) used the comments to revise the analysis.

Bluetooth (Background)

Another initially promising approach was that of using portable Bluetooth detectors (which can identify Bluetooth-enabled devices such as some vehicles, cell phones, and laptops) to tabulate these devices, which, along with the limited number of continuous count stations, could provide some type of ratio of devices to vehicles. The research team initially thought that even if this ratio did not provide occupancy directly, it could be monitored for changes over time in order to understand how occupancy might be changing. Because various VDOT functional units have these Bluetooth detectors, and because there are on average one or two continuous count stations in each city or county in Virginia, such an approach was appealing because it could be used statewide. As of April 9, 2022, VDOT (2022) reported 287 loop-based continuous count stations; some jurisdictions had more (e.g., 18 in Fairfax County) and other jurisdictions had less (e.g., 1 in Charlottesville and 0 in Mathews County).

However, a conversation between the three members of the research team and a veteran user of these devices (M. Fontaine, personal communication, April 7, 2022) showed several complications with this approach. The most damaging was that the percentage of Bluetooth devices caught by the detectors varies as a function of variables that are unrelated to occupancy. Although the experience of VDOT staff has been that between 2% and 6% of devices are detected, this percentage varies as a function of vehicle speed (where faster travel makes detection less likely); device application (e.g., a cell phone seeking Bluetooth pairing might send out a signal only for a short period of time such that the detector, which requires a line of sight to the device, cannot detect the phone); passenger (e.g., some occupants might not have Bluetooth-enabled devices, some might have multiple devices); vehicle age; and device security (e.g., some apps or devices might use randomized media access control addresses such that a single device would be recorded as two separate devices if the randomization occurred within the line of sight of the detector).

Although the variation in detection rates is arguably the largest single obstacle to this approach, three additional challenges exist with respect to the portable detectors available to VDOT staff. The first concerns occlusion: as the detector requires a line of sight to the device, it will tend to capture more devices on a lane nearer the detector, which is problematic for multilane freeways (although this is not a problem with fixed-site overhead detectors). The second (particular to temporary counters only) is battery life; the detectors last for roughly 1 week without the need to change batteries, such that they are suitable for short-term counts (if the other challenges are solved). For assessing long-term seasonal variation, the Bluetooth systems that can be installed permanently on regular power are required. The third is that the fairly small detection rates (e.g., 2% to 6%) amplify these imperfections.

Bluetooth (Research Question and Method of Resolution)

A simple field test was designed and conducted on April 22, 2022, to evaluate the feasibility of this approach. The research team placed a Bluetooth reader near a low-speed two-lane (one lane in each direction) roadway and made a round trip run with a single vehicle past the detector; the distance between the start and end points was roughly 800 feet. Thus, a vehicle traveled relatively slowly, typically between 10 and 20 mph for roughly 30 to 45 seconds, where the vehicle passed the detector during that time period. Then, the vehicle turned around, traveled past the detector again, and reached the starting point. Then, the research team made four more sets of runs where in each set two vehicles (one in each direction) crossed the path of the detector at the same time on the starting trip and again on the return trip. The number of cell phones placed in the vehicles varied from one to four.

For each cell phone, one of two settings was used: (1) on mode (leave Bluetooth turned on for the entire run), or (2) discovery mode (turn Bluetooth off and on just before starting the run; then, turn Bluetooth off and on just before beginning the return trip.) This second option means the cell phone is actively searching for Bluetooth devices. If the Bluetooth is left on, then at some point the cell phone will move from discovery mode to on mode.

Manual Observation Approaches

Background

Two methods rely on human observers to count manually the number of occupants in a vehicle: windshield and carousel (D'Ambrosio, 2011). For the former, an observer counts the number of occupants by looking through the windshield of passing vehicles. For the latter, an observer travels 10 to 15 mph slower than the average traffic speed and counts the number of persons in passing vehicles. Heidtman et al. (1997) pointed out that for a multi-lane corridor, the carousel method is more cost effective than the windshield method, suggesting the use of the carousel method on Interstates and the windshield method on other type of roadway facilities. Green et al. (2015) reported no statistically significant difference between the two methods at the 5% level, and the author noted it is more appropriate to use the carousel method for higher speed travel and the windshield method for lower speed travel.

Both methods have limitations. First, they are labor intensive, requiring manual data collection at each site where data are needed. Second, they are available only during the daytime and can be limited by safety considerations. The carousel method requires two observers, and consideration must be given to finding a location where the vehicle can change directions. The windshield method requires that the data collector be away from the traffic stream yet sufficiently close to see occupants in passing vehicles. Third, both methods can require a large sample size: Gan et al. (2005) suggested that 44 days of field collection were needed to differentiate the morning (7 AM-9 AM), midday (11 AM-1 PM), and evening (4 PM-6 PM) peak periods. Fourth, the methods can be subject to data collection bias: in a 2-year examination of I-85, Elango and Guensler (2014) used 100 students to collect morning and evening peak-period vehicle occupancy "mostly on Tuesdays, Wednesdays, and Thursdays." The authors reported some potential bias attributed to the observer: in one case, the percentage of single occupant vehicles (SOVs) in an HOV lane was 10.6%, but for a subset of nine observation periods (provided by six individuals) the sub-average was 35.3%, which the authors noted was "inconsistent across different sessions within the same lane type and also different from data from other data collectors."

Research Question and Method of Resolution

A key question was how many samples these methods could provide. Accordingly, the research team deployed these methods at various sites in Virginia to make that determination. By doing this at a few sites (ultimately five where another entity also measured occupancy), the findings of Green et al. (2005) that the carousel and windshield methods gave similar results could also be tested.

Crashes

Background

Crash data have been used to estimate occupancy in New York (Asante et al., 1996), Florida (Gan et al., 2005; Liu, 2007) and nationally (Krile et al., 2019). One concern has been whether occupancies from vehicles involved in crashes provide a biased sample compared to occupancies extracted from all vehicles on the roadway. Asante et al. (1996) questioned whether crash-based occupancies could be lower than overall occupancy since drivers of multi-occupant vehicles might drive more defensively than drivers of SOVs. Engström et al. (2007) found that crash risk decreases with multiple passengers except in the case of drivers age 18-24. Geyer and Ragland (2005) found that occupancy influences crash risk but only after accounting for age: for males age 45+, the inclusion of passengers in the car significantly reduces fatal crash risk, but this was not the case for males age 20-24. Further, the age of the passengers matters: for males age 16-19, having adult passengers made causation of a fatal crash less likely but having teenage passengers made crash causation more likely. Asante et al. (1996) also questioned if crash risk varies by gender, which was confirmed by Geyer and Ragland (2005). Based on crashes in Norway from 2000-2016, Høye (2018) concluded that although newer vehicles have additional safety features, the finding that newer cars are associated with greater safety "is probably mainly due to the relationship between car age and driver behavior"—that is, the author stated that certain actions (e.g., exceeding the speed limit, not wearing a restraint, and driving while intoxicated) are more likely to occur in older vehicles.

Because of the potential for bias, crash-based occupancies have been "corrected" with field observations (which can be obtained from the windshield or carousel method). Asante et al. (1996) developed a regression-based technique where the dependent variable was the occupancy detected by manual observation and considered to be the ground truth. The two independent variables were the occupancy extracted from crash data and an intercept. If crash-based occupancies were perfectly accurate, one would find that ground truth occupancy should be estimated as 0.00 + 1.00 (crash-based occupancy). Instead, the authors found that the ground truth occupancy should be estimated as 0.30 + 0.69 (crash-based occupancy). Krile et al. (2019), who had access to only fatal crashes through the Fatal Accident Reporting System, combined these data through Bayesian analyses with data from the 2017 NHTS to estimate occupancies.

Research Question and Method of Resolution

The most pressing question is the extent to which Virginia crash data give a biased estimate of occupancy. Accordingly, a process was devised where Virginia crash data were collected and compared to field data at multiple sites, and an estimate of the amount of bias was developed.

Summary of Questions for Each Occupancy Estimation Approach

Table 5 shows that the study question, and the method for addressing it given the resources available to the research team, varied for each of the four approaches. For the first approach, image processing, no field testing was performed; rather, the team interviewed a provider (InVision) to ascertain the costs for using the system. For the second approach, non-visual (probes such as Bluetooth detectors and applications such as StreetLight InSight), cost is less critical because VDOT already has a subscription or owns the devices; for this category, the main question is whether the approach can give an occupancy such that a field test at a small number of sites is feasible. For the third and fourth approaches—human observations and crashes—the costs and feasibility are well known but the critical questions are whether these methods provide a large and unbiased sample; accordingly, a larger scale data collection effort was required.

Table 5. Summary of Research Questions for Four Potential Occupancy Estimation Approaches

Category (Example)	Key Research Question	Method of Resolution
Image processing (InVision)	Is the approach affordable?	Interview one provider to ascertain costs.
Non-visual (StreetLight InSight, Wejo, Bluetooth)	Can the approach yield occupancies?	Apply the approach at a single location to determine if the results give reasonable estimates of occupancy.
Human observations (carousel, windshield)	Does the approach yield a sample size large enough for analysis?	Apply the approach at multiple sites to determine how many samples can be obtained and if such a sample enables one to detect differences by day, time, and functional class.
Crashes (FR300)	Does the approach yield a biased sample?	Calculate the amount of bias and devise a method to correct that bias.

Collect Virginia-Specific Occupancy Data for Developing an Occupancy Program

Currently, VDOT pays for the collection of occupancies on a quarterly basis at a few interstate sites in the Hampton Roads and Northern Virginia districts. These locations often support the HOV operations program and include GP lanes in the vicinity of an HOV facility or HOV lanes. The data are collected by The Traffic Group using the windshield method, with one observer per lane, and are available for the 2017-2021 time period. To complement this data set, the research team commissioned The Traffic Group to collect data at other sites of interest to the technical review panel: a primary facility and a secondary facility. Where possible, the research team collected data at the same site and the same time using the carousel method; in this way, the windshield and carousel methods could be compared. Finally, historical data prior to 2017 were obtained from VDOT district staff. Thus, recognizing that some observations of occupancies would be useful for examining the occupancy detection approaches described in Table 5, the research team obtained three sets of field observations: windshield method counts, carousel method counts, and historical data.

Windshield Method

When counting occupancy, data collectors were typically parked in a median or grassy area 15 to 20 feet away from the right shoulder (A. Hunt, personal communication, September 22, 2020). Although seven vehicle types are tabulated (personal vehicle, passenger van, single unit truck, multi-trailer, local transit bus, other bus, and commercial bus), only the occupancy for personal vehicles is recorded. Passenger vans denote non-personal vans that serve either transit or an airline, and for those vans the number of occupants is reported as either 1 or 2+ (Kraft, 2022). These data were collected at 36 sites (the first 24 in the Hampton Roads District and the next 12 in the Northern Virginia District), as shown in Table 6.

Table 6. Sites Using the Windshield Method

No.	Road	Time		Direction	Location (Dates[a])
1	I-64	AM	5-8:30	WB	1.0 mi E. of Indian River Rd Exit 286, HOV lane (July 25, 2019)
2		AM			1.0 mi E. of Indian River Rd Exit 286, 3 GP lanes
3		PM	3-6:00	EB	1.0 mi W. of Indian River Rd Exit 286, HOV lane (July 18, 2019)
4		PM			1.0 mi W. of Indian River Rd Exit 286 (3 GP lanes)
5		AM	5-7:30	WB	Exit 276 I-564/I-64 Split, HOV lane[b] (July 17, 2019 WB and July 16, 2019 EB)
6		PM	3-6:00	EB	
7		AM	5-7:30	WB	Norview Ave Exit 279, 3 GP lanes and ramps (July 17, 2019 WB and July 16, 2019 EB)
8		PM	3-6:00	EB	
9		AM	5-8:30	EB	Exit 258, J Clyde Morris Interchange, HOV lane (July 23, 2019)
10		AM			Exit 258, J Clyde Morris Interchange, 3 GP lanes
11		AM	5-8:30	WB	Exit 258, J Clyde Morris Interchange, HOV lane (July 24, 2019)
12		AM			Exit 258, J Clyde Morris Interchange, 3 GP lanes)
13	I-264	PM	3-6:00	WB	Exit 258, J Clyde Morris Interchange, HOV lane (July 24, 2019)
14		PM			Exit 258, J Clyde Morris Interchange, 3 GP lanes)
15		AM	5-8:30	WB	Independence Blvd Exit 17, HOV lane (July 18, 2019)
16		AM			Independence Blvd Exit 17 (3 general lanes, shoulder, and ramps)
17		AM	5-8:30	WB	1.0 mi W. of Exit 13 Military Hwy, HOV lane (July 16, 2019)
18		AM			1.0 mi W. of Exit 13 Military Hwy (3 GP lanes)
19		PM	3-6:00	EB	Witchduck Rd Exit 16 HOV lane (July 17, 2019)
20		PM			Witchduck Rd Exit 16 3 GP lanes and shoulder
21	Rte 164	PM	4-6:00	EB	Between Rte 135 College Dr and West Norfolk Rd (March 31, 2022)
22				WB	
23	Rte 626	AM	6-8:00	NB/SB	Shoulders Hill Rd in Suffolk (April 6, 2022)
24		PM	4-6:00		
25	Rte 28	AM	6:30-7:30	NB	Between Rte 50 and I-66 (October 6, 2021)
26		PM	3:30-4:30		
27		AM	6:30-7:30	SB	
28		PM	3:30-4:30		
29	Rte 286	AM	8-9:00	NB	Between Rte 267 and Rte 50 (also known as the Fairfax County Parkway), (October 6, 2021)
30		PM	5-6:00		
31		AM	8-9:00	SB	
32		PM	5-6:00		
33	Rte 608	AM	7-8:00	NB	Between Rte 602 and Rte 666 (also known as West Ox Rd), (September 30, 2021)
34		PM	4:30-5:30		
35		AM	7-8:00	SB	
36		PM	4:30-5:30		

WB = westbound; EB = eastbound; NB = northbound; SB = southbound; GP = general purpose; HOV = high occupancy vehicle.

[a] If no date of data collection is shown, then data were collected on the same day as in the preceding row.

[b] There are 2 HOV lanes at this location: one connecting to I-564 and the other connecting to I-64.

Carousel Method

The carousel method was performed by the research team at five locations (Table 7) at the same time that the windshield method was deployed by The Traffic Group, which enabled an approximate comparison of the two methods. The reason for this approximation was that the windshield method gives a point location whereas the carousel method reflects occupancies obtained in a line (see Figure 1). Further, it was not possible to use the middle interchange in a timely manner, which is why the path shown for the carousel method extends well beyond the point location of the windshield method.

The carousel method entailed two (except in one case three) probe vehicles per site, with the starting times 5 minutes apart. Each probe vehicle had two occupants: the driver, who traveled in the far right lane at what he or she believed to be 10 to 15 mph below the average traffic speed (but always at or under the speed limit), and the tabulator, who sat in the back seat, facing backward, and recorded the number of occupants in each vehicle passing in each lane (middle lane and far left lane). The probe vehicle was either a van or an SUV, which made observations easier, although factors such as tinted windows could make observations more difficult. For each run, the start time and end time were recorded along with the lane number, number of occupants in each passing vehicle, and vehicle type (Table 8).

Table 7. Sites Using the Carousel Method (PM Peak Only)

District	No.	Road	Time	Direction	Location (Dates of Data Collection)
Hampton Roads	1	I-64	3-4:30	EB	Between Exits 276 and 281, 2 left GP lanes (July 14, 2021)
	21	Rte 164	4-6:00	EB	Between Rte 135 College Dr and West Norfolk Rd (March 31, 2022)
	22			WB	
Northern Virginia	26	Rte 28	3:30-4:30	SB	Between Exit 662 Westfields Blvd and the Air and Space Museum Pkwy, 2 GP lanes (October 6, 2021)
	24			NB	

WB = westbound; EB = eastbound; NB = northbound; SB = southbound; GP = general purpose.

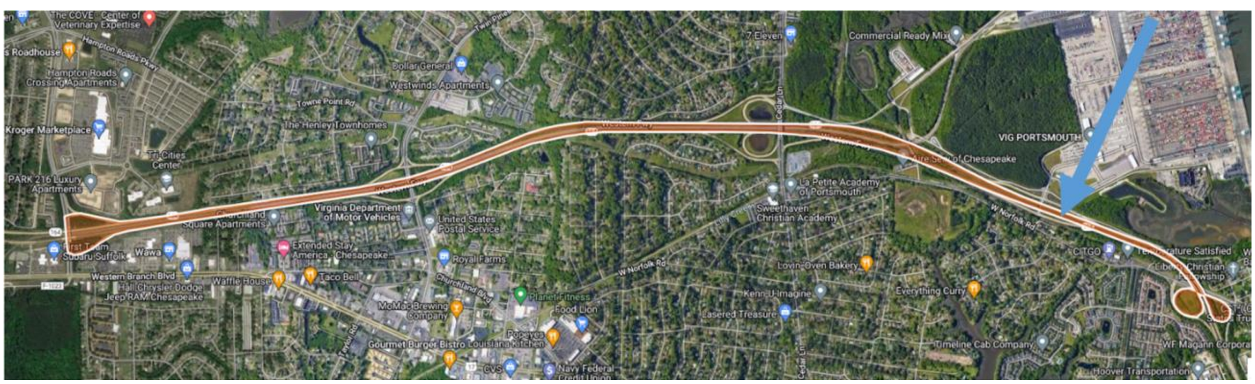

Figure 1. Path for Sites 21 and 22 (Rte 164). Imagery © 2022 Commonwealth of Virginia, Maxar Technologies, U.S. Geological Survey, USDA/FPAC/GEO. The brown segment indicates the travel path for the carousel method. The blue arrow indicates the point location for the windshield method.

Table 8. Example of Tabulating Each Carousel Run

Time	Lane		Occupants					Vehicle Type					
(15 min)	2	3	1	2	3	4	5+	PC	M	B	BT	HT	OTH
Start at 3:33	X		X					X					
		X		X				X					
	X		X					X					
		X	X						X				
	X				X								Ambulance
End at 3:38	X		X					X					

PC = passenger car including pick-up trucks and vans; M = motorcycle; B = buses (school buses, large and small transit buses); BT = box truck (UPS and other similar style commercial vehicles); HT = heavy truck (classified as dump trucks and tractor trailers); OTH = describe what the vehicle type is if not belonging to other categories. Each row represents 1 vehicle (e.g., for the first row, one passenger car with one occupant in Lane 2 is witnessed).

Historical Occupancy Data

In 2019, between 5 AM and 10 AM over a 2-day period, occupancies were collected at an additional 24 locations (Sites 37 through 60), all of which are in the Northern Virginia District along facilities in the I-395 and I-66 corridors, as shown in Table 9.

Table 9. Historical Counts From the Northern Virginia District

No.	Road	Direction	Location (Dates of Data Collection[a])
37	I-66	EB	Between Sycamore St (Exit 69) and N. Glebe Rd (VA 120) (Exit 71) (April 23-24, 2019)
38		WB	
39	US 29	NB	W. of VA 120 (March 28 and April 2, 2019)
40		SB	
41	VA 237	EB	W. of VA 120 (July 24-25, 2019)
42		WB	
43	Wilson Blvd	EB	W. of VA 120 (April 9-10, 2019)
44		WB	
45	US 50	EB	W. of VA 120, (April 3-4, 2019)
46		WB	
47	I-395	NB	S. of Exit 8 and N. of Glebe Rd (VA 120)—HOV lanes (May 1-2, 2019)
48			S. of Exit 8 and N. of Glebe Rd (VA 120)—GP lanes
49	Columbia Pike (Rte 244)	NB[b]	W. of VA 120 (March 26 and April 11, 2019)
50		SB[b]	
51	S. Walter Reed Drive	NB	S. of Glebe Road (VA 120) (March 26-27, 2019)
52		SB	
53	Mt. Vernon Ave	NB	
54		SB	
55	US Rte 1	NB	S. of Glebe Road (VA 120) (April 10-11, 2019)
56		SB	
57	Potomac Ave	NB	S. of Glebe Road (VA 120) (April 4 and 9, 2019)
58		SB	
59	George Washington Parkway	NB	S. of Glebe Road (VA 120) (April 10-11, 2019)
60		SB	

WB = westbound; EB = eastbound; NB = northbound; SB = southbound; HOV = high occupancy vehicle; GP = general purpose.
[a] If no date of data collection is shown, then data were collected on the same day shown in the preceding row.
[b] Columbia Pike runs EB and WB but is labeled NB and SB in the spreadsheet. The research team presumed that NB corresponds to EB since the spreadsheet is generally organized by commuting direction (e.g., in the morning, NB travel on U.S. Rte 1 or EB travel on Rte 244 would lead to the central business district).

The manner of data collection for vehicle occupancies, such as windshield or carousel, was not provided (McCall and Gao, 2019). Complete occupancies were not available; rather, only three sets of occupancies were recorded: SOV, two persons per vehicle, and three or more persons per vehicle.

Develop a Repeatable Procedure for Obtaining Occupancy in Virginia

Based on the results of the first three tasks, a repeatable procedure was developed for estimating occupancy in Virginia. This method had four components: extract occupancy from crash data, correct crash bias at the jurisdiction level, correct crash bias at the corridor level, and quantify accuracy.

Extract Occupancy From Crash Data

Crash data for 2013-2021, provided by Simmons (2021a, 2021b, 2022), included typical details (e.g., location, type, driver age, and vehicle type) and vehicle occupancy. The last data element is not publicly available but rather requires a special tabulation and includes the number of passengers even if they were not injured. A majority of crashes do not involve an injury: in 2020, Virginia saw 68,704 crashes without an injury and 32,505 crashes with one or more injuries. Four geoprocessing steps were used to obtain a map of occupancies extracted from crash data:

1. Join vehicle occupancy records with crash records.
2. Create the occupancy map layer and the Virginia roadway map layer.
3. Associate occupancies with roadway segments.
4. Reduce occupancies that appear to be incorrect.

Step 1. Join Vehicle Occupancy Records and Crash Records.

Because crash records and vehicle occupancy records are in separate Excel files, they may be joined based on the crash document number.

1. For each year, import the vehicle occupancy table and the crash data.
2. Right click the vehicle occupancy table, and then click Add Join.
3. Set the document number as the Input Join Field and the Output Join Field.
4. Run the join tool.

The result is that the vehicle occupancy table will then include crash-based attributes. Because a single crash may involve multiple vehicles, a single occupancy record may correspond to multiple crash records. To avoid duplication, the vehicle occupancy table is the input table in this step (Figure 2).

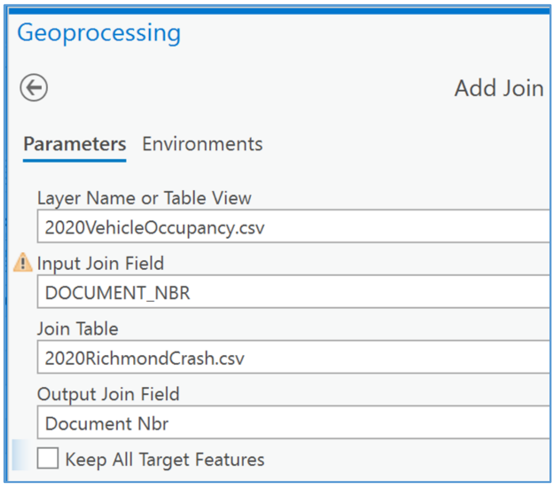

Figure 2. Joining the Crash Information and the Vehicle Occupancy Table

Step 2. Create the Occupancy Map Layer and the Virginia Roadway Map Layer.

The joined occupancy data from Step 1 may be displayed as point locations based on the longitude and latitude. Then, the Virginia Roadway Map, which can be found within the Pathways for Planning application (VDOT, 2021a), can also be displayed. An example of occupancy locations for Henrico County is shown in Figure 3.

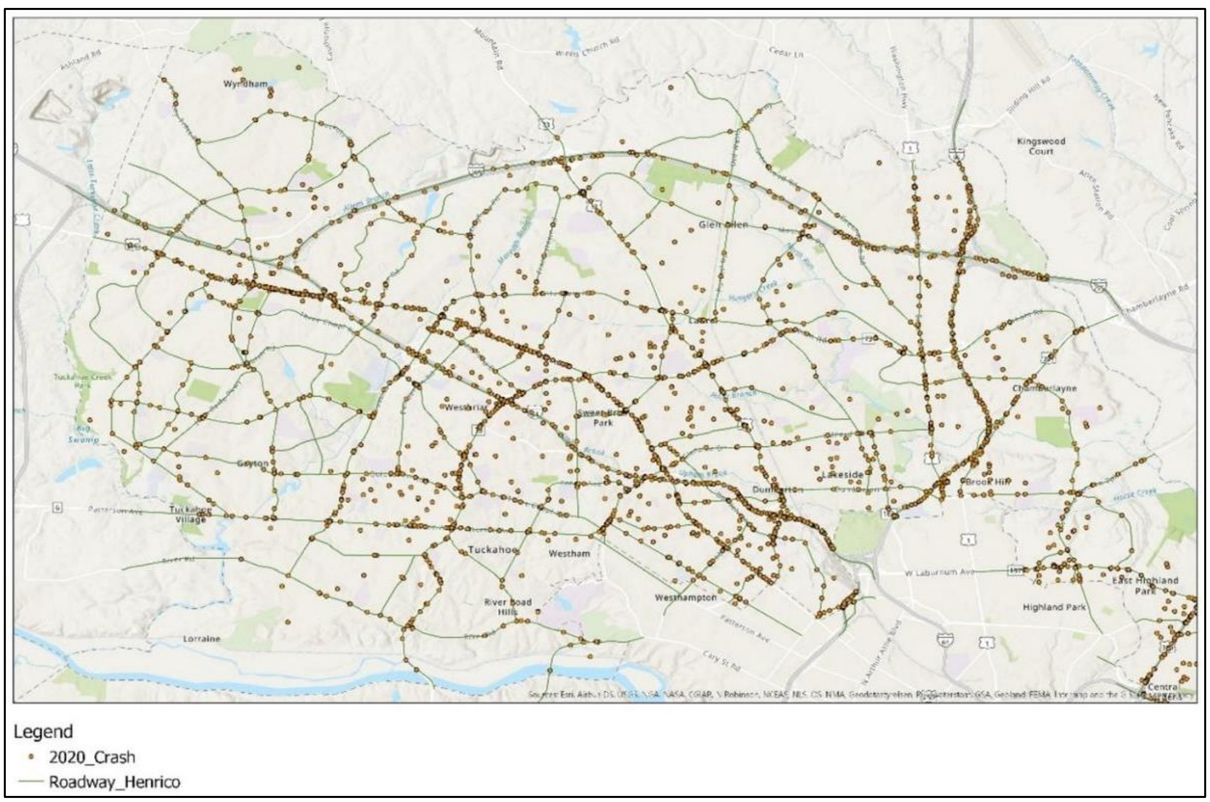

Figure 3. 2020 Crash Map for Henrico County

Step 3. Associate Occupancies With Roadway Segments.

An occupancy observed in a crash is a point that needs to be associated with a specific roadway, and if the results will be shared publicly, multiple occupancy records should be aggregated in order to avoid associating an occupancy with a specific crash report number given the memorandum of understanding between VDOT and the Virginia Department of Motor Vehicles (DMV) (Di, 2021). The spatial join tool accomplishes this purpose. Judgment is required for the search distance: a larger radius will increase the probability of capturing all crashes (such as those where the final point of impact is some distance from the roadside), yet there is also a risk that too large a radius will capture crashes not affiliated with the target roadway. For example, Figure 4, left, shows crashes that are attributable to Stony Point Road, but Figure 4, right, with a larger radius shows that some crashes are included that are more likely to be affiliated with adjacent Richmond Road. A radius of 200 feet (not shown) further increases the likelihood of obtaining crashes that are not affiliated with Stony Point Road.

Figure 5 shows the spatial join geoprocessing step where the merge rule for the vehicle occupancy attribute is "Mean," which indicates that for each road segment, the average value of the vehicle occupancy for all crashes within the 50-foot search distance is the assigned occupancy. It should be noted that selection of the mean is preferable to selection of the median because the latter will always be an integer such as 1, 2, or 3. For an area-based analysis, such as crashes by block group or jurisdiction, the key concern was to minimize double counting of occupancies. Thus, the smaller radius of 50 feet was chosen in this step. The result is that each roadway has a unique AVO and a 24-hour map of occupancies can be created.

Figure 4. Identification of Occupancies With a 50-Foot Search Distance (*left*) and a 100-Foot Search Distance (*right*)

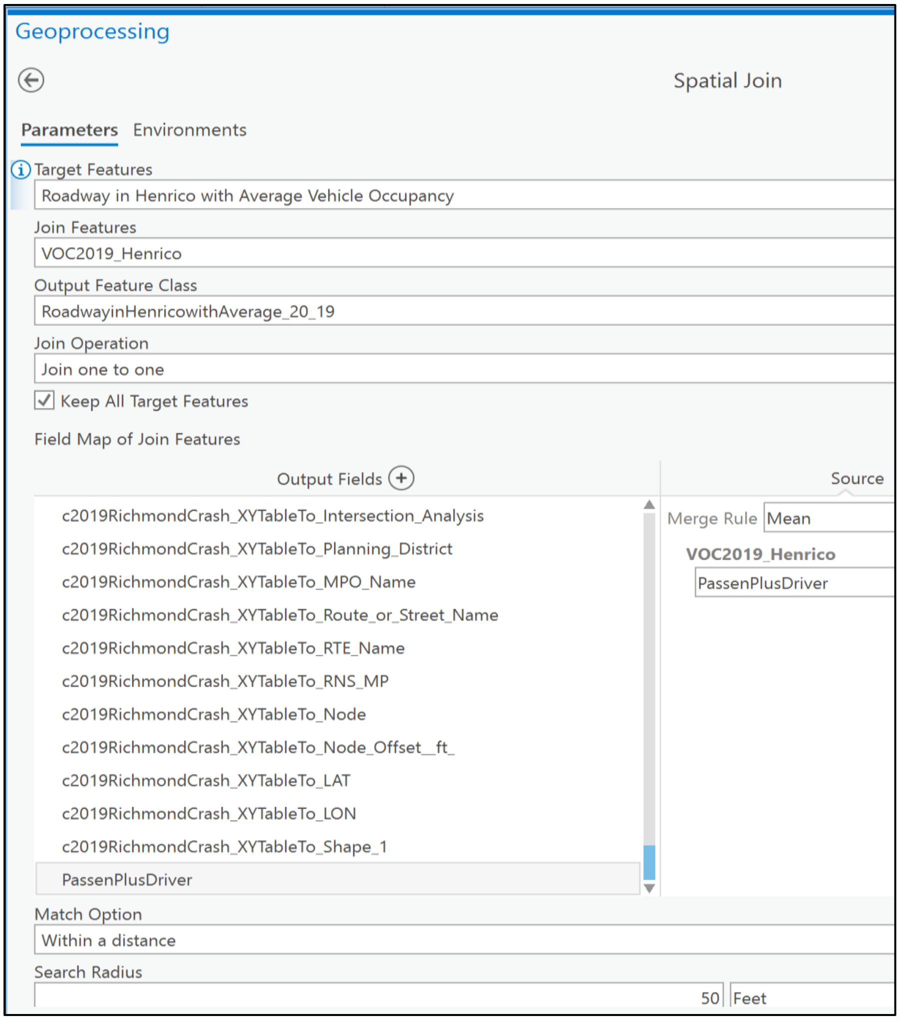

Figure 5. Spatial Join Geoprocessing Setting

Step 4. Eliminate Occupancies That Appear to Be Incorrect.

In 0.07% of the vehicles examined in the 2021 crash data set for the Hampton Roads and Northern Virginia districts, occupancies were considered by the research team to be so high that they were likely incorrect. This concerned 13 of the 18,820 vehicles in the Northern Virginia District and 14 of the 21,975 vehicles in the Hampton Roads District. These occupancies were always reported as 10, 20, 30, or 40. An examination of the Virginia DMV crash reports (Form FR300) (hereinafter "FR300") showed that the occupancies in Virginia's crash records system matched what was reported by law enforcement. Although the occupancy cannot be proven to be incorrect, examination of other information on the FR300 such as injuries and vehicle type suggested that the reported occupancy was highly unlikely.

For example, for one 10-occupant passenger vehicle traveling at 40 mph, there was an injury to the driver and one passenger. For another 10-occupant passenger vehicle traveling at 50 mph, the driver was fatally injured and one passenger was injured. For a 40-occupant passenger vehicle traveling at 30 mph, there were no injuries. In these types of cases where there were 10, 20, 30, and 40 occupants, the vehicle was excluded.

Correct Crash Bias at the Jurisdiction Level (Type 1)

Generally, crash bias represents the difference, in terms of the vehicle occupancy distribution, between the vehicles that are involved in a crash and those that are not involved in a crash. The goal of bias control is to render the vehicle occupancy distribution of the former closer to that of the latter. The mechanism for performing this correction differs depending on whether one is not using field data (Type 1) or is using field data (Type 2).

Theory of Type 1 Bias Correction

At the statewide or VDOT district level, the sample size of vehicles involved in a crash is so large that all reasonable occupancies are represented. However, for smaller localities, there may be instances where certain occupancy groups (e.g., five persons in a vehicle) are never observed. It is possible, but cannot be proven, that such a situation results because of an association between certain variables that affect crash causation and occupancy. A simple Type 1 bias correction method entails two steps: (1) quantify potential bias using the eta-squared value, and (2) correct this bias in smaller jurisdictions.

Quantify Potential Bias With the Eta-Squared Value

Eta-squared (η^2) is the proportion of variance in the dependent variable that can be attributed to the independent variable (Tabachnick and Fidell, 2000). The use of eta-squared helps detect whether there is an association between variables of interest (Howell, 2012), such as driver gender and occupancy. Equation 2 illustrates this calculation for all crashes in the Hampton Roads District in 2019 where groups are male, female, and not available. Generally, an η^2 value of less than 0.01 means negligible association; a value of at least 0.01 but less than 0.06 means a small association; and 0.14 is the threshold for a medium association (Miles and Shevlin, 2001). Thus, Equation 2 shows that since η^2 is less than 0.01, the association between gender and occupancy is negligible when the 24-hour period and the entire district are considered. Equation 2 was implemented through SPSS Crosstabs.

$$\eta^2 = \frac{\text{Sum of squares between groups}}{\text{Total sum of squares}} = \frac{7.770}{17697.272} = 0.0004 \qquad \text{[Eq. 2]}$$

Six variables were considered via Equation 2, based on 24-hour 2019 passenger vehicle crash data at both the district and jurisdiction levels.

1. *Crash severity:* A, B, C, K, and O. (K = fatality; A = incapacitating injury; B = non-incapacitating injury; C = possible injury; O = property damage-only crash (FHWA, 2013)

2. *Driver age group:* driver age ≤ 25 and driver age > 25

3. *Vehicle year:* vehicle made before 2005, vehicle made 2005-2009, vehicle made 2010-2014, and vehicle made 2015 or later

4. *Driver gender:* female, male, and N/A

5. *Collision type:* rear end, deer, other animal, pedestrian, backed into, angle, head on, sideswipe-same direction, sideswipe-opposite direction, fixed object in road, non-collision, fixed object off road, and others

6. *Functional class:* interstate and interstate ramp, major collector, minor collector, other freeways and expressways, other principal arterial, and others.

Although four of these variables—vehicle year, driver gender, driver age, and functional class—could influence the probability of a crash, two of these variables—crash severity and collision type—are outcomes of the crash and thus do not influence its probability. The research team included these two variables in case they influenced the likelihood of a crash being reported.

Correction of Bias in Smaller Localities

Table 10 contrasts two distributions of vehicle occupancies from 2019 24-hour crash data: (1) that of the Hampton Roads District (Column 2), and (2) that of a smaller jurisdiction, Williamsburg, in Column 3. Column 2 shows that all occupancies from one to seven were observed for the Hampton Roads District, whereas no five-, six-, or seven-occupant vehicles were observed for Williamsburg. It is certainly possible that such vehicles existed but were not involved in a crash listed in Table 10.

The research team used a technique that corrected only the occupancy levels where no vehicles were observed in a crash, such as the occupancies of 5, 6, and 7 shown in Column 3 of Table 10. The method is based on two assumptions for such occupancies. First, the probability of crashes at each occupancy level exceeds zero such that Column 4 should be a nonzero decimal number. Second, because no crashes were observed, the corrected number of vehicles in Column 4 should be less than 1.00. Accordingly, Equation 3 is used to modify such occupancies.

Table 10. Example of Type 1 Bias Correction, 2019 Hampton Roads District Crashes

Occupancy (1)	No. of Vehicles: Hampton Roads (2)	No. of Vehicles: Williamsburg (Uncorrected) (3)	No. of Vehicles: Williamsburg (Corrected) (4)
1	42,708	314	314
2	5,081	61	61
3	1,310	14	14
4	563	6	6
5	167	0	314*(167)/(42708) = 0.99[a]
6	61	0	314*(61)/(42708) = 0.448
7	18	0	314*(18)/(42708) = 0.132
8[b]	5	0	0
Total	49,913	395	396.57[c]
AVO	1.21	1.27	1.29

AVO = average vehicle occupancy.
[a] This value was calculated as 1.23 but reduced to 0.99 as the number of vehicles should be between 0 and 1.
[b] If passenger vehicles with 8 occupants were observed in a locality, they were included in Columns 3 and 4 (without modification). However, if no such occupancies were observed, they were not included.
[c] Williamsburg did not have any crashes with an occupancy greater than 7. If a locality had such crashes, however, occupancies were used directly without any bias correction, as was the case for occupancies of 1, 2, and 4.

$$W_{5\ \text{corrected}} = \min(W_1 \frac{H_5}{H_1}, 0.99) = 314 \frac{167}{42{,}708} = 0.99 \qquad \text{[Eq. 3]}$$

where

$W_{5\ \text{corrected}}$ = estimated number of five-occupant vehicles in Williamsburg
W_1 = number of SOVs in Williamsburg
H_1 and H_5 = the single occupant and five occupant vehicles in the Hampton Roads District.

The result is given in Column 4 and increases the Williamsburg occupancy slightly from 1.27 to 1.29.

Correct Crash Bias at the Corridor Level (Type 2)

Type 2 bias correction is more suitable for specific corridors where there are a limited number of occupancies—but as a consequence, it is more detailed than Type 1. One must determine variables that could be influenced by occupancy, develop a model that relates occupancy to these models, and then calibrate the model with field observations.

Theory of Type 2 Bias Correction

Because the calibration process requires sites for model fitting, two conflicting goals are balanced. One goal is to consider many variables, because it may be the case that certain variables that are associated with occupancy influence crash likelihood. The other goal is to have a small number of variables when the model is calibrated, if possible, because there are a limited number of sites supporting the calibration. For that reason, variable identification is a fairly detailed process. Accordingly, in addition to the eta-squared test, a second method—the Apriori method—was used to identify variables.

Detect Candidate Variables With the Apriori Method

The Apriori method has is feasible for analyzing the factors that influence highway crash risk (Yang et al., 2019). The association rules combined with their support value generated by the Apriori algorithm indicates the main factors (e.g., driver age) and the factor values (e.g., driver age $\leq$ 25) that affect crash frequency. The Apriori method detects whether an association exists between occupancy levels (1, 2, 3, …) and crash characteristics such as roadway type, driver age, and crash type (e.g., rear end collisions). The Apriori method provides several outputs, as illustrated in Table 11, based on an example of 1,000 crashes where two factors are of interest: factor A (female driver under age 25), and factor B (vehicle occupancy of 2).

Table 11. Example Outputs From the Apriori Algorithm

Output	Theory	Computation	Result
Support (A)	A / Total crashes	150/1000	0.15
Support (A∪B)	(Crashes with A and B) / Total crashes	(80)/1000	0.08
Confidence (A→B)	Crashes with A and B / Crashes with A	0.08/0.15	0.53
Support (B)	B / Total crashes	120/1000	0.12
Lift (A,B)	Confidence (A→B) / Support (B)	0.53/0.12	4.42
Leverage (A→B)	P(A⋂B) – P(A)P(B)	80/1000 – 0.15*0.12	0.062
Conviction (A→B)	(1-Support (B)) / (1-Confidence (A→B))	(1 – 0.12) / (1 – 0.53)	1.87

A = number of crashes where the driver is female and younger than age 25; A is 150 in this data set. B = number of vehicles with an occupancy of 2; B is 120 in this data set. There are 80 crashes that involve a female driver under age 25 where the vehicle occupancy was 2. These data are drawn from a set of 1,000 crashes where 600 have a vehicle occupancy of 1 and 400 have a vehicle occupancy of 2.

The confidence variable estimates the conditional probability of B given A (Hahsler, 2022). Thus, in Table 11, the value 0.53 estimates the conditional probability of a crash involving a vehicle occupancy of 2 (Factor B), given that the crash involved a female driver under age 25 (Factor A). Leverage indicates the extent to which A and B are statistically independent. In this analysis, if the absolute value of leverage is less than 0.01% (e.g., 1 occurrence of 10,000 crashes), then A and B are considered independent. Otherwise, a positive leverage means A and B are positively correlated and a negative leverage means they are negatively correlated.

A lift value greater than 1 indicates a strong association between A and B. A lift value less than 1 indicates And B are not likely to appear together in the data set. A lift value of exactly 1 indicates that the occurrence of B has no effect on the occurrence of A. Thus, with a lift value of 4.42, Table 11 suggests that there is a highly positive association between a crash involving a female driver under age 25 and a crash with an occupancy of 2.

The Apriori test requires that a variety of rules be considered. To minimize the number of rules, only rules having a confidence value of 0.3 or higher and a support value of 0.001 or higher were retained. This process results in a large number of rules that then must be manually reviewed. If the rules are retained, lift and leverage values help one choose which factors have effects on occupancy (from crashes) and are thus left as factors in the bias correction model. For example, the relatively large value of lift (4.42) compared to 1 and the relatively large value of leverage (0.062) compared to 0.01% in Table 11 suggest a highly positive association between female drivers under age 25 and occupancy = 2 in the crash data set. In this example, therefore, driver gender and driver age are considered to affect crash likelihood when there are passengers in the vehicle, and thus these two variables are left in the bias correction model as independent variables. For rules with a lift value lower than 1 and a leverage value lower than 0.01%, the factors are not included in the bias correction model.

Four additional variables, along with those examined in Type 1 bias correction, were examined:

1. *Jurisdictions:* all jurisdictions in the Hampton Roads District

2. *Week:* weekday (Tuesday, Wednesday, or Thursday) or weekend (Saturday or Sunday)

3. *Period:* 24 hours, AM peak, PM peak, and off-peak

4. *Light condition:* dawn, daylight, dusk, darkness road lighted, darkness road not lighted, darkness unknown road lighting and unknown.

Develop a Model to Correct Crash Bias

Neither test indicates the precise formulation of the bias correction model or shows causation. Accordingly, stepwise linear regression was used to relate field observations of occupancy to those based on vehicles involved in crashes. SPSS was used for developing the bias correction model. The occupancy from the windshield method was used as the dependent variable. Independent variables included the AVO (based on 2017-2019 crashes) for the following crash types: property damage only (PDO), injury, all crashes, male driver, female driver, and rear end. Stepwise linear regression was performed to find the simplest model and to exclude non-significant independent variables.

Table 6 showed 20 sites where occupancy was collected in the field in 2019, 10 of which were later found to be suitable for developing a Type 2 bias correction model based on peak period travel during a weekday. However, for 2019, crash data at those 10 sites yielded only 150 vehicles—that is, an average of 15 observations of occupancy per site. Further, VDOT (2017) noted that although a single year of crash data can be tolerated in some situations, a recommended practice in crash analysis is to use multiple years of crash data—typically at least three. Accordingly, to avoid trends associated with the COVID-19 pandemic, 2019 occupancies were used with crash data from 2017-2019, which raised the number of occupancies (for vehicles involved in a crash) from 15 to 39 per site.

Quantify Accuracy and Applicability of the Type 2 Bias Correction Method

It was generally not possible to quantify the accuracy of the Type 1 bias correction method, as the true occupancy by jurisdiction is not known. However, it was possible to quantify, on a limited basis, the accuracy of the Type 2 bias correction method.

The 10 sites with field data were split into two groups: a training data set (70% of the sites) and a testing data set (30% of the sites). The first data set was used to rebuild a bias correction model, and then the prediction error was calculated for the 30% testing data set. The splits of 70% and 30% were based on a review of Gholamy et al. (2018). Then, the impact that this error would have on altering project rankings (based on the Hampton Roads District case study described in Table 3) was determined.

The 10 sites used to build the bias correction model were all interstate sites. Because VDOT commonly uses administrative class to categorize roadways, the t-test (Eq. 4) was used to determine if the mean occupancies by administrative roadway class (interstate, primary, secondary, or other) were significantly different. In Equation 4, each pair of groups (e.g., interstate vs. primary) is compared and N is the sample size for each group.

$$T= \frac{\text{Mean}_{\text{group1}}-\text{Mean}_{\text{group2}}}{\sqrt{s^2(\frac{1}{N_{\text{group1}}}+\frac{1}{N_{\text{group2}}})}} \text{ and } s^2 = \frac{\sum(x-\text{Mean}_{\text{group1}})^2+\sum(x-\text{Mean}_{\text{group2}})^2}{N_{\text{group1}}+N_{\text{group2}}-2} \qquad \text{[Eq. 4]}$$

This helped determine whether bias correction model based on interstate sites could be applied to other locations.

Determine the Variation in Occupancy by Site Characteristics

When occupancies are obtained, three site characteristics are commonly used by VDOT to describe a particular site: time of day, day of week, and functional class. Thus, the impact of these factors on site occupancy variance was determined using the F-test, where the larger variance is always Group 1 and the smaller variance is Group 2. The p-value of this test corresponds to 1 −Cumulative density function of the F distribution based on the F-statistic (Eq. 5). The degrees of freedom for the numerator is one less than the number of vehicles in Group 1. The degrees of freedom for the denominator is one less than the number of vehicles in Group 2.

F-statistic = (Variance in Group 1) / (Variance in Group 2) [Eq. 5]

The reason for using the F-test (to detect difference in variance as per Equation 5) rather than using the t-test (to detect differences in means as per Equation 4) is that the occupancy distributions for each group are similar: there will always be a large proportion of one-occupant vehicles. The use of the variance test allows one to determine if the proportion of higher occupant vehicles (e.g., 2+) differs by group, even in situations where the sample sizes are fairly small. Then, the occupancy associated with each group was computed. Three types of groups were considered using Equation 5: time of day, type of day, and functional class.

For all comparisons, only fall and spring periods were considered. In the fall, this period began with the Tuesday following Labor Day, ended with the Thursday before Thanksgiving, and excluded Veterans Day. In the spring, this period began with the first Tuesday during the week following New Year’s Day (e.g., if New Year’s Day was on Sunday, the period started on Tuesday January 10; if New Year’s Day was on Saturday, this period started on Tuesday, January 4). The period ended the last Thursday prior to Memorial Day and excluded (in 2021) Inauguration Day, which was observed on Wednesday, January 20. Other holidays in this time period, President’s Day and Martin Luther King, Jr., Day, were observed on Monday or Friday and thus did not affect the analysis. Dates were obtained from Time and Date AS (2022).

Time of Day

For time of day, three periods were considered: morning peak (7 AM-9 AM), evening peak (4 PM-6 PM), and off-peak (10 AM-3 PM and 8 PM-6 AM). The transition hours of 6 AM-7 AM, 3 PM-4 PM, and 6 PM-8 PM were not used in order to avoid an arbitrary classification (e.g., some might consider 6:30 PM to be part of the peak period but others may consider it as part of the off-peak period).

Type of Day

Two types of day were considered: a middle weekday (Tuesday, Wednesday, and Thursday) and a weekend (Saturday and Sunday).

Functional Class

Functional class had one of seven categories (VDOT, 2021b): (1) interstates, (2) other freeways or expressways, (3) other principal arterial, (4) minor arterial, (5) major collector, (6) minor collector, or (7) others. The first four categories also include ramps (e.g., a ramp leading to an expressway is classified as Category 2).

Field Data Collection Method

A fourth site characteristic, which is applicable when occupancies are observed in the field rather than extracted from crash data, is the method of field data collection. The mean occupancies for sites where both the carousel method and the windshield method were available were compared, and the t-test for differences in means (Eq. 4) was used to determine if these means were significantly different.

RESULTS

Four sets of results were obtained:

1. importance of vehicle occupancy
2. methods for estimating vehicle occupancy
3. Virginia occupancies
4. variation in occupancy by day, time, and functional class.

Importance of Vehicle Occupancy

A spreadsheet was devised that enabled the research team to examine how changing the occupancy for individual projects could affect the final score. For instance, to surpass the next higher ranking project, Holland Road needed an occupancy increase of 0.19, increasing its score to 12.11 (Table 12). Although similar, Tables 3 and 12 illustrate that the importance of occupancy is relative: for Holland Road, either an occupancy decrease of 0.04 (Table 3) or an occupancy increase of 0.19 (Table 12) is needed to change how the project is ranked.

Table 12. Impact of Increasing Holland Road Project Occupancy on Project Rankings

Situation	Project	Increase in Person Throughput (1)	Delay Reduction in Person-Hours (2)	Congestion Score (3)	Other PM Scores (4)	Total Benefit Score (5)	Requested Cost in $10 Million (6)	SMART SCALE Score (7)
Holland occupancy unchanged[a]	7005	34.34	0.00	0.415	2.70	3.12	$0.26	12.09
	Holland (6690)	348.27	121.50	8.688	10.37	19.06	$1.68	11.35
Holland occupancy increases by 0.19[b]	Holland (6690)	399.57	139.39	9.968	10.37	20.34	$1.68	12.11

PM = performance measure.
[a] The data in Rows 1 and 2 match those available from the Commonwealth Transportation Board (2021a-d).
[b] The data in the last row were determined by the research team based on a presumed occupancy increase of 0.19, from 1.29 to 1.48, with the benefits computed as the ratio of 1.48/1.29.

Simulation Where Only Occupancy Varies

Holland Road demonstrates that the importance of occupancy varies by project: two projects with very different scores will not see even a large occupancy change affect their relative ranking—but such a change may be relevant for two similar scoring projects. A simulation was performed to determine, on average, how changes in occupancy could affect rankings. These changes do not reflect the actual accuracy of the occupancy estimates as the accuracy is not known. Rather, the changes indicate the importance of occupancy for project prioritization. The results of this simulation are given in Table 13.

Starting with a presumed baseline occupancy of 1.29, Row 2 in Table 13 shows the number of projects whose ranking changes if the initially even-ranked projects (e.g., Projects 2, 4, 6…38) saw their occupancy decrease by -0.05 to 1.24: only 2 of the 38 projects saw their rankings change. Row 2 also shows, however, that if one were instead to decrease the occupancy by -0.05 for the odd-ranked projects (e.g., projects initially ranked 1, 3, 5…37), then 4 of the 38 projects would see their rank shift.

Table 13. Change in Project Rankings as a Result of Changing Occupancy

Row	Deviation	Baseline Occupancy	Add Deviation to All Even-Ranked Projects	Add Deviation to All Odd-Ranked Projects
1	0.00	1.29	0	0
2	-0.05	1.24	2	4
3	0.05	1.34	4	2
4	-0.10	1.19	6	11
5	0.10	1.39	10	4
6	-0.15	1.14	8	12
7	0.15	1.44	14	7
8	-0.20	1.09	10	12
9	0.20	1.49	16	11
10	-0.25	1.04	10	12
11	0.25	1.54	16	11

Table 13 suggests that based on the Hampton Roads District, a change in occupancy of 0.10 from a particular baseline (Rows 4 and 5) could alter the rankings for 4 to 11 projects of the 38 total—that is, it could affect between 11% and 29% of all project rankings. If the occupancy were to deviate by 0.20 (Rows 8 and 9), then 11 to 16 projects, or 26% to 42%, could see their project ranking change. A deviation of 0.05 might affect at most (roughly) 10% of rankings. The importance of occupancy would be less for agencies that placed a lower emphasis on person throughput or person delay. Of note, 4 of the 38 projects were transit projects; changes in their occupancy as done here effectively resulted in them being treated as roadway projects in the simulation. However, the rankings of those 4 projects never changed in the simulation.

Simulation Where Other Factors Vary

All project factors—not just those related to occupancy—are subject to some uncertainty. The question arises: to what extent does uncertainty in occupancy compare with the uncertainty of these other factors? The research team is not aware of any work that has directly quantified uncertainty in these project scores.

However, there was an earlier data set that may be used to estimate this uncertainty in an indirect manner. This earlier data set included an attribute for certain lane widening projects from previous years and was known as an “alternative contingency percentage.” This attribute was the stated contingency cost divided by an adjusted base construction cost. Because the base construction cost included miscellaneous items, this alternative contingency percentage was larger than the stated contingency and was designed to represent fully any factors that could affect costs. Such alternative contingency percentages ranged from a low of 0% to a high of almost 57%, with a mean value of 18% and a standard deviation of 15% (P. Singla and J. Miller, unpublished data, 2020).

An experiment was devised that used the uncertainty from this earlier data set as follows. For each project, 45% of the score based on congestion mitigation (which is influenced by occupancy) was left unchanged. Recall that the remaining five areas of safety, accessibility, environment, economic development, and coordination constitute 55% of the score. A normal distribution was simulated where the distribution had a mean of 1.000 and a standard deviation of 15%. Then, a single value was drawn from this distribution and used to modify the 55% of the score that includes the non-congestion factors. For instance, for Holland Road, the value drawn from the distribution was 1.028—close to, but not exactly, the mean of 1.000. Column 4 of Table 12 shows that for Project 6690 (Holland Road), the non-congestion scores summed to 10.37. The simulation increased this score from 10.37 to 10.66 (e.g., 1.028*10.37)—a modest change of about 4%. This modest change, coupled with changes of scores for other projects, did not affect the ranking for Project 6690. However, Project 7005 saw its ranking rise—partly because its other non-congestion score rose by 15% and partly because the project that ranked higher (not shown in Table 12) saw its non-congestion score drop by 12%.

Table 14. Change in Project Rankings as a Result of Changing Occupancy and Other Factors

Row (1)	Deviation (2)	Baseline Occupancy (3)	Change in Project Rankings (Ground Truth Is the Original Rankings)		Change in Project Rankings (Ground Truth Is the Revised Rankings Based on Random Alterations to the Non-Congestion Factors)	
			Add Deviation to All Even-Ranked Projects (4)	Add Deviation to All Odd-Ranked Projects (5)	Add Deviation to All Even-Ranked Projects (6)	Add Deviation to All Odd-Ranked Projects (7)
1	0.00	1.29	23	23	0	0
2	-0.05	1.24	23	24	0	2
3	0.05	1.34	22	24	0	4
4	-0.10	1.19	21	24	2	4
5	0.10	1.39	24	25	2	7
6	-0.15	1.14	22	24	4	4
7	0.15	1.44	24	23	7	9
8	-0.20	1.09	20	23	6	10
9	0.20	1.49	24	24	7	9
10	-0.25	1.04	22	23	8	12
11	0.25	1.54	24	25	9	11

Table 14 shows three sets of simulation results.

1. *Change non-congestion factors only*. Row 1, Columns 4 and 5, show that 23 projects had a change in ranking when occupancy was held constant but other factors were allowed to vary. One may recall that when occupancy was changed but other factors were held constant, only 16 projects had a change in ranking (last row of Table 13). This result was not surprising: the impact of altering factors that account for 55% of a project's prioritization score is greater than that of altering a multiplier that affects part of the remaining 45% of the score.

2. *Change all factors simultaneously*. After the non-congestion factors in Row 1 were changed, changing the occupancy further, as shown in Rows 2 through 11 and Columns 4 and 5, had only a modest impact on project rankings: the number of affected project rankings remained between 20 and 25. In short, when the non-congestion factors have been altered, changes to occupancy have a modest effect.

3. *Redo Table 13 with new non-congestion factors*. Another inquiry was to presume that changed non-congestion factors gave new rankings and rerun the experiment shown in Table 13 where only the occupancy is changed. These results are shown in Columns 6 and 7 of Table 14. The results are not as dramatic as those shown in Table 13. For instance, a shift in occupancy of 0.10 altered project rankings for 2 to 7 of the 38 projects (rather than 4 to 11 of the projects in Table 13). The lesson is that the same change in occupancy (0.10) may have different impacts depending on the relative rankings of projects.

After the development of this example, the research team learned that Virginia has used rates based on the 2016 ACS, which, although focused on just the work trip (as opposed to all trip purposes), was viewed as advantageous by VDOT leadership because such an occupancy was more likely applicable for the peak period, which is a focus of the SMART SCALE evaluation (Buchanan, 2022). Virginia presently uses a single statewide rate of 1.2 for all projects (Jackson, 2022). However, examples of jurisdiction-specific rates based on ACS data are 1.10 (lowest, which is Chesterfield), 1.13 (Albemarle), 1.16 (Arlington), and 1.27 (highest, which is Stafford). In the Hampton Roads area, occupancies are given for seven jurisdictions (Chesapeake, Hampton, Newport News, Norfolk, Portsmouth, Suffolk, and Virginia Beach) and range from 1.12 to 1.20 with a mean of 1.14 (if occupancies from those seven jurisdictions are weighted equally). Occupancies from other jurisdictions in the Hampton Roads District, such as York County or James City County, were listed as not available.

Repetition of the simulations of Table 13 with the Hampton Roads District means that a baseline occupancy of 1.14 (rather than a baseline occupancy of 1.29) gave results that were similar but with occupancy having a slightly greater impact due to the nature of the simulation: a change in occupancy of 0.05 had a larger impact on a smaller baseline occupancy than a larger baseline occupancy. With a deviation of 0.05, Table 13 showed that 2 to 4 projects could see their ranks shift, whereas a new analysis with a lower occupancy showed that from 2 to 6 projects could see their ranks shift. A deviation of 0.10 had shifted ranks for 4 to 11 projects in Table 13; the new analysis caused a shift of 4 to 12 projects. With a mean occupancy of 1.14, the impact of a negative deviation of 0.15 could not be examined. However, a positive deviation of 0.15 could shift from 7 to 14 projects (Table 13), and the new analysis could shift rankings for 9 to 16 projects. No change was observed for a positive deviation of 0.20: from 11 to 16 projects could see their rank shift. In short, the results of Table 13 appear generally to convey the sensitivity of project prioritization to changes in occupancy for this particular case study.

Comparison If Traffic Assignment Varies

One may return to the situation described in Table 13 and, for simplicity, presume a link with 1,200 vehicles and an occupancy of 1.25. As shown in Table 15, a change of 0.05 in occupancy corresponds to a reduction in person throughput of 60. Similarly, a change in the link vehicle volume of 48 also results in a 60-person throughput reduction. Because person throughput is simply the product of volume and occupancy, Table 15 shows that a 4% change in either quantity yields a 4% reduction in person throughput.

For readers who would like a simple heuristic rule without the complications of Table 15 and a Virginia-specific data set, they may note that average peak-hour occupancies when weighted by city or county equally in the Hampton Roads District based on ACS data were around 1.14 (Buchanan, 2022). The fact that this quantity is larger than 1.0 means that the impact of a change in occupancy alone will be slightly less than the impact of a change in the link volume. A simple observation, therefore, is that at present for Virginia, with this average occupancy of 1.14, a change in occupancy of 0.05 corresponds to a change in link volume of 4.4%.

Table 15. Relating the Impact of a Change in Occupancy to an Equivalent Change in Link Volume

Scenario	Link Volume	Occupancy	Person Throughput (% Change From Base)
Base case	1200	1.25	1,500 (0% as this is the base)
Alter occupancy	1200	1.20	1,440 (4%)
Alter link volume	1152	1.25	1,440 (4%)

Methods for Estimating Vehicle Occupancy

Existing Practices

The survey was distributed to district planners in each of VDOT's nine districts via Google Forms, and the survey of the other 49 state DOTs was emailed to staff affiliated with traffic monitoring programs. The Appendix summarizes the questions posed in the two survey instruments.

Virginia

Responses were received from eight of the nine VDOT districts: Culpeper, Fredericksburg, Staunton, Bristol, Lynchburg, Richmond, Northern Virginia, and Hampton Roads. Of those, only two district respondents provide AVO factors to VDOT's Central Office for MAP-21 performance measure reporting: Northern Virginia and Hampton Roads. Those districts are largely focused on interstate HOV facilities (I-64/I-264 in Hampton Roads and I-95/I-395, including the express lanes, in Northern Virginia.) The Hampton Roads District collects those data twice per year, and the Northern Virginia District collects them every other year; both districts use conventional methods for the data collection (e.g., field personnel). The Northern Virginia District's occupancies (e.g., 1.72 and 1.47 on I-95 at Newington in 2014 and 2016, respectively) tended to be higher than those for the Hampton Roads District (e.g., 1.21 and 1.31 on HOV sections of I-64 and I-264 in 2020 and 2018, respectively).

Except for the Northern Virginia District, no district has collected vehicle occupancy data for reasons other than federal requirements: that district has conducted corridor studies to provide technical assistance to an MPO. However, four of the eight responding districts (Bristol, Fredericksburg, Lynchburg, and Northern Virginia) indicated ways in which vehicle occupancy data could be useful. Occupancy data could support evaluating the effectiveness of a new congestion management program (three districts), validating travel demand modeling results (two districts), forecasting trends (two districts), conducting energy analyses (two districts), and conducting crash analyses (one district).

Current Approaches in Other States

Of the 49 surveys sent to other state DOTs, 20 responses were received, for a response rate of 41%. The Florida DOT had two respondents, which is why Table 16 shows two titles for that DOT.

Table 16. Responding DOTs and Respondent Titles

DOT	Respondent Title
Alaska	Transportation Programs Data Manager
Illinois	Data Management Unit Chief
Indiana	Traffic Statistics Supervisor
Iowa	Traffic Collection and Processing Coordinator
Colorado	N/P
Nebraska	Traffic Data Collection & Analysis Manager
Florida	HPMS Coordinator
	Manager, Performance & Trends
Texas	HPMS Coordinator
Michigan	Data Collection and Reporting Section Manager
Pennsylvania	Transportation Planning Supervisor
Georgia	Statistics Management Group Leader
South Carolina	Chief System Performance Engineer
Delaware	HPMS Program
Massachusetts	N/P
Vermont	Policy, Planning & Research Bureau Director
Montana	N/P
Wyoming	Policy & Planning Analyst
Tennessee	HPMS Coordinator
Rhode Island	Senior Civil Engineer/HPMS Coordinator
New Jersey	Section Chief, Planning

N/P = not provided; HPMS = Highway Performance Monitoring System.

Nine states report AVO factors to FHWA's HPMS portal: Florida, Idaho, Montana, Nebraska, New Jersey, Rhode Island, Tennessee, Texas, and Wyoming, and these states use the default FHWA-provided factors derived from the NHTS. As is the case with Virginia, four of these states (Florida, Montana, New Jersey, and Texas) process HPMS submittals through RITIS' National Performance Management Research Data Set Analytics dashboard. The other nine states do not report factors, and one state was unsure.

Four states (Michigan, Montana, South Carolina, and Vermont) have collected vehicle occupancy data, with all four including a reason as travel demand models. Vermont also noted that occupancy data are useful for "typical planning studies," and Montana noted tracking of occupancy trends specifically. Three of these states use surveys. South Carolina and Vermont use the NHTS (where states can purchase additional NHTS add-on samples that allow them to estimate occupancy for a smaller geographic area than an entire state) [FHWA, undated]). Although all three states use federal State Planning and Research funds for the survey costs, Vermont's statewide transportation agency shares the costs with Vermont's only MPO and the University of Vermont. Michigan uses a household travel survey. By contrast, only Montana uses field data collection: on a quarterly basis, DOT personnel collect occupancy data for 2 hours to sample each roadway functional class.

Suggestions From Other States

For the same survey, eight states provided information about ways to obtain vehicle occupancy in the future. New Jersey, Rhode Island, and South Carolina suggested survey-based approaches, although New Jersey noted that the Census Transportation Planning Package had not been useful for obtaining occupancies and Rhode Island noted that the cost was prohibitive.

Colorado and Iowa noted the possibility of field approaches: the former noted a 2016 draft vehicle occupancy study (Colorado State University [2016], provided by Livecchi [2021]), and the latter noted the use of a seat belt survey, which could also provide occupancy information (Allen et al., 2021). Although noting the use of NHTS add-ons in the past, Florida noted that they are considering using an FHWA method based on crash data, which the research team thinks refers to the work by Krile et al. (2019). Two states suggested new approaches. Indiana mentioned StreetLight and INRIX, whereas Montana mentioned StreetLight and RITIS as well as noting more generally "data mining companies"). Indiana also noted the possibility of using Bluetooth detectors and a "Miovision type video camera set at a low height to record video to be reviewed manually to see if it is possible to determine how many people are in a vehicle." A ninth state not mentioned here—Alaska—indicated an interest in collecting vehicle occupancy data.

Potential Future Practices

The research team explored four other technology-based solutions for detecting occupancy.

1. StreetLight InSight (to which VDOT subscribes)

2. Wejo data (where a 2-week sample data set was made available to VTRC staff for a limited period of time)

3. Bluetooth detectors

4. a portable vehicle occupant detection system.

The team field-tested the first two technologies. The team interviewed an expert regarding the third technology and then conducted a brief test to confirm the expert's assessment. The team met with a company representative for the fourth technology (in May 2021 and again in May 2022).

StreetLight InSight

As suggested by Montana and Indiana representatives, StreetLight InSight was examined. A single zone was created on I-66 Eastbound (Figure 6, left), with the zone being one direction to be certain only eastbound traffic was captured. This zone was chosen because the research team believed it to be highly probable that auto occupancies would be higher during times of HOT lane use and lower at other times when vehicles with any occupancy could legally use the lanes. Then, a similar zone was created in the westbound direction (Figure 6, right).

Based on avoidance of Thanksgiving week, the week with New Year's Day, and the intervening weeks, time periods were selected that would capture times when the HOT lanes were in operation (5:30 AM-9:30 AM in the eastbound direction for 2018-2021) and times when HOT lanes were not in operation (all other times), with the first and last half-hour of each period excluded from the analysis such that the HOT lane times were 6 AM-9 AM. For the westbound direction, HOT lanes are in operation 3 PM-7 PM).

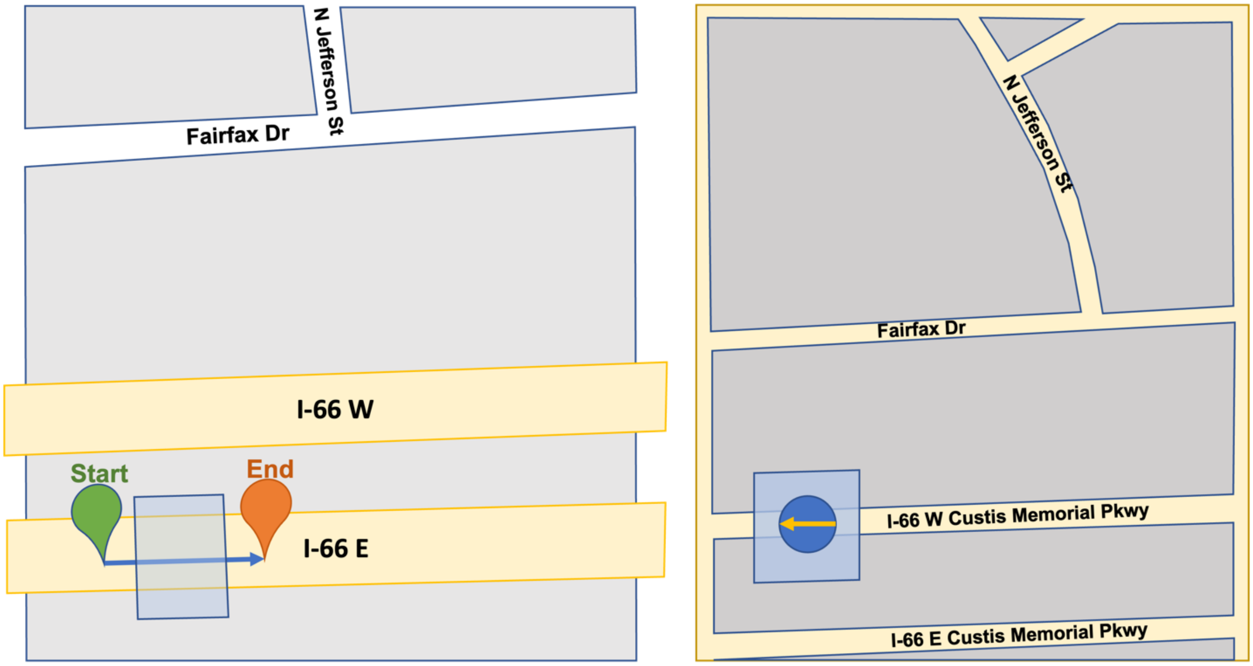

Figure 6. Representation of Zone YX_I-66 EBJefferson (Pass-Through, Unidirectional, Which Is HOT M-F in the Eastbound Direction for 5:30-9:30 AM, and Representation of Zone YX_I66WB_Jefferson (Pass-Through, Unidirectional, Which Is HOT M-F in the Westbound Direction for 3:00 PM-7:00 PM). Both zones are on I-66 in the vicinity of North Jefferson Street.

Because it was not feasible to use half-hour increments, the research team focused on the 4 PM-6 PM window. These analyses were run 18 times: twice per direction; once for each year of 2018, 2019, and 2021; and then once with each of the three output variables. The results are shown in Table 17.

Table 17. Sample Results From Two Locations (2 Years of Data)

Dir.	Station	Date	Time	Days	Volume[a]	Device Trips[b]	SL Sample / SL Volume[c]
EB	GP	Jan. 8-Nov. 16, 2018	10 AM-7 PM	225	28,863	82,870	2.871
	HOT		6 AM-9 AM		14,744	42,881	2.908
	GP	Jan. 7-Nov. 22, 2019	10 AM-7 PM	230	33,734	287,306	8.517
	HOT		6 AM-9 AM		21,684	184,836	8.524
	GP	June 7-Sept 15, 2021	10 AM-7 PM	73	34,556	52,474	1.519
	HOT		6 AM-9 AM		9,523	14,444	1.517
WB	GP	Jan. 8-Nov. 16, 2018	6 AM-2 PM	225	23,671	66,837	2.824
	HOT		4 PM-6 PM		11,741	33,062	2.816
	GP	Jan. 7- Nov. 22, 2019	6 AM-2 PM	230	26,320	227,451	8.642
	HOT		4 PM-6 PM		15,410	133,304	8.650
	GP	June 7-Sept 15, 2021	6 AM-2 PM	73	22,987	31,828	1.385
	HOT		4 PM-6 PM		9,380	12,995	1.385

Dir. = direction; WB = westbound; EB = eastbound; GP = general purpose lanes; HOT = high occupancy toll lanes.
[a] Formal name is "StreetLight Volume."
[b] Formal name is "StreetLight Sample Trip Counts (Device Trips)."
[c] This is the ratio of StreetLight Volume to StreetLight Sample Trip Counts (Device Trips).

The results appear to confirm that the ratio of device trips to volume does not provide an indication of occupancy. Clear changes were evident by year; for example, the ratio of device trips to volume was highest for 2019 and lowest for 2021. It is the case that the year with the smallest number of days (2021) had the smallest number of device trips (which was to be expected since more device trips would generally be acquired over a longer period). However, the fact that 2018 and 2019 had similar period lengths and vastly different numbers of device trips confirmed the views of staff who noted that changes in device trips over time are likely a product of different numbers of suppliers entering the market. Crucially, there was not a consistent difference between these ratios for HOT and SOV even in the same time period; for instance, prior to the COVID 19 pandemic, the HOT ratio (of device trips to volume) was higher in the eastbound direction but lower in the westbound direction. Given that HOT lanes should have higher occupancies than GP lanes, it appears likely that this platform, at this point in time, cannot be used to determine auto occupancy.

The results of this analysis were shared with StreetLight InSight staff who reviewed them (Rea, 2021), and then the results were shared with the StreetLight InSight user community via the Slack platform on December 2, 2021.

It should be noted that this study cannot prove that the HOT lanes had higher occupancy than the GP lanes because exact occupancies are not available. However, previous work (McCall and Gao, 2019) suggested that HOT lanes are likely to have higher occupancies than GP lanes. For April 23 and 24, 2019, for the 6 AM-9 AM period, I-66 Eastbound (when I-66 functioned as a HOT facility) had a considerably higher estimated occupancy of 1.78 compared to I-66 Westbound (when I-66 functioned as a GP facility) with an estimated occupancy of 1.11. The occupancy is only "estimated" because the data set included SOVs, vehicles with two occupants, and then vehicles with 3+ occupants, which the research team presumed to have an occupancy of 3.2.

Experiments With Wejo Data

Although Wejo data were not mentioned explicitly by any interviewees, the Montana representative had suggested considering data mining companies. The research team used a 2-week sample provided by Wejo for an area roughly equivalent to Henrico County to develop some draft estimates of occupancy. This process also led the research team to develop questions concerning the definitions of data elements that were used to estimate occupancy. Wejo staff (Lee-Warner, 2022) responded to those questions. These answers were then used by the research team to revise these occupancy estimates. The Wejo data set does not provide occupancy for the entire vehicle but rather provides occupancies for the front seat. Since most vehicles had an occupancy of 1 or 2, however, the research team sought to determine if this information could provide realistic vehicle occupancies.

The most promising avenue of exploration appeared to be using a variable known as "seat occupancy status" that is applied to the seat identifier of "front passenger." Possible values for this variable are unoccupied, occupied, or probably occupied. These data suggest an occupancy of either 1.795 or 1.503 (using data points) or 1.799 or 1.448 (using journeys), with the higher number including the two values of "occupied" and "probably occupied" and the lower number including only the "occupied" status.

Whether one uses data points or journeys, a key question to answer is whether it is correct to assume that category of "probably occupied" should be assumed to simply mean "occupied." In response to this question, Wejo staff noted that there were few false positives. Application of this reasoning to the Henrico data set, such that the "probably occupied" was equated to "occupied," means that the occupancy is the 1.795 figure noted previously. Wejo staff also noted that the "penetration rate" for both journeys and attributes will generally be similar. Because the back seat is not examined in this approach, it should be noted that the full vehicle occupancy is not being estimated.

The only locational data associated with the 2-week data set extracted for this exercise were zip codes. However, Wejo staff also pointed out that for individual datapoints, the latitude and longitude could be obtained, which could then be used to associate those datapoints with specific roadway links.

Examination of other approaches, such as using the "seat occupancy status" with the seat identifier of "driver" or using the "seatbelt status" variable with the seat identifier of "passenger," was not as promising. For example, when the data are restricted solely to those reflecting the seat identifier of "front passenger," there are 7,954 journeys where the front passenger seat is "occupied." When the numbers of journeys where the front passenger is "latched" or "unlatched" are summed, a very different number of 10,758 journeys is obtained. The reason is that different actions, such as sitting in a seat, opening a door, or putting on a seat belt, are each a "state change" (Lee-Warner, 2022) that may occur at a different time and thus may yield different sample sizes).

Bluetooth Detectors

The survey respondent from Indiana had mentioned the possibility of exploring this technology to determine vehicle occupancy. However, the results of the field test generally confirmed an explanation given to the research team by a veteran user of these devices: The Bluetooth detectors generally capture only devices that are operating in Bluetooth discovery mode (M. Fontaine, personal communication, April 21, 2022). Of 16 runs where the research team intended to have the Bluetooth devices on but not in discovery mode, 15 runs were missed. In 1 case, a device was picked up; however, it is possible that not enough time had elapsed since the device had been turned on for it to move out of discovery mode. For the 22 instances where the research team intended to set the device to discovery mode, the device was identified by the detector 16 times (about 70% of the time). There were two instances where a cell phone possessed by the research team was detected, but at a time when the vehicles were not passing by the detector; one possible explanation is that the detector somehow picked up a device when it was sitting in a parked vehicle roughly 180 feet from the detector.

This experiment confirmed a further explanation provided by the same veteran user: the reason for the low percentages of devices detected (e.g., 2% to 6%) is that the detectors work only when the device is in discovery mode. The experiments also suggested that even with a device being deliberately turned on and off and the zone of detection quickly entered, there is not complete identification of Bluetooth devices.

Use of a Portable Vehicle Occupancy System—InVision

Information about one portable system was provided in a meeting between VDOT and InVision staff (Karim Ali, personal communication, May 3, 2022). If a state wants to obtain the iVOD system, the state will purchase it not from InVision but rather from a systems integrator (or a subcontractor) who would build the system (using off-the-shelf components). There is some training required to use the system: generally, two to four staff who are trained on how to install and calibrate the system are needed. That said, the training is not onerous; for instance, the camera does not have to be positioned perfectly for the system to work. The exact dollar costs were not discussed in the meeting, but one observation was that this system is 60% lower than the cost of competing systems (which are not as accurate). For a future pilot study, depending on VDOT's needs, one possibility would be to have the system installed and then get access to the data for 1 week; the cost is estimated to be $30,000 to $50,000.

Virginia Occupancies

Occupancy Directly From Crashes

Table 18 gives the 2019 occupancy and number of vehicles providing this occupancy by time period for localities in the Hampton Roads District for the fall and spring periods as defined in the "Methods" section.

Table 18. 2019 Average Vehicle Occupancy by Jurisdiction in the Hampton Roads District (Passenger Vehicles Only)

Locality	Average Vehicle Occupancy				Sample Size[a]			
	24-Hour	AM Peak	PM Peak	Off-Peak	24-Hour	AM Peak	PM Peak	Off-Peak
Chesapeake	1.19	1.15	1.16	1.21	4,658	538	1,110	1,852
Franklin	1.50	1.67	1.39	1.44	141	9	33	45
Hampton	1.23	1.20	1.22	1.23	6,192	597	1,211	2,878
Isle of Wight	1.17	1.14	1.21	1.17	668	70	137	293
James City	1.23	1.14	1.23	1.25	1,441	120	288	686
Newport News	1.13	1.08	1.12	1.15	6,772	613	1,343	3,160
Norfolk	1.21	1.13	1.25	1.23	8,261	981	1,379	3,739
Poquoson	1.18	1.33	1.19	1.13	110	6	26	61
Portsmouth	1.22	1.11	1.26	1.23	2,395	227	439	1,183
Smithfield	1.21	1.38	1.00	1.32	152	13	25	65
Southampton	1.32	1.44	1.32	1.27	238	25	34	118
Suffolk	1.16	1.09	1.18	1.15	2,812	296	507	1,273
Surry	1.19	1.00	1.22	1.19	125	11	23	52
Virginia Beach	1.20	1.14	1.21	1.20	11,535	1,321	2,245	5,165
Williamsburg	1.27	1.00	1.34	1.27	395	20	62	192
York	1.32	1.32	1.31	1.36	2,085	222	403	962
Hampton Roads District	1.21	1.15	1.21	1.22	49,913	5,225	9,554	22,746

[a] AM peak is 7 AM-9 AM; PM peak is 4 PM-6 PM; and off-peak is 10 AM-3 PM and 8 PM-6 AM and includes only Tuesdays, Wednesdays, and Thursdays during the fall and spring periods. The 24-hour sample size includes all times on weekdays and all times on weekends but is similarly restricted to fall and spring.

At a glance, there is a substantial range in these occupancies: over a 24-hour period, AVO ranged from 1.13 (Newport News) to 1.50 (Franklin). This range was bigger for specific time periods, such as 1.00 (Williamsburg) to 1.67 (Franklin) during the AM peak or 1.00 (Smithfield) to 1.39 (Franklin) for the PM peak. However, the sample size by locality varied greatly: Norfolk's AM peak occupancy of 1.13 was based on a sample size more than 400 times larger than that of Williamsburg (occupancy of 1.00). Table 18 also shows the sample size—that is, the number of vehicles—which is larger than the number of crashes.

The 95% confidence interval for the mean accounts for this sample size variation. Equation 6 indicates how to determine the 95% confidence interval (Hogg and Ledolter, 1992). Table 19 shows that some of the variation in the point estimates of AVO from Table 18 were attributable to small sample sizes. For instance, at a 95% confidence level, the true mean occupancy for Franklin during the AM peak could be anywhere between 1.20 and 2.13—information not evident from examination of Table 18.

$$\text{95\% Confidence interval} = \text{Mean} \pm 1.96 \times \text{Standard deviation} \div \sqrt{\text{Sample size}} \qquad \text{[Eq. 6]}$$

When only those localities with a larger sample size—say 200 vehicles or more—were considered, variation by jurisdiction shrank substantially. For instance, the AM peak occupancy based on Table 18 ranges from 1.08 (Newport News) to 1.32 (York).

Table 19. Confidence Intervals for 2019 Average Vehicle Occupancy (Passenger Vehicles Only)

Locality	24-Hour	AM Peak[a]	PM Peak[a]	Off-Peak[a]
Chesapeake	1.18-1.21	1.11-1.19	1.13-1.19	1.19-1.24
Franklin	1.37-1.64	1.20-2.13	1.13-1.66	1.22-1.67
Hampton	1.22-1.25	1.15-1.25	1.18-1.25	1.21-1.26
Isle of Wight	1.13-1.20	1.01-1.28	1.11-1.31	1.12-1.22
James City	1.20-1.27	1.07-1.22	1.15-1.30	1.20-1.30
Newport News	1.12-1.14	1.05-1.11	1.09-1.14	1.13-1.17
Norfolk	1.20-1.22	1.10-1.16	1.22-1.29	1.21-1.25
Poquoson	1.08-1.28	1.00-1.99[b]	1.00-1.46[b]	1.01-1.25
Portsmouth	1.20-1.25	1.06-1.16	1.20-1.32	1.19-1.26
Smithfield	1.13-1.29	1.03-1.74	1.00-1.00	1.18-1.47
Southampton	1.23-1.40	1.10-1.78	1.09-1.55	1.15-1.39
Suffolk	1.14-1.18	1.05-1.13	1.13-1.22	1.12-1.18
Surry	1.10-1.28	1.00-1.00[c]	1.05-1.39	1.05-1.34
Virginia Beach	1.18-1.21	1.11-1.17	1.19-1.24	1.19-1.22
Williamsburg	1.21-1.33	1.00-1.00	1.15-1.53	1.18-1.35
York	1.29-1.36	1.23-1.42	1.24-1.38[c]	1.31-1.41
Hampton Roads District	1.21-1.22	1.14-1.17	1.20-1.22	1.22-1.23

[a] AM peak is 7 AM-9 AM; PM peak is 4 PM-6 PM; and off-peak is 10 AM-3 PM and 8 PM-6 AM and includes only Tuesdays, Wednesdays, and Thursdays during the fall and spring periods. The 24-hour sample size includes all times on weekdays and all times on weekends but is similarly restricted to fall and spring.
[b] The lower bound computed via Equation 6 was less than 1.00, and thus 1.00 was used as the lower bound.
[c] All vehicles in the sample had an occupancy of 1, which yields a zero width confidence interval.

Occupancy With Type 1 Bias Correction

Type 1 bias correction is suitable at the city or county level, where one first assesses potential bias and second corrects this bias.

Potential Bias Based on the Eta-Squared Value

Table 20 presents the results in descending order of sample size, from 49,914 vehicles (entire Hampton Roads District) to 110 (Poquoson). Generally, as the sample size shrinks, more variables become associated with occupancy: the largest locality (Virginia Beach) had just one such variable (crash severity), whereas Poquoson had all six variables associated with occupancy.

The results in Table 20 cannot prove that these variables influenced the probability of a crash as it could be the case that localities truly have different occupancies or that the crash sample size influences the occupancy. However, they are an indication of a possible association. For instance, the research team hypothesized that there is a nonzero probability of a crash involving an occupancy level above 1. However, the AM peak occupancy for Surry (1.00 in Table 18 based on 11 vehicles) was quite small and might reflect some amount of bias.

Table 20. Eta-Squared Values Between Occupancy and Other Variables (2019 24-Hour Crash Data)

Jurisdiction	No. of Vehicles	Eta-Squared					
		Crash Severity	Collision Type	Driver Age Group	Driver Gender	Functional Class	Vehicle Year
Hampton Roads District	49,913	Medium	Negligible	Negligible	Negligible	Negligible	Negligible
Virginia Beach	11,535	Small	Negligible	Negligible	Negligible	Negligible	Negligible
Norfolk	8,261	Negligible	Negligible	Negligible	Negligible	Negligible	Negligible
Newport News	6,772	Small	Negligible	Negligible	Negligible	Small	Negligible
Hampton	6,192	Small	Negligible	Negligible	Small	Negligible	Negligible
Chesapeake	4,658	Small	Negligible	Negligible	Negligible	Negligible	Negligible
Suffolk	2,812	Small	Negligible	Negligible	Negligible	Negligible	Negligible
Portsmouth	2,395	Small	Negligible	Negligible	Negligible	Negligible	Negligible
York	2,085	Small	Negligible	Negligible	Negligible	Small	Negligible
James City	1,441	Negligible	Negligible	Negligible	Negligible	Negligible	Negligible
Isle of Wight	668	Medium	Small	Negligible	Small	Negligible	Negligible
Williamsburg	395	Small	Small	Negligible	Small	Negligible	Small
Southampton	238	Small	Small	Small	Small	Small	Negligible
Smithfield	152	Medium	Negligible	Negligible	Small	Negligible	Negligible
Franklin	141	Small	Medium	Negligible	Medium	Small	Small
Surry	125	Medium	Large	Negligible	Small	Negligible	Small
Poquoson	110	Small	Small	Small	Small	Medium	Medium

Eta-squared < 0.01, the association is negligible; eta-squared < 0.06, the association is small; eta-squared <0.14, the association is medium; eta-squared >= 0.14, the association is large.

One way to understand the levels of association in Table 20 is to compare them with changes in AVO shown in Tables 21 and 22. Crash severity shows a medium association with occupancy, and this is evident from the 95% confidence intervals in that the upper bound of PDO crashes (1.16) is more than 0.15 units below the lower bound of severe injury crashes (1.33). Conceptually, this result was supported by Żuchowski (2012), who noted that the risk of severe head and chest injury in the rear seats is higher than in a driver's seat, such that occupancy and injury risk share an association.

By contrast, a negligible association was shown for all other variables in Table 20 (at the Hampton Roads District level). Table 22 shows that for four of these (collision type, vehicle year, driver gender, and driver age), the 24-hour AVO varied by no more than 0.04 for a given factor. For functional class, which also had a negligible impact in Table 20, the variation can be as large as 0.10 in occupancy, from a high of 1.26 for interstates to a low of 1.16 for "All Others," which could include local streets. Thus, the eta-squared indication of "negligible" is not necessarily a guarantee of no association between occupancy and a given factor; however, it is a sign that a factor has less of an impact on occupancy than would be the case for an association of small or medium.

Table 21. 24-Hour AVO by Crash Severity and Its Confidence Interval

Crash Severity	95% Confidence Interval	Sample Size
K. Fatal Injury	1.32-1.59	217
A. Severe Injury	1.33-1.39	2,241
B. Visible Injury	1.28-1.31	10,096
C. Nonvisible Injury	1.24-1.27	7,666
PDO. Property Damage Only	1.15-1.16	29,693

AVO = average vehicle occupancy.

Table 22. 24-Hour AVO for Each Category in 2019 Hampton Roads District Crashes

Variable	24-Hour AVO						
Functional Class	Interstate and Ramp	Major Collector	Minor Arterial	Minor Collector	Other Principal Arterial	Other Freeways and Expressways	All Others
	1.26	1.20	1.21	1.19	1.19	1.17	1.16
Crash Severity	K	A	B	C	PDO		
	1.46	1.36	1.30	1.25	1.16		
Collision Type	Rear End	Angle	Head On	Fixed Object Off Road	All Others		
	1.21	1.21	1.21	1.24	1.20		
Vehicle Year	Before 2005	2005-2009	2010-2014	2015 and later			
	1.21	1.18	1.22	1.21			
Driver Gender	Female	Male					
	1.23	1.21					
Driver Age	<=25	>25					
	1.21	1.21					

PDO = property damage only.

Correction of Bias for Localities

Table 23 compares the corrected and uncorrected AVO by jurisdiction in the Hampton Roads District. For the 24-hour AVO, the eta-squared results in Table 20 show that this bias correction was not applicable for Norfolk and James City because all variables showed a negligible correlation with occupancy for those two jurisdictions. Because Chesapeake, Hampton, Newport News, Portsmouth, Suffolk, Virginia Beach, and York County do not have any occupancies where there are zero vehicles, Equation 6 is not applicable. However, the smaller jurisdictions showed differences between AVO and bias-corrected AVO, with these differences tending to increase as the sample size dropped. For instance, for 24-hour occupancy, bias correction altered Southampton's AVO by 0.01, from 1.32 to 1.33. Yet for Surry, which had less than one-half the number of vehicles, bias correction altered the AVO by 0.05, from 1.19 to 1.24.

By time period, the impacts of Type 1 bias correction tended to be larger for cases where there was a small number of vehicles. For instance, during the AM peak, bias correction had the greatest impacts for Poquoson, Williamsburg, and Surry, altering AVO by amounts of 0.08, 0.12, and 0.15, respectively—and the number of vehicles in the sample for each jurisdiction was between 6 and 20. By contrast, Suffolk—with almost 300 AM peak period vehicles—saw bias correction had an influence of just 0.02. During the PM peak period, Smithfield (with just 25 vehicles) saw bias correction change occupancy by 0.16; in contrast, Isle of Wight (with 137 vehicles) saw bias correction change occupancy by just 0.02. However, small sample size was not a perfect predictor of the impact of bias correction: notably, during the AM period, bias correction affected Franklin's AVO by only 0.01—yet Franklin had just nine vehicles during that period.

Occupancy With Type 2 Bias Correction

Because of the smaller sample size that is available when collecting corridor-specific occupancies rather than district-wide occupancies, the results of the Type 2 method of bias correction are more detailed than those of Type 1 and were considered in five categories:

1. detection of candidate variables with the Apriori method
2. detection of candidate variables with the eta-squared method
3. development of a smaller list of candidate variables
4. development of a bias correction model
5. evaluation of the model.

Detection of Candidate Variables With the Apriori Method

Table 24 shows the results of the Apriori test, which tested many rules for occupancies of 2 to7 but found only two that attained a confidence of at least 0.30: (1) for 2-occupant vehicles, the driver gender is more likely to be male since lift is greater than 1 and leverage is greater than 0; and (2) for 2-occupant vehicles, crashes are less likely to happen during daylight since lift is less than 1 and leverage is less than 0.

Table 23. Summary of 2019 Occupancy With Type 1 Bias Correction

Locality	24-Hour[a]		AM Peak[a]		PM Peak[a]		Off-Peak[a]	
	Original	Corrected	Original	Corrected	Original	Corrected	Original	Corrected
Chesapeake	1.19	1.19	1.15	1.15	1.16	1.17	1.21	1.21
Franklin	1.50	1.52	1.67	1.68	1.39	1.45	1.44	1.46
Hampton	1.23	1.23	1.20	1.20	1.22	1.22	1.23	1.23
Isle of Wight	1.17	1.18	1.14	1.16	1.21	1.23	1.17	1.19
James City	1.23	1.23	1.14	1.18	1.23	1.23	1.25	1.25
Newport News	1.13	1.13	1.08	1.08	1.12	1.10	1.15	1.15
Norfolk	1.21	1.21	1.13	1.14	1.25	1.25	1.23	1.23
Poquoson	1.18	1.20	1.33	1.41	1.19	1.24	1.13	1.19
Portsmouth	1.22	1.22	1.11	1.12	1.26	1.27	1.23	1.23
Smithfield	1.21	1.23	1.38	1.41	1.00	1.16	1.32	1.34
Southampton	1.32	1.33	1.44	1.47	1.32	1.34	1.27	1.29
Suffolk	1.16	1.16	1.09	1.11	1.18	1.18	1.15	1.16
Surry	1.19	1.24	1.00	1.15	1.22	1.31	1.19	1.25
Virginia Beach	1.20	1.19	1.14	1.14	1.21	1.21	1.20	1.21
Williamsburg	1.27	1.29	1.00	1.12	1.34	1.36	1.27	1.29
York	1.32	1.32	1.32	1.33	1.31	1.31	1.36	1.36
Hampton Roads District	1.21	N/A[b]	1.15	N/A[b]	1.21	N/A[b]	1.22	N/A[b]

[a] AM peak is 7 AM-9 AM; PM peak is 4 PM-6 PM; and off-peak is 10 AM-3 PM and 8 PM-6 AM and includes only Tuesdays, Wednesdays, and Thursdays during the fall and spring periods. The 24-hour sample size includes all times on weekdays and all times on weekends but is similarly restricted to fall and spring.
[b] N/A = not applicable, as the occupancy distribution of the entire district was used to correct the occupancy distribution for small localities in Type 1 bias correction.

Table 24. Apriori Test Results in 2019 Hampton Roads District Crashes (24 Hours)

Rule No.	Antecedent	Consequents	Support	Confidence	Lift	Leverage	Conviction
1	Occupancy = 2	Driver Gender (Male)	0.0528	0.5114	1.0118	0.0006	1.0122
2		Light Condition (2. Daylight)	0.0717	0.6949	0.9796	-0.0015	0.9527

No rules were found for antecedents of occupancy = 3, 4, 5, 6, or 7.

Detection of Candidate Variables With the Eta-Squared Method

Table 25 shows the eta-squared results by time period and by jurisdiction, but only for situations where there were at least 1,000 vehicles. This use of 1,000 helps reduce the number of candidate variables that are evaluated. Vehicle occupancy is related with crash severity for all the time periods and is the most critical variable. The other variables have limited applicability; for instance, functional class was associated with vehicle occupancy for just two cases: Virginia Beach in the AM peak period, and Newport News in the off-peak period. Driver gender and collision type similarly showed an association for just two cases: collision type and vehicle age each showed just one case.

Table 25. Eta-Squared Results Between Occupancy and Explanatory Variables

Time Period[a]	Jurisdiction	Vehicle No. (Descending)	Eta-Squared: Crash Severity	Collision Type	Driver Age Group	Driver Gender	Functional Class	Vehicle Year
AM Peak	Hampton Roads District	5,225	Small	Negligible	Negligible	Negligible	Negligible	Small
	Virginia Beach	1,321	Small	Negligible	Negligible	Negligible	Small	Negligible
PM Peak	Hampton Roads District	9,554	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Virginia Beach	2,245	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Norfolk	1,379	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Newport News	1,343	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Hampton	1,211	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Chesapeake	1,110	Small	Negligible	Negligible	Negligible	Negligible	Negligible
Off-Peak	Hampton Roads District	22,746	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Virginia Beach	5,165	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Norfolk	3,739	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Newport News	3,160	Small	Small	Negligible	Negligible	Small	Negligible
	Hampton	2,878	Small	Negligible	Negligible	Small	Negligible	Negligible
	Chesapeake	1,852	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Suffolk	1,273	Small	Negligible	Negligible	Negligible	Negligible	Negligible
	Portsmouth	1,183	Small	Negligible	Negligible	Small	Negligible	Negligible

Eta-squared < 0.01, the association is negligible; eta-squared < 0.06, the association is small; eta-squared < 0.14, the association is medium; eta-squared >= 0.14, the association is large; those cities with fewer than 1,000 crashes were excluded from the table.
[a] AM peak is 7 AM-9 AM; PM peak is 4 PM-6 PM; and off-peak is 10 AM-3 PM and 8 PM-6 AM and includes only Tuesdays, Wednesdays, and Thursdays during the fall and spring periods. The 24-hour sample size includes all times on weekdays and all times on weekends but is similarly restricted to fall and spring.

Smaller List of Candidate Variables

These results show that crash severity should be included in the model (Table 26). Driver gender, light condition, functional class, and collision type should also be included when the model is built if they are statistically significant; otherwise, they can be removed.

Table 26. Summary of Variables Considered in Bias Correction Model Development

Variable	Interpretation (Test)[a]	Decision (Reason)
Crash severity	Vehicle occupancy is associated with crash severity for all 26 cases. (eta-squared)	Must include in the model as at least 1 test showed that this variable is consistently related to occupancy
Driver gender	Given that there are 2 passengers in a vehicle, the probability of being involved in a crash is higher if the driver is male than if the driver is female (Apriori Rule 1) Driver gender is associated with occupancy for 2 of 24 cases (eta-squared)	Include only if statistically significant as only 1 test showed that this variable is related to occupancy and only for a minority of cases
Light condition	Given that there are 2 passengers in a vehicle, the probability of being involved in a crash is higher if it is not daylight than if it is daylight. (Apriori Rule 2)	
Functional class	Functional class is related to vehicle occupancy in 4 of 24 cases. (eta-squared)	
Collision type	Collision type is related to vehicle occupancy in 1 of 24 cases. (eta-squared)	

[a] For the eta-squared test, there are 24 cases where the geographic area had more than 1,000 vehicles and at least 1 variable showed an association with occupancy: 8 cases in Table 20, and 16 cases in Table 26.

Vehicle year was ultimately not considered for inclusion in the model. Although vehicle year had a level of small association for the entire Hampton Roads District for the AM peak (Table 25), there was no association for individual localities. Further experimentation with the Apriori test showed that a vehicle occupancy of 1 was not associated with the vehicle year. By contrast, a vehicle occupancy of 1 was associated with rear end collisions and angle collisions.

Development of a Bias Correction Model

For 2019, 10 sites on I-64 and I-264 where occupancies were collected using the windshield method during the AM and PM peak periods were used as the calibration data set. Column 4 of Table 27 shows the observed occupancies at each site that were collected using the windshield method. Columns 5 through 10 show occupancies based on 3 years of crash data (2017-2019).

For Columns 5 through 10, crashes were identified that were consistent with these locations. For instance, Figure 7 shows crashes in the vicinity of Site 5, which was a count location for westbound vehicles near Exit 17, where counts were taken on the HOV facility, three GP lanes, the shoulder, and ramps. Dark blue points indicate crashes that were not used in the analysis, and light blue points indicate crashes that were used in the analysis. For instance, based on the count location at the orange triangle, six sets of crashes appear to be consistent with this count location: (1) vehicles on the mainline facility traveling westbound after passing through the count location; (2) vehicles on ramps entering the mainline facility; (3) vehicles on ramps exiting the mainline facility; (4) vehicles on the mainline facility just prior to passing through the count location; (5) vehicles at the next exit westbound since they are leaving the mainline facility; and (6) vehicles on the mainline facility near the next westbound exit prior to the entrance ramps since they would also have passed through the count location.

Table 27. Sites Used for Type 2 Bias Correction Model

Data Collected From Field Observations				AVO Extracted From Crash Data					
Site No. (1)	Time Period[a] (2)	Location (3)	Observed AVO (4)	All Crashes (5)	PDO (6)	Injury (7)	Male (8)	Female (9)	Rear End (10)
1	WB AM	Indian River Rd Exit 286	1.08	1.06	1.08	1	1	1.11	1.04
2	WB AM	Norview Ave Exit 279	1.06	1	1	1	1	1	1
3	EB AM	J Clyde Morris Interchange	1.06	1.05	1	1.16	1.03	1.07	1
4	WB AM	J Clyde Morris Interchange	1.09	1.06	1.04	1.17	1.05	1.09	1.04
5	WB AM	Independence Blvd Exit 17	1.09	1.03	1	1.07	1.07	1	1.03
6	WB AM	Military Hwy Exit 13	1.08	1	1	1	1	1	1
7	WB PM	J Clyde Morris Interchange	1.14	1.16	1.07	1.3	1.16	1.18	1.14
8	EB PM	Witchduck Rd Exit 16	1.13	1.22	1.07	1.41	1.04	1.42	1.22
9	EB PM	Indian River Rd Exit 286	1.23	1.08	1.10	1	1	1.14	1.09
10	EB PM	Norview Ave Exit 279	1.20	1.10	1.13	1.05	1.10	1.10	1.10

WB = westbound; EB = eastbound; AVO = average vehicle occupancy; PDO = property damage only.
[a] The AM and PM time period varied by location and was defined by when the data were collected in 2019. For example, the AM peak period for Indian River Rd Exit 286, is 5-8:30 AM, and the AM peak period for Norview Ave Exit 279 is 5-7:30 AM).

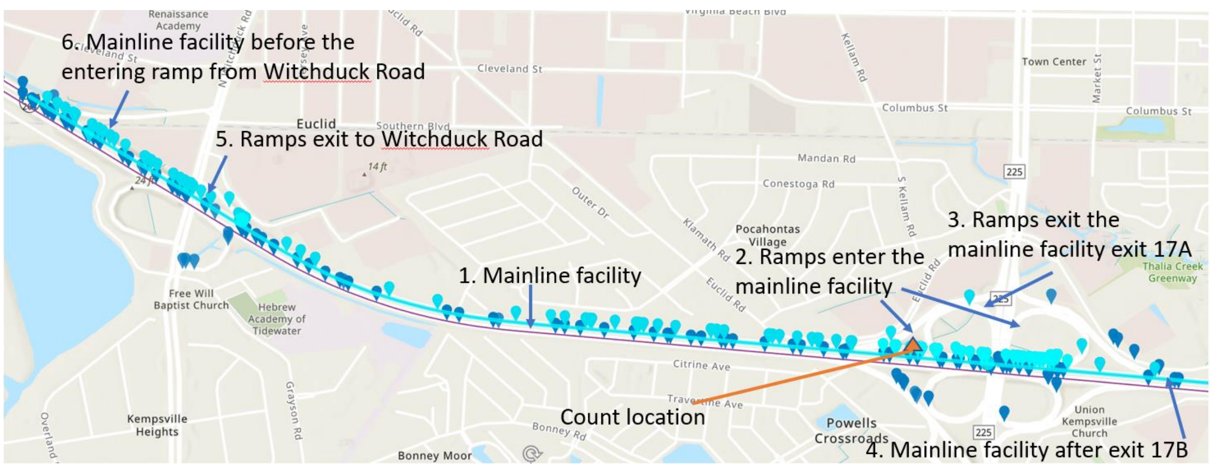

Figure 7. 2019 Crashes in the Vicinity of Site 5. Sources of the basemap: Esri, Airbus DS, USGS, NGA, NASA, CGIAR, N Robinson, NCEAS, NLS, OS, NMA, Geodatastyrelsen, Rijkswaterstaat, GSA, Geoland, FEMA, Intermap and the GIS use community, Esri Community Maps Contributors, City of Chesapeake, City of Virginia Beach, VGIN, ©OpenStreetMap, Microsoft, Esri, HERE, GARMIN, SafeGraph, GeoTechnologies, Inc, METI/NASA, USGS, EPA, NPS, US Census Bureau, USDA. Annotation added by the research team.

A model was built based on the data in Table 27. Of the six types of occupancy considered, only one—occupancy for vehicles involved in a PDO crash—was significant. This result matches the finding that both association tests—eta-squared and Apriori—suggested that crash severity is an indicator of vehicle occupancy. The result of this calibration, Equation 7, suggests that using PDO crashes to estimate AVO is more appropriate than using both PDO and injury crashes. Equation 7 explains almost two-thirds (65%) of the variance, and the p-value of the model is less than 0.01. For the training data, the average and median absolute error (between predicted and observed AVO) are 0.02 and 0.01, respectively.

$$\mathrm{AVO_{estimate}} = 0.048 + 1.018 \times \mathrm{AVO_{PDO}} \qquad \text{[Eq. 7]}$$

Evaluation of the Bias Correction Model

The evaluation had two components: (1) how does the model perform with sites not used to build the model, and (2) at what locations is the model applicable?

The 10 sites in Table 27 were randomly split into approximately 70% for training and 30% for testing. Based on seven training sites, a testing model was built (Eq. 8), with an adjusted R-square of 0.95.

$$\mathrm{AVO_{estimate}} = 0.061 + 1.004 \times \mathrm{AVO_{PDO}} \qquad \text{[Eq. 8]}$$

Figure 8 shows that the residual plot for the training model (Eq. 7) generally appeared unbiased (evenly distributed near horizontal 0 axis) and homoscedastic (the standard deviation could be interpreted evenly across the plot), suggesting that the model does not need to be transformed. Then, when Equation 8 (built from seven sites) was applied to the remaining three sites not used to develop Equation 8, the average and median absolute error between the predicted and observed AVO were 0.04 and 0.05, respectively, suggesting that a rough heuristic is that the error associated with Type 2 bias correction is around 0.05 when the model is applied to a data set from which the model is not calibrated.

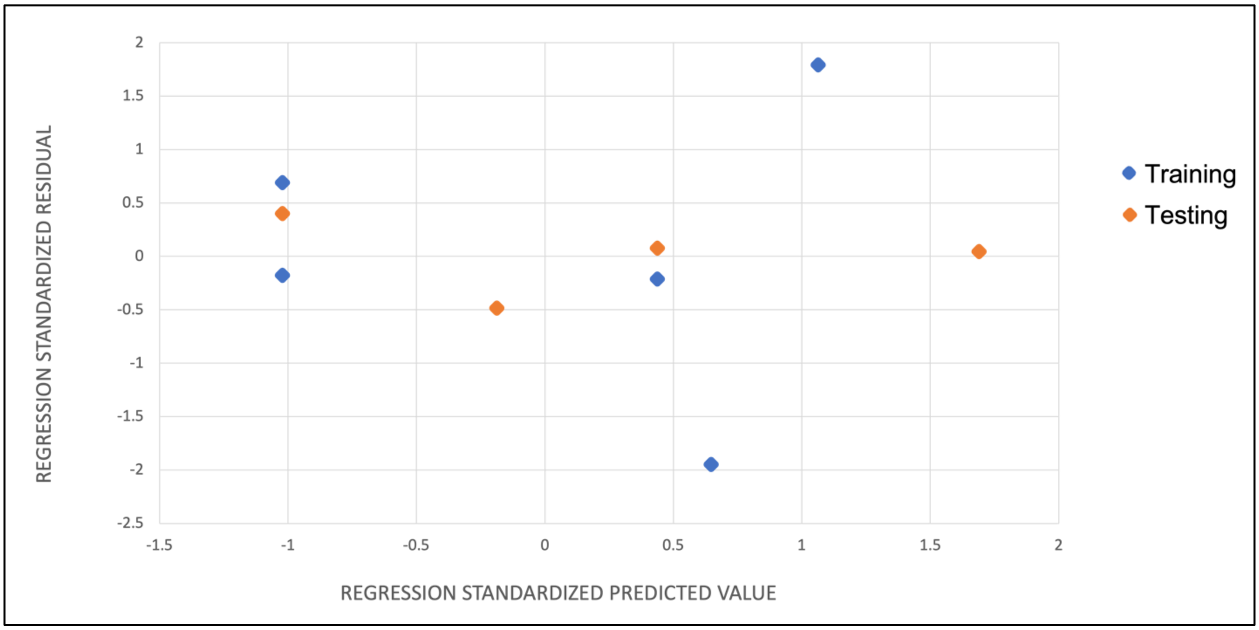

Figure 8. Residual Plot for Type 2 Bias Correction Model

How important is this error of 0.05? In terms of project prioritization, Table 13 is instructive. Starting with a presumed baseline occupancy of 1.29, Row 2 in Table 13 shows the number of projects whose ranking changes if the initially even-ranked projects (e.g., projects 2, 4, 6…38) saw their occupancy decrease by -0.05: only 2 of the 38 projects saw their rankings change. Row 1 also shows, however, that if one were instead to decrease the occupancy by -0.05 for the odd-ranked projects (e.g., projects initially ranked 1, 3, 5…37), then 4 of the 38 projects would see their rank shift. Thus, this impact of an error of about 0.05 would be expected to affect between 5% and 11% of project rankings in the case study that was the focus of Table 13. It should be noted that Equation 8 is for evaluation purposes only: in practice, because it is based on all 10 sites, Equation 7 should be used.

The final question regarding model evaluation concerns the sites at which the model can be used. The data used to calibrate Equation 7 originated from interstate sites, yet Table 22 shows that collectors had occupancies of 1.20-1.21, which are materially lower than interstate occupancies of 1.26. A question is thus whether the model in Equation 7 is suitable for non-interstate sites.

Columns 1 through 5 of Table 28 show the AVO by administrative class for 2019 PDO crashes in the Hampton Roads District for weekdays only. Although interstate and primary occupancies do not show a significant difference (p = 0.35), there is a difference in occupancy between interstates and secondary roadways, as well as between interstates and other roadways. For this reason, Equation 7 should not be used for facilities other than interstates and primaries. Further, because these calibration data are weekday peak periods, they should not be used for correction of weekend occupancies.

For all roadway administrative classes, vehicles involved in injury crashes (Column 7) consistently had a higher occupancy than vehicles involved in PDO crashes (Column 3). This suggests that a bias correction model of the type shown in Equation 7, which was developed for interstates, may also be developed for the other administrative classes. Because the difference between these two columns varies by class, Equation 7 may need to be re-calibrated to obtain a class-specific coefficient and intercept.

Table 28. Occupancy by Administrative Class for 2019 Hampton Roads District Weekday Crashes

	Property Damage Only Crashes				Injury Crashes	
Roadway System (1)	**Sample Size (2)**	**Confidence Interval (3)**	**Variance (4)**	**p-Value[a] (5)**	**Sample Size (6)**	**Confidence Interval (7)**
Interstate	6,399	1.21-1.24	0.453	NA	3203	1.31-1.36
Primary	2,442	1.20-1.24	0.378	0.35	1561	1.33-1.41
Secondary	1,245	1.15-1.21	0.300	<0.01	778	1.26-1.36
Other	19,607	1.12-1.13	0.219	<0.01	14678	1.26-1.28

[a] Equation 4 is used to compute the p-value based on a comparison of each administrative class with the interstate administrative class.

Variation in Occupancy by Site Characteristics

Vehicles involved in crashes in 2019 in the Hampton Roads District were also used for determining if there was a statistically significant variation in occupancy by three factors: (1)

time of day (24-hours, AM peak [7 AM-9 AM], PM peak [4 PM-6 PM], and off-peak [10 AM-3 PM and 8 PM-6 AM); (2) weekday (Tuesday, Wednesday, and Thursday) vs. weekend (Saturday and Sunday); and (3) functional class. No bias correction was applied for these tests given the large sample size such that, as shown in Column 2 of Table 10, all occupancies were represented. Then, for the small number of sites where use of both the carousel and windshield methods was feasible, Equation 4 was used to compare the means from these two methods.

Occupancy by Day of Week

Table 29 shows that the nominal weekend occupancy (1.30) was higher than that of a weekday (1.18), and since the 95% confidence intervals do not overlap, the means are different. The p-value based on the F-statistic ($p < 0.01$) also shows that the variance in these occupancies was significantly different; it should be noted that the higher variance (0.55) is associated with the higher mean occupancy (1.30).

Table 29. F-Test Results for Occupancy by Day of Week in Hampton Roads District 2019 Crashes

Group	No. of Vehicles	Occupancy	95% Confidence Interval	Variance	p-Value
Weekend	11,605	1.30	1.29-1.32	0.5495	<0.01
Weekday[a]	22,757	1.18	1.17-1.18	0.2972	

[a] Includes only Tuesdays, Wednesdays, and Thursdays.

Occupancy by Time of Day

Table 30 shows occupancy by time of day. The nominal mean occupancies for the PM peak, off-peak, and 24-hour period were all within 0.01 and were 0.06 (or 0.07) higher than the AM peak occupancy. The F-test showed that the differences in variance between each pair of groups were all statistically significant ($p < 0.01$) with one exception: a comparison of the PM peak and 24-hour occupancy showed a p-value of 0.49, such that occupancies for those two time periods were not significantly different. In terms of practical significance, the key observation was the lower occupancy associated with the AM peak.

Table 30. Occupancy by Time of Day in Hampton Roads District 2019 Crashes

Period	No. of Vehicles	Occupancy	95% Confidence Interval	Variance
Off-Peak	22,746	1.22	1.22-1.23	0.3902
24-Hour	49,913	1.21	1.21-1.22	0.3660
PM Peak	9,554	1.21	1.20-1.22	0.3657
AM Peak	5,225	1.15	1.14-1.17	0.2617

Occupancy by Functional Class

Table 31 lists the occupancy by functional class in descending order of occupancy. The facilities with the highest occupancy (interstates and ramps, with 1.26) and the facilities with the lowest occupancy (others, with 1.16) had variances that were significantly different from those of all other classes. Generally, higher average vehicle occupancies were associated with higher variances.

Table 31. Occupancy by Functional Class in Hampton Roads District 2019 Crashes

Functional Classification	No. of Vehicles	AVO	(95% Confidence Interval)	Variance
Interstate and Ramp	9,643	1.26	1.24-1.27	0.4935
Minor Arterial	14,277	1.21	1.20-1.22	0.3566
Major Collector	7,220	1.20	1.18-1.21	0.3322
Minor Collector	654	1.19	1.14-1.23	0.3637
Other Principal Arterial	16,939	1.19	1.19-1.20	0.3208
Other Freeways and Expressways	907	1.17	1.14-1.21	0.2997
Others	273	1.16	1.11-1.21	0.1718

AVO = average vehicle occupancy.

A statistical comparison of occupancy variance between every possible pair of all other functional classes (Table 32) also showed significant differences with two exceptions: minor collector vs. minor arterial ($p = 0.35$) and other principal arterial vs. other freeways and expressways ($p = 0.09$). In parentheses, Table 32 also shows the p-values for differences in means if they differed from the p-values for differences in variance. The F-test showed that variance in occupancy differed by functional class statistically, but as a practical matter, once interstates and the "other" category are removed, the midpoint occupancies by functional class are within a band of 0.04, from 1.17 (other freeways and expressways) to 1.21 (minor arterial). In this sense, the t-test for differences in means (Eq. 4) may be a good surrogate for practical differences in occupancy.

Table 32. P-Values for Differences in Functional Class Occupancy[a]

Functional Classification	Minor Arterial	Major Collector	Minor Collector	Other Principal Arterial	Other Freeways and Expressways	Others
Interstate and Ramp	<0.01	<0.01	<0.01	<0.01	<0.01	<0.01 (0.03)
Minor Arterial		< 0.01(0.03)	0.35(0.16)	<0.01	<0.01 (0.02)	<0.01 (0.03)
Major Collector			0.05(0.37)	0.04 (0.41)	0.02 (0.12)	<0.01 (0.10)
Minor Collector				0.01 (0.40)	<0.01 (0.31)	<0.01 (0.22)
Other Principal Arterial					0.09 (0.13)	<0.01 (0.10)
Other Freeways and Expressways						<0.01 (0.36)

[a] The first number reflects the p-value for differences in variance (Eq. 5), and the second number reflects the p-value for differences in mean (Eq. 4) if the second number differed from the first. For instance, major collectors and minor collectors show a difference in occupancy variance ($p = 0.05$) but not a difference in occupancy mean ($p = 0.37$).

Occupancy by Field Data Collection Method

Table 33 shows the 95% confidence interval for mean occupancies based on two different field data collection methods: the carousel method, and the windshield method. The absolute value of the mean difference was about 0.07 per site, with four of these five sites showing a statistically significant difference based on Equation 6. By itself, a difference of 0.07 may have a practical impact; one may recall the case study that showed that a smaller difference (of 0.05) could affect between 5% and 11% of project rankings and a larger difference (of 0.10) could affect between 10% and 32% of project rankings.

Table 33. Comparison Between Carousel and Windshield Average Vehicle Occupancy

No[a]	Location	95% Confidence Interval		Sample Size		Comparison of Means	
		Carousel	Windshield	Carousel	Windshield	Difference	p-Value
1	I-64 (EB)	1.13-1.18	1.23-1.25	1,367	15,214	0.08	< 0.01
2	Rte 164 (EB)	1.10-1.17	1.03-1.04	500	3,266	0.09	< 0.01
3	Rte 164 (WB)	1.07-1.12	1.04-1.05	532	5,907	0.04	< 0.01
4	Rte 28 (NB)	1.16-1.28	1.13-1.16	252	2,208	0.08	0.01
5	Rte 28 (SB)	1.15-1.27	1.16-1.19	325	3,489	0.04	0.11

WB = westbound; EB = eastbound.
[a] Site 1 is between Exits 276 and 281 (July 14, 2021). Sites 2 and 3 are between Rte 135 College Dr and West Norfolk Rd (March 31, 2022). Site 3 is between Exit 662 Westfields Blvd and the Air and Space Museum Pkwy (October 6, 2021).

In general, different methods may logically yield different sample sizes. For example, some differences among carousel data collection teams are expected because the teams departed roughly 5 minutes apart in order to increase the number of vehicles captured. For this particular case, however, there are at least two plausible explanations for this difference.

The first explanation is variation among the members of the research team that used the carousel method. To examine this possibility, Table 34 compares the 95% confidence intervals for each of the two (or three) sets of data collectors using the carousel method. The composition of each team was not necessarily the same for each site; e.g., the members of Team A for Site 1 were not necessarily the same as the members of Team A for Site 2. Based on Equation 6, there was no significant difference in any of the means except for the case of Site 2 ($p = 0.01$). Thus, it is certainly plausible that differences in either the behavior of the team driver or the team occupancy recorder could have led to the different rates in Table 34.

The second explanation is the variation in the vehicles observed between the two methods. Figure 9 contrasts the carousel location (the brown segment) and the windshield location (the single point) for Sites 2 and 3.

Table 34. Comparison of Occupancies for Individual Carousel Method Data Collectors

No[a]	Location	Team A	Team B	Team C	Difference
1	I-64 (EB)	1.11-1.20	1.13-1.21	1.12-1.18	0.02
2	Rte 164 (EB)	1.06-1.14	1.12-1.23	Not used	0.07
3	Rte 164 (WB)	1.05-1.11	1.07-1.15	Not used	0.03
4	Rte 28 (NB)	1.10-1.28	1.15-1.32	Not used	0.05
5	Rte 28 (SB)	1.12-1.26	1.14-1.32	Not used	0.04

WB = westbound; EB = eastbound; NB = northbound; SB = southbound.
[a] Site 1 is between Exits 276 and 281 (July 14, 2021). Sites 2 and 3 are between Rte 135 College Dr and West Norfolk Rd (March 31, 2022). Site 3 is between Exit 662 Westfields Blvd and the Air and Space Museum Pkwy (October 6, 2021).

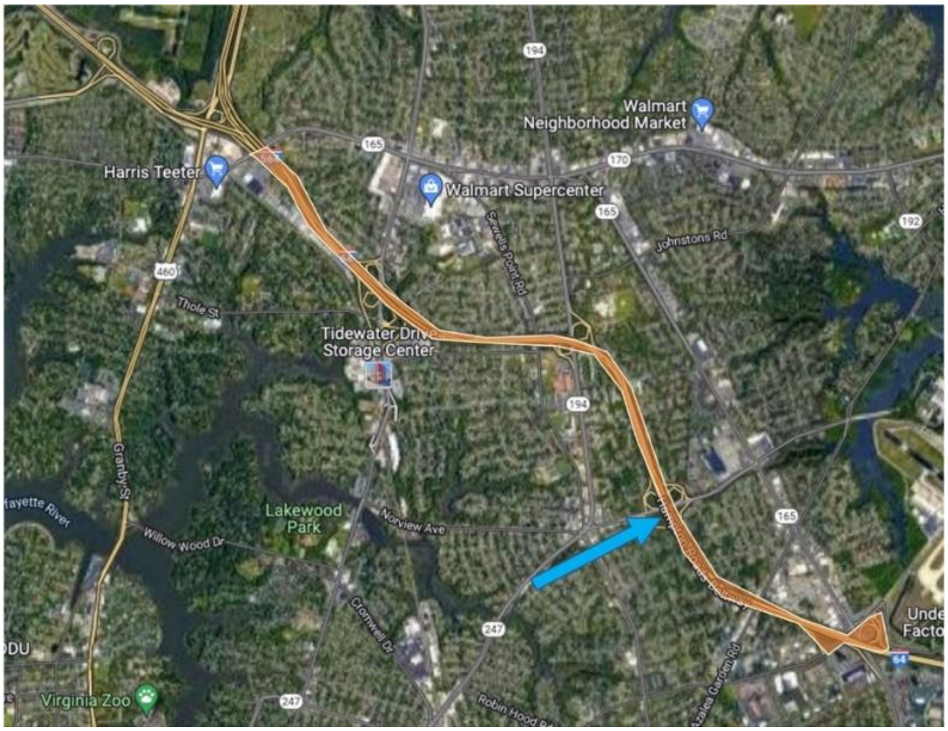

Figure 9. Path for Sites 2 and 3 (Route 164). Imagery © 2022 Commonwealth of Virginia, Landsat / Copernicus, Maxar Technologies, U.S. Geological Survey, USDA/FPAC/GEO, Map data. The brown segment is the travel path for the carousel method. The blue arrow indicates the point location for the windshield method.

It is thus possible that the difference results because the carousel method and the windshield method are not obtaining an identical set of vehicles. For instance, one may suppose a vehicle enters Route 164 at the Route 194 interchange (near the center of the figure). Further, one may suppose this vehicle travels north and west on Route 164, passing the interchange closest to the Tidewater Drive Shopping Center and then the Harris Teeter, near the upper left of the figure. That vehicle will be captured by the carousel method as its travel path overlaps the brown segment. However, that vehicle will not be captured by the windshield method, as its travel path does not overlap the point indicated by the blue arrow.

DISCUSSION

Use of Crash Data for Estimating Vehicle Occupancy

There are two possible (and related) observations regarding why, in Virginia, crash data have not previously been considered a source of occupancy.

The first observation is that on an older (1978) version of the FR300, total occupants were not reported. In fact, in an evaluation of Virginia crash records systems at that time, Hargroves and Hargroves (1981) pointed out that unlike other states, Virginia's crash report form did not include the "Total number of passengers" (quotes in the original). At that time, a passenger was listed only if injured or fatally injured: toward the bottom of the first page of the form, the officer would list the date of birth for each injured or fatally injured occupant (DMV, 1978). A September 2003 version of the crash report form retains the same information for the officer to list the date of birth of injured or fatally injured occupants. However, the 2003 version also contains a separate location to indicate the passenger age count (Transportation Safety Training Center, 2003). Further, instructions provided for the September 2003 version of the form (Virginia DMV, 2003) noted that the officer should "indicate in the space provided the number of passengers (excluding driver) in each age category." A training manual (Virginia DMV, 2017) indicated these instructions more strongly: for data element 61 ("ALL Passengers Age Count"), instructions stated that law enforcement should record the number of passengers, not including the driver, "***regardless*** of passenger injury or fatality" (emphasis in the original).

However, such data are generally not publicly available. Rather, as per a memorandum of understanding between the Virginia DMV and VDOT, the total number of occupants, when linked to a specific crash document number, may not be shared outside of these organizations (Di, 2021). This data element, known as "Total_Pass_All_Age," may only be obtained through a special tabulation performed by staff of VDOT's TED, and the results can be shared only if they are aggregated (as was done in this study where occupancies from many crashes were tabulated to provide a mean occupancy for a particular corridor or jurisdiction). For that reason, other individuals may have had the same viewpoint as the research team when this project began: since in the past, data for uninjured occupants were not recorded, and since the data element for total occupants is not currently available (unless one knows to request a special tabulation such as that provided by Simmons [2022]), occupancy from crash data might reflect only injured occupants.

The advice from a presenter at a November 19, 2020, webinar sponsored by FHWA—that states use their own crash databases for deriving occupancy rather than rely on Fatal Accident Reporting System data used by FHWA—carries more weight since Virginia generally has occupancy for all crashes and not just fatal or fatal and injury crashes. As a point of comparison, crash data for 2019 (Virginia DMV, 2021) indicated 128,172 crashes. By contrast, for the 1 year when Virginia purchased add-on samples for the NHTS, the sample size was about one-half that amount (57,303) and such data were not available for other years.

Comparison of Methods for Estimating Vehicle Occupancy

Some of the technology-based solutions that were identified in this study for estimating occupancy, such as the use of StreetLight InSight data or the use of Bluetooth detectors, cannot be used to estimate occupancy at the present time. Other technologies, such as portable systems based on image processing, may have potential, but they were not fully investigated as part of this study. Thus, it is possible that other methods for estimating occupancy, in addition to the approaches listed in Table 35, may merit consideration. However, as the timeframe and method of evaluation of such technologies are not known, this study does not include a specific recommendation for continued evaluation. Rather, the study recommends that VDOT implement the use of crash data for estimating occupancy, on a pilot basis, where that method could complement other methods currently in use.

Table 35 summarizes the pros, cons, and approximate sample sizes and costs of these methods. Clearly, the efficiency in terms of cost per data point is variable; for example, the cost of professionally trained data collectors using the windshield method is lower than the cost of members of the research team using the carousel method. The applicability of these methods also varies by technique; for instance, one might not use the carousel or windshield method to estimate occupancy for an entire jurisdiction; rather, these two methods could be used in conjunction with crash data for the purpose of bias correction. The costs and sample sizes are approximate and are not necessarily reported in the same unit. For example, Census data are ultimately based on interviews whereas crash data are based on vehicles; further, although the research team can give the number of hours required for the carousel method, the hours required for the windshield method are not known but are reflected in dollars paid for this service.)

Table 35. Sample of Methods Useful for Estimating Occupancy

Method	Pros	Cons	Applicability	Cost (Sample Size)
ACS	Freely available	Provides data only for the work trip	Work trips starting from a particular jurisdiction	1 person-hour (roughly 3,761 interviews)[a]
NHTS		Not suitable for a sub-state analysis unless additional samples are purchased	Trips by purpose for Virginia	1 person-hour (2,707 trips)[b]
Carousel	Can be quickly deployed	Labor intensive	A specific roadway segment	97 person-hours (1,363 vehicles)[c]
Windshield	Observers not in the traffic stream	Labor intensive		$1,440 (8,955 vehicles)[d]
Crash data	Field data collection not required	May be subject to crash bias	Varying geographical sizes (corridors to statewide) provided sufficient crash data exist	160 person-hours (more than 49,000 vehicles)[e]

ACS = American Community Survey; NHTS = National Household Travel Survey.

[a] Table K209803 (unweighted total population sample) in the 1-year 2019 ACS indicates this number of interviews for the City of Norfolk, noting they are "actual and synthetic." Data from ACS can be used to determine the number of workers driving alone with the number of workers in 2-person, 3-person, and 4+-person carpools.

[b] Based on a January 7, 2022, extraction (by the research team) of vehicle occupancy by purpose for all of Virginia for cars and SUVs from the 2017 NHTS.

[c] A carousel run for I-64 EB from East Little Creek Road to Exit 281A was performed on July 14, 2021. This required 89 person-hours based on the following: 2 hours for a pre-meeting for six data collectors (12 hours total); 3 hours training for 3 back-seat data collectors (9 hours); 3.5 hours travel time to the location for 6 data collectors (21 hours total); 0.5 hour preparation time near the site for 6 data collectors (3 hours total); 2 hours of collecting data during the carousel run for 6 data collectors (12 hours total); 0.5 hours sorting the data collecting sheets prior to departure (3 hours total); 3.5 hours travel back to the office for 6 data collectors (21 hours total); 8-hour data recording to the central computer, and 8-hour data processing for 1 data processor (16 hours total). Six data collectors collected 1,363 personal vehicles during the 2-hour carousel run.

[d] For a site on Rte 608 (West Ox Rd) between Rte 602 and Rte 666, the windshield data collection had a total cost of $1,440, based on a unit cost of $360 per hour per lane. This unit price included all preparation, travel, data collection, and data processing.

[e] Estimated based on data processing time for 2019 Hampton Roads crash data for every county, city, or town: crash data requesting and downloading (24 hours); data merging and cleaning (40 hours); GIS data processing and exporting for target areas (40 hours); bias correction for each county, city, or town (40 hours); and interpretation of results (16) hours).

A review of Ulberg et al. (1988) revealed that regardless of the techniques used, a detailed error analysis (where there is a discrepancy between estimated values and some ground truth value) can be used to improve an occupancy data collection program. For example, although observer error exists, the authors showed that time of day contributed almost 3 times as much variation as observer error such that accounting for time of day is critical; further, this variation will logically affect data collection cost.

Summary of Applicability of Crash Data for Estimating Vehicle Occupancy

Table 36 summarizes approaches to use crash data to estimate AVO as a function of the size of the study area. The premise underlying Table 36 is that as the number of vehicle observations shrink, which generally happens as either the time period or the size of the study area shrinks, the likelihood that crash data will present a biased sample increases. It should be noted that this study cannot prove the accuracy of this premise; rather, it is an inference based on the observation that the eta-squared test tended to show less bias as the number of vehicles increased.

Although bias correction is feasible and appears to improve the estimation of occupancy, this study did not prove that bias correction is essential. For example, one may consider Type 1 bias correction where one wants an estimate of occupancy for a jurisdiction, whether for a 24-hour period, an AM peak, a PM peak, or an off-peak time on a weekday. As long as the sample size was at least 100 vehicles, Type 1 bias correction affected AVO by 0.02 at most; in some cases, the impact was negligible. However, Type 1 bias correction mattered more for smaller sample sizes, becoming as large as 0.16 in the case of Smithfield during the PM peak. In fact, the average—not maximum—impact of bias correction for sample sizes of under 100 vehicles was 0.06.

Table 36. Summary of Methods of Obtaining AVO in Different Geographical Levels

<table>
<tr><th colspan="2">Study Area</th><th>Suggested Approach</th><th>Crashes</th><th>Rationale</th></tr>
<tr><td colspan="2">Districtwide or larger</td><td>Crashes without bias correction</td><td>1 year (2019)</td><td>The 1-year crash sample size at the district level is quite large (thousands of vehicles sampled), and no causal factors, except one case of vehicle year, were associated with occupancy at the district level.[a]</td></tr>
<tr><td colspan="2">City, county, or town</td><td>Crashes with Step 1 bias correction</td><td>1 year (2019)</td><td>For jurisdictions where the eta-squared test shows an association between crash causal factors and occupancy, and where any occupancy levels (2-7) are not observed, Step 1 bias correction addresses the concern regarding a small sample size.</td></tr>
<tr><td rowspan="3">Corridor level</td><td>Interstate and Primary</td><td>Crashes with Step 2 bias correction model</td><td>3 years (2017-2019)</td><td>Step 2 bias correction model can be tailored to a specific type of facility. The small number of crashes suggests that 3 years of crash data should be used.</td></tr>
<tr><td>Secondary</td><td rowspan="2">Crashes with Step 2 bias correction model but additional field data are needed to calibrate the model</td><td rowspan="2">3 years (2017-2019)</td><td rowspan="2">Field data are needed to calibrate the model.</td></tr>
<tr><td>Others</td></tr>
</table>

[a] Crash severity is associated with occupancy at the district level but is not a crash causal factor per se. In one case, vehicle year (AM peak) did affect occupancy.

Type 2 bias correction has the potential to be helpful, but this impact would be modest. One may recall that Table 27 lists 10 sites, where Column 4 shows the observed occupancy collected in the field, and Column 5 shows the occupancy based on crash data. Ideally, these two columns would be identical. The average of the absolute difference between the observed occupancies (Column 4) and occupancy from vehicles in all crashes (Column 5) was 0.06 for the 10 sites. Application of the training bias correction model from Equation 8 (which was built based on just 7 of those 10 sites) to the remaining 3 sites yielded an average absolute difference between observed occupancy (Column 4) and the model-estimated occupancy (not shown in the table) of 0.05.

It appears that the differences in occupancy attributable to crash bias are roughly comparable (i.e., within 0.03) to the differences in occupancy that can result from variation in field data collection methods. For instance, Table 36 showed a mean difference in occupancy of about 0.04 among research team members performing the carousel method when there was no variation in site definition or data collection method; except for the fact that data collectors were offset by about 5 minutes, one would have expected no difference. Table 36 showed a mean difference in occupancy of about 0.07 between methods (carousel vs. windshield); however, part of this difference may have been attributable to the carousel method capturing vehicles on adjacent segments that were not captured by the windshield method, as reflected in Figures 1 and 9. These values (0.04 or 0.07) are roughly comparable to the bias correction impacts noted of 0.06 (Type 1 bias correction for samples of under 200 vehicles) or 0.05 (Type 2 bias correction for a particular corridor). Because extraction of occupancy from crash records is feasible, it merits further consideration for use in Virginia as an alternative to field data collection.

CONCLUSIONS

- *Link-specific occupancies have modest potential to affect project prioritization.* In a case study in the Hampton Roads District where congestion mitigation accounted for 45% of a project ranking, a change in occupancy of 0.05 affected between 5% and 11% of project rankings, depending on which projects had their occupancies altered. A change in occupancy of 0.10 affected between 10% and 32% of project rankings, and a change of 0.20 affected between 26% and 42% of project rankings. These observations were tempered by the fact that shifts in rankings were not usually more than 1 of 38.

- *If it were the case that different projects could have different vehicle occupancies, then in Virginia's prioritization process, a change in link occupancy would have a slightly lesser impact on person throughput than a change in link volume.* Data provided by Buchanan (2022) showed different peak-period link occupancies by jurisdiction. When only jurisdictions in the Hampton Roads District were considered, the research team tabulated a mean occupancy of 1.14. Because person throughput is the product of vehicle volume and occupancy, an occupancy change for one project of 0.05 corresponds to a volume change of 4.4% for the same project. Presently, however, Virginia uses a default vehicle occupancy of 1.2 for all projects (Jackson, 2022).

- *Most states did not collect occupancy data as of 2021*. Of the 21 states from which a survey response was received, only 5 had collected these data. Three have used surveys (Michigan, South Carolina, and Vermont), and 2 have used field data (Virginia and Montana). Virginia uses field data on a limited basis for HOV facilities in the Hampton Roads and Northern Virginia districts. In contrast to all other states, Montana routinely collects occupancy data using field observations with sufficient samples to stratify by functional class.

- *The use of crash data is a feasible way to estimate occupancy due to the large sample size.* Because Virginia records the total number of occupants in all crashes regardless of injury status, there are a large number of observations of vehicle occupancy (e.g., more than 49,000 observations for just two seasons—fall and spring—in a single VDOT district). It should be noted that a special tabulation performed by VDOT TED staff is required to provide these occupancies.

- *Crash data may require some type of bias correction depending on the geographic scope of the analysis and the number of vehicles.* Type 1 bias correction ensures that all occupancy groups, such as two occupants per vehicle, are synthesized in the crash data set and is appropriate when determining occupancy for small localities. With larger sample sizes (e.g., at least 200 vehicles), the impact of this bias correction was never above 0.02, but with smaller sample sizes (no more than 100 vehicles), the impact of this bias correction was on average 0.06. Type 2 bias correction, which entails the collection of field data and development of a bias correction model, is suitable at the corridor level; use of the Type 2 bias correction model showed a difference of 0.05 between field observations and corrected data where the bias correction model was applied to sites not used to calibrate the model.

- *Occupancy varied by 0.12 or less when time of day, day of week, and functional class were considered*. A statistically significant variation in occupancy was found in comparisons of the following: (1) midweek occupancy (95% confidence interval was 1.17 to 1.18) vs. weekend occupancy (95% confidence interval of 1.29 to 1.32), and (2) and weekday AM peak occupancy (95% confidence interval of 1.14 to 1.17) vs. weekday off-peak occupancy (95% confidence interval of 1.22 to 1.23). By functional class, the highest occupancy was for interstates (95% confidence interval of 1.24 to 1.27) and the lowest was for “others” (95% confidence interval of 1.11 to 1.21).

- *Other approaches for estimating occupancy cannot be eliminated from future consideration*. Traditional methods for determining occupancy, such as the carousel method and the windshield method, remain useful both to obtain spot occupancies and to conduct Type 2 calibration. The study also identified other technologies, notably, portable occupancy systems, that remain candidates for evaluation. Thus, in the future, some periodic reassessment of approaches for determining occupancy may be warranted.

RECOMMENDATIONS

1. *VDOT’s Traffic and Mobility Planning Division (TMPD) should extract crash data on a pilot basis in one VDOT district to support an occupancy monitoring program*. The crash data

should be based on VDOT's crash records system but should include vehicle occupancy for all passengers, not just injured passengers; should be based on the customized query provided by VDOT's TED; and should include all crashes in the VDOT district. Using occupancies based solely on observed crash data without any bias correction yields occupancies that tend to differ from unbiased occupancies by about 0.06 at the corridor level, about 0.06 for smaller sample sizes at the jurisdiction level, and for no more than 0.02 for larger sample sizes at the jurisdiction level. For this reason, even if Recommendation 2 cannot be implemented, implementation of Recommendation 1 alone would offer a way to estimate occupancy.

2. *VDOT's TMPD should apply Type 1 and Type 2 bias correction to the data collected from the implementation of Recommendation 1 on a pilot basis in the same district.* Type 1 bias correction can be implemented using a spreadsheet without further field data collection and is suitable for jurisdictions, whereas Type 2 bias correction requires the collection of data and estimation of models and is suitable for corridors. By applying these corrections on a pilot basis, the TMPD can determine if the magnitude of the difference between corrected and uncorrected data justifies the effort required.

IMPLEMENTATION AND BENEFITS

Researchers and the technical review panel (listed in the Acknowledgments) for the project collaborate to craft a plan to implement the study recommendations and to determine the benefits of doing so. This is to ensure that the implementation plan is developed and approved with the participation and support of those involved with VDOT operations. The implementation plan and the accompanying benefits are provided here.

Implementation

For Recommendations 1 and 2, VTRC staff will assist with the pilot effort required. It is expected that this pilot effort will require about 18 months.

Recommendation 1 will be implemented on a pilot basis in one VDOT district where crash data extracted directly from crash reports and linked to occupancy data based on a custom query provided by VDOT's TED will be used to determine occupancy for the entire district and select localities. A map will also be devised and made available as a GIS layer. Scripts to automate this processing partially will be developed. Thus, this project will demonstrate how to implement these recommendations such that for one VDOT district and the jurisdictions within that district there is a work flow in place to obtain crash occupancy.

For implementation of Recommendation 2, the occupancies from the pilot in Recommendation 1 will be adjusted for potential crash bias, which tends to grow at smaller geographic levels or with smaller sets of data. This will be demonstrated on one particular corridor of interest to the technical review panel. For Recommendation 2, the staff hours required for implementation will be developed. For instance, Type 1 bias correction requires the development of a spreadsheet but not the collection of field data and is expected to require substantially fewer hours than Type 2 bias correction, as the latter requires data collection, model development, and model testing.

Benefits

The results of implementing Recommendations 1 and 2 can help VDOT determine whether the benefits of an occupancy program justify the effort required to support such a program. This study showed that in some situations, having a more geographically specific estimate of vehicle occupancy can help one better evaluate transportation planning initiatives than would be the case if one assumed a statewide average. Field observations show variation within specific corridors (e.g., during the PM peak period, 1.13 at one site on I-264 and 1.23 at another site on I-64). Crash data show variation by locality (e.g., over a 24-hour period, 1.16 in Suffolk and 1.32 in York). The research team cannot prove that detailed occupancy estimates have a specific monetary value, as Virginia has proceeded in the past without such data. However, there appear to be three potential benefits in terms project prioritization, other planning tasks, and funding flexibility.

Potential Benefit 1: Project Prioritization

A sample of 38 projects in one VDOT district showed the relevance of occupancy for project prioritization if Virginia's process were to be modified such that a uniform occupancy was not used for all projects. Because of its multiplicative effect on congestion mitigation, occupancy helped account for 45% of the project's score in that district. A deviation of 0.10 in occupancy from ground truth could influence the rankings of between 4 and 11 projects (e.g., 11% to 29% of the sample of 38 projects). The question arises: Would such changes in rankings affect prioritization? If all projects can be built, then the answer is no. If only some projects can be built, then because projects tended to shift only one ranking, a more likely impact is that just one project would not be built that otherwise would be built and vice versa. In that case, with an average cost of $17 million per project, the change in rankings means that around $34 million in expenditures could materially be affected.

The impact of more precise vehicle occupancy in terms of project prioritization are greater in locations where congestion mitigation (in terms of person delay and person throughput) accounts for more of a project's weight. Occupancy is not the most important factor in project prioritization, but it is a relevant one: as shown herein, a change of 0.10 in terms of occupancy had roughly the same impact as a change of 8.8% in terms of traffic volume. In short, as resources permit, there may be a benefit in terms of project prioritization of using more geographically specific occupancies.

Potential Benefit 2: Other Planning Tasks

The following question may be asked: If location-specific occupancies were not used for project prioritization but were needed for other planning tasks, such as corridor studies, travel demand models, or alternatives analysis, would the benefits of implementing Recommendation 1 (i.e., cost savings from using crash data instead of field data collection) justify the costs (i.e., the time required to develop and maintain a process for deriving vehicle occupancy from crash data)? An estimate of data collection costs at one site with the manual method was $1,440. If Virginia wanted to obtain occupancies for each Virginia city or county, then if one site per city or county was assumed, the cost of field data collection would be a bit less than $200,000. Thus, if a statewide crash processing system can be developed for less than that amount, implementing Recommendation 1 would appear to be beneficial.

However, if vehicle occupancies were sought not at the larger city or county level but rather at the smaller block group level, it would be misleading to suppose that implementing Recommendation 1 alone would suffice because the smaller number of crashes at the block group level necessitates the implementation of Recommendation 2—field data collection for the purposes of calibration. In sum, the use of crash data to estimate occupancy appears likely to provide benefits in that the costs will be lower than relying on field data collection alone. However, for smaller locations, such as block groups or corridors, the use of crash data will require some field data collection; therefore, the critical longer term question for VDOT will be whether there is a need for location-specific occupancies rather than a single statewide figure.

Potential Benefit 3: Funding Flexibility

Guidance from FHWA (Halla, 2022) suggested that detailed occupancy data could inform the use of federal funds. In reference to the ability to "flex" funds from the National Highway Performance Program (NHPP) for transit, Halla (2022) explained that FHWA encourages the use of multimodal-related projects that achieve certain goals, one of which is to "reduce single occupancy vehicle travel and associated air pollution in communities near high-volume corridors." Virginia's fiscal year 2022 apportionment exceeds $734 million in the NHPP (FHWA, 2021). Logically, detailed occupancy data, such as those feasible from this report, would be an important background measurement for determining whether a given corridor saw a change in single occupant vehicles and thus could support greater flexibility with Virginia's share of NHPP funds.

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APPENDIX

SURVEY INSTRUMENTS

Figures A1 and A2 show summaries of the questions posed to VDOT districts and other states, respectively. (The complete questionnaires are available from the research team.)

1. Does your district provide average vehicle occupancy to Central Office for MAP-21 performance measure reporting? (The two districts that answered yes—Northern Virginia and Hampton Roads—where then asked these four bulleted questions.)

    - For what roadways is vehicle occupancy reported?
    - What method (s) is used to collect vehicle occupancy in your district?
    - How often are occupancies collected?
    - What are the most recent occupancies reported for each roadway? (example: I-64 = 1.47; Rte 29 = 1.56; etc.)

2. Has your district ever collected vehicle occupancy on any roadways within the district for purposes other than federal reporting? (The one district that answered yes—Northern Virginia—was then asked these five bulleted questions.)

    - For what purpose(s) were vehicle occupancies collected (select all that apply)?
        - Special transportation studies (e.g., corridor studies)
        - Land development studies (e.g., site plan review)
        - Site-specific transportation projects
        - Collaborative effort with a locality, MPO, TPO, and/or PDC
        - Other:
    - What methods were used to obtain occupancy data?
    - How often are occupancy data collected?
        - Once a year
        - Once every other year
        - No established frequency
        - Other:
    - What funding source is used for collecting data?
    - Are these data available? (If yes, we will follow up with you.)

3. Has there been any discussion or interest in your district on collecting vehicle occupancy data in support of the following initiatives (select all that apply)?

    - Evaluating the effectiveness of a transportation system management action, such as a new congestion management program
    - Verifying compliance with state regulation
    - Assessing changes in air quality indices based on person consumption and to monitor the energy efficiency of travel
    - Validating urban transportation planning models
    - Identifying emerging transportations trends that may occur due to increases in fuel prices, restrictions on fuel consumption, weight restrictions on commercial vehicles, changes in speed limits, and motorist response to reduce unnecessary travel
    - Predicting trends that would allow the policy formation and planning process to address emerging issues
    - No discussions and/or interest
    - Other:

Figure A1. Summary of Survey of VDOT Districts

1. Does your DOT report average vehicle occupancy (AVO) factors for travel time reliability measures to FHWA's Highway Performance Monitoring System (HPMS)?

   ___ Yes ___ No ___ Unknown

   If yes, what source is used to report the data?

   ___ FHWA-provided AVO factors from the National Household Travel Survey
   ___ State DOT developed estimates
   ___ Other (please explain or provide a contact)

2. Has your DOT ever collected vehicle occupancy data?

   ___ Yes ___ No ___ Unknown

   (If *yes to Question 2*, please complete questions 2a-2d. If *no* or *unknown*, please refer to question 2e).

   a. For what purposes were the data obtained?

   b. What methods were used to collect the data?

   c. What funding source(s) were used to pay for data collection?

   d. Were DOT decisions affected by observed occupancy? (if *yes*, what were they?)

   e. [For DOTs that haven't collected vehicle occupancy data] Has there been any interest in your DOT in collecting vehicle occupancy data?

      ___ Yes ___ No ___ Unknown

3. Do you have any suggestions for DOTs seeking to better assess vehicle occupancy in their state?

Figure A2. Survey of Other State Departments of Transportation