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Probing into Driver Speeding Patterns and Their Influence on Child Occupancy in Urban Areas

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Abstract

Many studies have investigated how child occupants lead to distraction-associated crashes. However, not many studies have focused on how the presence of child passengers influences drivers' speeding behavior. This study examines how the presence of child passengers can affect driving behavior considering sociodemographic characteristics such as driver's age, gender, ethnicity, employment, and driving aggressiveness. The current study used resourceful, open-source data based on urban areas in Texas to identify the key patterns of speeding behavior and associated safety surrogates in the presence or absence of child occupants. A unique data analysis procedure known as Taxicab Correspondence Analysis (TCA) was used to analyze the data. The results indicate that speeding patterns are affected by child occupancy during a trip. The results find that regardless of the presence of child passengers, female and unemployed drivers are more likely to drive defensively and male and employed drivers are more likely to drive aggressively. The findings also indicate that drivers from the young age group (20–29 years old) are strongly associated with speeding trips without child occupancy. However, young parent drivers from this age group are strongly associated with non-speeding trips and driving defensively. The study also finds that the impact of child occupancy on driving behaviors varies across different ethnicities. These findings will benefit transportation agencies in identifying aggressive driver groups and developing countermeasures to mitigate speeding behaviors, especially for trips with child occupancy.

Keywords

safety, occupant protection, child restraints, traffic law enforcement, speeding

Aggressive driving is a type of dangerous driving that can lead to injury or even death (*1*). Speeding, as a dominant component of aggressive driving behavior, is dangerous and can lead to crashes, causing a significant portion of traffic fatalities according to the National Highway Traffic Safety Administration. This shows how severe the consequences of speeding could be (*2*). The number of crashes that involve children is huge; for children under fifteen in motor-vehicle crashes, more than 1,000 are killed and more than 17,000 are injured each year in the United States (*3*). Studying the association between speeding patterns and child occupancy is crucial in protecting the health and property of adults along with the lives of children.

In the realm of studying the relationship between speeding and child occupancy, previous research has often yielded single conclusions that are confined to specific dimensions, relying primarily on prevalence examination or crash data analysis. Consequently, the exploration of comprehensive patterns that encompass multiple factors influencing this type of speeding behavior has remained scarce. However, advancements in information technology have ushered in an era of increased data availability from diverse sources, leading to potentially vast quantities of data. Leveraging efficient data analysis techniques, such as machine learning,

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enables the discovery of deeper insights by unraveling multidimensional relationships using these new data sources.

The objective of this paper was to identify patterns of speeding behavior with child occupancy by employing household travel survey data from eleven study areas in Texas, featuring a diverse sample of 2,349 drivers spanning various age groups from fifteen to seventy-five. The data were processed using the Taxicab Correspondence Analysis (TCA), a dimension reduction algorithm. The study investigates the interplay between speeding behavior, driver's aggression, and demographic factors including age, gender, employment, locality, and ethnicity in trips with and without children. TCA is particularly well suited for analyzing categorical or nominal data, which are often used when studying demographic factors like age, gender, employment, locality, and ethnicity. By capturing the relationships and associations among these categorical variables, TCA can provide insights into how these factors interrelate with speeding behavior and child occupancy. TCA allows for the exploration of multidimensional relationships. As the objective of the study is to identify patterns that involve multiple factors influencing speeding behavior with child occupancy, TCA's ability to uncover complex relationships and dependencies between variables can contribute to a more comprehensive understanding of these patterns.

Literature Review

The current literature review specifically examines the topics of aggressive driving, speeding, and their correlation with the presence of children in vehicles. It aims to gather and analyze existing studies, research papers, and scholarly articles that have explored these areas. By reviewing the available literature, the aim is to gain a deeper understanding of how aggressive driving and speeding behaviors are influenced when children are present in the vehicle.

Unfortunately, cases of aggressive speeding driving are increasing in many countries (*4*). Studies have shown that the majority of speeding behaviors are related to driver demographic factors such as age (*5*), personality (i.e., the aggressiveness of driving) (*6*), gender (*4*, *7*), and experiences (*8*). Drivers between sixteen and twenty-five, especially males, are reported to have a high risk of speeding behavior with another passenger present (*5*). With increases in age, there is a decrease in aggression, driving anger, and risky behavior (*9*). Other factors associated with speeding behavior are the time of day (such as in peak hours), road characteristics (such as the presence of a wide median and shoulder) (*10*), vehicle characteristics (such as the power of the engine) (*7*), pressure from other drivers (*11*), employment, and geography. It is reported that daily job stress can affect the actions of drivers, leading to potentially aggressive driving behaviors such as speeding (*12–17*). Among all influential factors, speeding behavior is sensitively affected by the presence of passengers. For example, in some previous studies, the intention of speeding can be higher in the "no passenger" than in the "passenger present" condition (*18*). However, the age of the passenger present matters. For instance, the presence of child passengers affects driving behavior in different ways. Current studies have revealed several findings concerning this area of study. Among social factors that influence driving behaviors, child occupancy is a crucial factor, especially for young females with a child (*19*). Children's behavior can lead to driver distraction and sometimes can increase the potential of crashes (*20*, *21*). Children are three times more likely than adults to lead to distractions (*22*). However, although the interactions between parents and children can lead to potential risks when they are distracted, the awareness of the presence of a child will increase the caution of drivers, causing them to take fewer risks while driving. According to the crash data from the U.S. Fatality Analysis Reporting System (FARS), when the passengers are only children, risk-taking behaviors are less reported (*23*). Also, among all the reasons for driver distraction, child-occupant driving was not a major contributing factor when compared with other factors like eating and drinking (*20*). A survey about parents' attitudes toward child-occupant driving was conducted in Australia and the results show that the majority of the parents will give a talk to their children when they are misbehaving and 20% of them will stop the vehicle (*24*). In fact, child occupancy seems to act as a positive role in increasing traffic safety, and speeding is less likely to happen with child occupancy. Spain-based crash data show that "defensive driving" behavior appears when drivers are with their children who are aged less than 15 years (*25*). The crash frequency decreases when there is a child passenger present according to a study that used naturalistic driving data, as the drivers tended to decrease their speed (*26*). Speeding or drunk driving also happens less frequently when a child is in the car (*27*). One possible reason is that the driver has a feeling of responsibility when a child is in the vehicle (*28*). Drivers with children behave responsively according to their perceptions of safety; for example, according to a survey of Scottish drivers, half of the drivers questioned drive slower than their usual speed and the other half keep their usual speed when children are on board (*29*), although driver characteristics such as age or experience could also influence the results. For example, teenage drivers tend to speed in the presence of a young passenger (*30*, *31*). Drivers with children are generally older than those

Table 1. Previous Studies on Child Occupancy and Speeding

Studies	Data sources	Research method
"Defensive driving" behavior (*25*)	Spanish National Registry of Traffic Crashes with victims	Retrospective paired case-control study
Drive with less speeding (*29*)	Surveys in-home interviews with quota samples of driver	Survey analysis
Teenage drivers tend to be speeding with the presence of a male teenage passenger (*30*)	Field observation	Analyses of crash statistics
Younger drivers tend to be speeding with only younger passengers (*31*)	5-year crash data Interstate-4 freeway (I-4) in Orlando, Florida, 36.3-mile stretch	Bivariate probit models, binary logit model
Parents are unlikely to take risks because of the feeling of responsibility (*28*)	Personal interviews (16 parents) and telephone survey (165 parents)	Analysis of survey data
Less common for young woman drivers with a child to be speeding (*27*)	Crash data from the US Fatality Analysis Reporting System (FARS) 1994–2013, characteristics include age, gender	Prevalence examination
Crash frequency is less when a child passenger presence with decreased speed (*26*)	Naturalistic driving data collected with onboard video cameras and sensors	Prevalence examination
Drivers with children do not tend to speed as often as other drivers do (*19*)	FARS 1982–2011, characteristics include age, gender, crash type and time of day, alcohol	Prevalence examination

without, and in general older drivers are reported to have fewer crash risks than younger ones as they have more experience with driving (*32*).

The previous studies that associate speeding with child occupancy, along with their data and methods, are listed in Table 1. The studies employ different research methods and data sources to investigate specific aspects of driving behavior. For instance, one study focused on "defensive driving" behavior using a retrospective paired case-control methodology and data from a national traffic crash registry. Another study examined the tendency of teenage drivers to speed when accompanied by a male teenage passenger through field observation and crash statistics analysis. Additionally, studies explored the impact of factors such as age, gender, presence of children, and feeling of responsibility on speeding behavior. Overall, these studies contribute to a broader understanding of the factors influencing driving behavior and can potentially inform efforts to improve road safety.

Previous studies on the relationship between speeding and child occupancy have typically provided limited conclusions based on prevalence or crash data analysis, lacking exploration of multidimensional patterns; however, advancements in information technology and data analysis techniques like machine learning present opportunities to uncover more comprehensive insights by analyzing diverse and abundant data sources.

Methodology

Taxicab Correspondence Analysis (TCA)

In recent years, there has been a notable trend in transportation safety research where Correspondence Analysis (CA), a method for reducing dimensions, has been increasingly applied to address safety-related concerns (*33–43*). This particular study seeks to utilize TCA instead. TCA distinguishes itself from CA by employing a distinct singular value decomposition (SVD) method based on the taxicab norm, known as taxicab SVD (TSVD). Although TCA shares similarities with CA, the key disparity lies in the geometric properties: CA operates in a Euclidean geometry, whereas TCA operates in a non-Euclidean taxicab geometry. By employing TCA, more robust and computationally efficient outcomes can be achieved, thanks to its uniform weight assignment. Furthermore, TCA has the potential to yield more easily understandable results for certain datasets (*40*).

Firstly, the TSVD of dataset Y with r rows and c columns is presented below. TSVD of a matrix Y is calculated in a stepwise manner. Consider, $v = (v_1, \ldots, v_r)'$ u = is an r-dimensional vector and the taxicab norm of v is $\|v\|_1 = \sum_{i=1}^{r} |v_i|$. T_c is the collection of all vectors of length c with coordinates $+1$ or -1. Thus, the total number of unique vectors in T_c is 2^c. T_r is similar for column points. To find the first principle axis v_1 of r row points, v_1 should satisfy:

$$\underbrace{max}_{v \in T_c} \|Yv\|_1 = \|Yv\|_{11}$$

where Yv is the projection of r row points on v and $\|Yv\|_1$ is the taxicab norm of the projection. λ_1 is the first taxicab principal axis dispersion measure:

$$\lambda_1 = \|Yv_1\|_1 \quad (1)$$

f_1 are the first-row principal factor scores:

$$f_1 = Yv_1 \quad (2)$$

λ_1 can be written as:

$$\lambda_1 = sgn(f_1{}')Yv_1 \tag{3}$$

λ_1 can be written as Equation 4 by putting $u_1 = sgn(f_1) \in T_r$:

$$\lambda_1 = u_1{}'Yv_1 \tag{4}$$

where u_1 is the first column axis of c column points of dataset Y. The first column principle factor scores g_1 can be written as:

$$g_1 = Y'u_1 \tag{5}$$

λ_1 can also be written as follows:

$$\lambda_1 = u_1{}'f_1 = v_1{}'g_1 \tag{6}$$

From Equations 1 to 5, the calculation of the first principle axis and the first principle score for both r row points and c column points (v_1, u_1, f_1, g_1) are presented. Then, Wedderburn's rank-one reduction formula is applied to calculate the second principal axis and the principle factor score for both row and column points of dataset Y. Here, the residual dataset $Y^{(1)}$ is calculated by:

$$Y^{(1)} = Y - \frac{f_1 g_1{}'}{\lambda_1} \tag{7}$$

Then, based on $Y^{(1)}$, (v_2, u_2, f_2, g_2) can be calculated by repeating the previous steps again. This process can be continued until the k^{th} iteration. Finally, the TSVD of a matrix Y will have the following form:

$$Y = \sum_{a=1}^{k} \frac{f_a g_a{}'}{\lambda_a} \tag{8}$$

To implement TCA into a contingency table Y, TSVD is applied to a correspondence matrix P = Y/n, which is similar to the original CA. P is a correspondence matrix with marginal proportions $p_{i.}$ and $p_{.j}$. The process is to apply TSVD to P and continue the same process as above until the k^{th} iteration.

The following steps are followed to perform the TCA analysis:

- Prepare the dataset that contains the variables of interest. Ensure that the variables are categorical or can be transformed into categorical variables.
- Construct a contingency table that represents the frequencies or proportions of the categories for each variable. This table will serve as the basis for the TCA analysis.
- Perform the summation of rows and columns in the contingency table to derive the marginal distributions for each variable. This computation reveals the comprehensive distribution of categories pertaining to each variable. Proceed with the calculation of expected values for each cell in the contingency table, assuming independence between the variables. These anticipated values reflect the theoretical outcome if the variables were indeed independent of one another. Determine the residuals by subtracting the expected values from the observed frequencies or proportions present in the contingency table. These residuals serve as indicators of deviations from independence and effectively capture the associations existing between the variables.
- Apply dimension reduction techniques, such as SVD or principal component analysis, to the residuals matrix. This reduces the dimensionality of the data and uncovers the underlying patterns and associations.
- Generate appropriate graphical representations, such as biplots or heatmaps, to visually depict the outcomes of the TCA analysis. These visualizations serve to illustrate the connections between variables and assist in facilitating subsequent analysis and interpretation. Evaluate the results of the dimension reduction process, which commonly comprises eigenvectors and eigenvalues. Interpret the eigenvectors to comprehend the interrelationships among variables and discern any discernible patterns or clusters within the data.

Data Overview

This study used a publicly available dataset (https://doi.org/10.15787/VTT1/YRTS1Z) from the SafeD Data Verse. Texas Department of Transportation (TxDOT) household travel survey data, travel diary, Global Positioning System (GPS) data for travel surveys, and HERE Streets spatial data set with posted speed limit data (https://www.here.com/products/mapping/map-data) were used to determine whether the drivers were speeding. Speed behaviors were determined by comparing the posted speed limit data and the actual driving speed. The data were collected from Texas for eleven study metropolitan areas (MPO) (see Figure 1).

The collected data were primarily divided in two age groups: drivers aged 16 to 55 years and older drivers (65+ years). Child occupancy is considered based on the occupancy of a child who is younger than 15 years old during the trips. Drivers younger than 20 years old or older than 65 years old are less likely to have children. Finally, the current study only utilized data collected from drivers that were 20 to 55 years old. The final dataset contains 3,219 trips with 480 unique drivers. Table 2

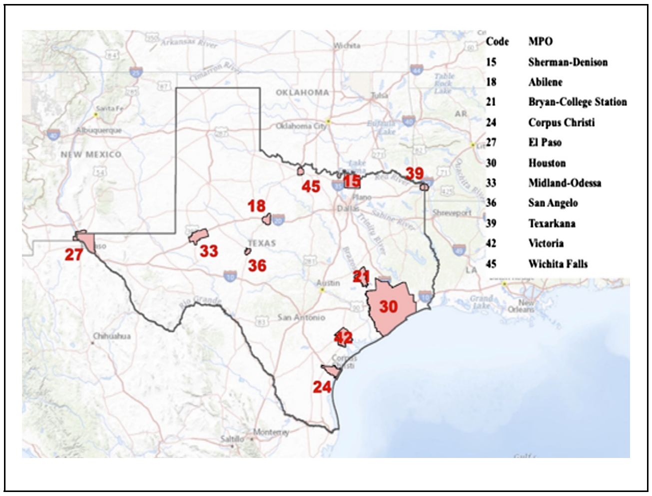

Figure 1. Study areas.

Table 2. Number of Trips are Drivers in each Study Area

Study_area_code	Trip count	Metropolitan area name	Drivers count
15	128	Sherman-Denison	23
18	163	Abilene	24
21	202	Bryan-College Station	31
24	150	Corpus Christi	21
27	515	El Paso	76
30	748	Houston	107
33	202	Midland-Odessa	30
36	249	San Angelo	37
39	435	Texarkana	65
42	166	Victoria	27
45	261	Wichita Falls	39

shows the number of trips and drivers from each MPO area after the data cleaning process.

Variables

With the exception of driver and trip identification information, this dataset contains demographic information about drivers including sex, age, ethnicity, and employment. Information about trip occupancy is also available. The research also collected trip occupancy information, such as the number of passengers (trip_occupancy_type) and if the trip had one or multiple passengers younger than 15 years old. Eleven study areas (MPOs across Texas, U.S.) are also coded in the dataset. Another important attribute in the final dataset is the "speeding_during_trip" variable, which indicates if the driver was speeding for at least 20% of the free-flow duration of the trip. Speeding means that the driving speed was over the posted speed limit at the moment. The free-flow duration is defined as the duration of the trips with free-flow speed. To simplify the data categories, "speeding_during_trip" was renamed as "speeding_trip." For a trip, if the driver was speeding for at least 20% of the free-flow duration, then "speeding_trip" = "yes," otherwise "speeding_trip" = "no."

Table 3. Speeding_trip_frequency Classification

Speeding_trips_freq	Percentage of speeding trips
Not at all	0%
Rarely	0–30%
Sometimes	30–50%
Often	greater than 50%

To further bolster the accuracy of this calculation, any parts of the GPS trips associated with parking lots and alleys were removed from the dataset. This study also added another categorical variable to measure drivers' driving aggression: "speeding_trip_freq." As shown in Table 3, this variable was classified into four categories by the percentage of speeding trips out of all trips recorded in the dataset for a driver. Drivers with fewer than five trips recorded in the dataset during the data collection period were eliminated from the analysis and for drivers with very few trips recorded, for example, fewer than five, driver aggression may not be a realistic indicator.

Summary Statistics

Summary of Cleaned Data. Table 4 lists the variables with descriptive information. The number of female drivers is higher than male drivers. There are 2,172 trips classified as non-speeding trips and 1,047 trips classified as speeding trips. Caucasian drivers are represented disproportionately higher compared with other ethnic groups. The proportion of employed drivers is higher than unemployed drivers. Trips with no child occupancy are disproportionately higher than trips that had child occupancy. The variable "have_child" refers to if the driver has at least one child, not to if the child was present in all the trips the driver made.

Trip-Related Descriptive Statistics by Gender Groups. Table 5 lists the frequency of trip-related descriptive statistics by gender. Out of all trips recorded in the dataset, non-speeding trips make up a higher percentage than speeding trips for both genders. Male drivers have more speeding trips than female drivers. For male or female drivers, most of their trips had no passengers. The majority of trips by male drivers had no child occupancy. On the contrary, the majority of trips by female drivers had child passengers.

Table 4. Description of Variables

Variable	Data type	Descriptive information
driver_id	Anonymized values	Identification of the driver (480 unique drivers)
trip_id	Anonymized values	Identification of the trip (3,219 trips)
study_area_code	Categorical	See Table 2
speeding_trip	Categorical	yes = 1,047 trips no = 2,172 trips
drivers_sex	Categorical	Female = 304 drivers Male = 176 drivers
drivers_age	Categorical	20–29 yrs old = 77 drivers 30–39 yrs old = 105 drivers 40–55 yrs old = 298 drivers
drivers_ethnicity	Categorical	Caucasian = 292 drivers African American = 49 drivers Hispanic = 129 drivers Other = 10 drivers
drivers_employment	Categorical	Unemployed = 138 drivers Employed = 342 drivers
trip_occupancy_type	Categorical	0 passengers = 2,260 trips 1 passengers = 643 trips 2 or more persons = 316 trips
have_child	Categorical	Yes = 204 No = 276
driver_w_child	Categorical	Drivers without children 0 years old to 15 years old as passengers during trips = 1,827 trips Drivers with children 0 years old to 15 years old as passengers during trips = 1,392 trips
speeding_trip_freq	Categorical	Not_at_all = 114 drivers Rarely = 133 drivers Sometimes = 127 drivers Often = 106 drivers

Table 5. Trip-Related Descriptive Statistics by Gender

	speeding_trip		trip_occupancy_type			drive_w_child	
Gender	yes	no	0	1	2	0	1
Male	419	759	895	169	114	1,034	144
Female	328	1,413	1,365	474	202	157	467

Note: Speeding trip is defined as a trip with 20% of free-flow driving duration speeding over the posted speed limit.

Driver-Related Descriptive Statistics by Gender Groups. Table 6 shows the frequency of driver-related descriptive statistics by gender. For both gender categories, there are more drivers from the age group of 40–55 years than the other two age groups. White/Caucasian drivers have more drivers than other ethnicities. With regard to driver's aggressiveness (speeding_trip_frequency), the number of drivers in each aggressiveness category is balanced. There are more employed drivers than unemployed drivers. Only one-third of male drivers had children present in at least one of their trips, and almost half of the female drivers had children present in at least one of their trips.

Results and Discussion

The following two sections illustrate the associations between speeding patterns and child occupancy. The comparisons are made between trips with or without child occupancy. TCA plots are generated for both trips with and without child occupancy. The closeness of the

Table 6. Driver-Related Descriptive Statistics by Gender

	driver_age			drivers_ethnicity			
Gender	20–29 yrs old	30–39 yrs old	40–55 yrs old	African American	Hispanic	White/Caucasian	other
Male	27	39	110	18	50	105	3
Female	50	66	188	31	79	187	7

	speeding_trip_freq				drivers_employment		have_child	
Gender	Not_at_all	Rarely	Sometimes	Often	employed	unemployed	yes	no
Male	39	47	47	43	149	27	57	119
Female	75	86	80	63	193	11	147	157

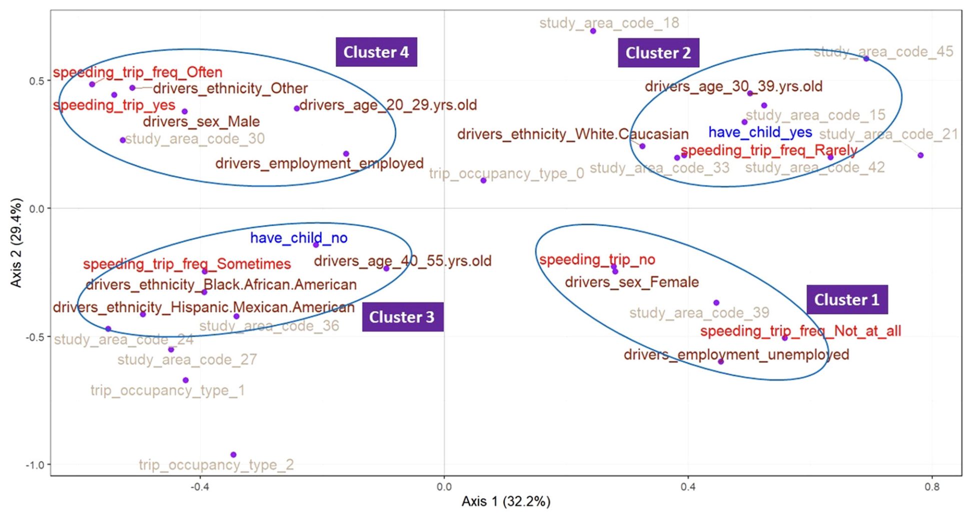

Figure 2. Driving speeding pattern without child occupancy.

categories in the plot indicates the magnitude of association among these categories. Closer categories mean a stronger association among these categories. Four clusters for trips without child occupancy and three clusters for trips with child occupancy are found to be strongly associated with speeding patterns. There are also other apparent clusters shown in the plot weakly associated with the speeding patterns, which will not be discussed in this section. For both cases, the variance explanation of the TCA analysis on the plane is over 60%.

Speeding Pattern without Child Occupancy

Figure 2 reveals four clusters associated with speeding patterns of trips without child occupancy. Two categories of the speeding pattern, speeding trip (speeding_trip_yes) and non-speeding trip (speeding_trip_no), are clustered into cluster 1 and cluster 4. Another two clusters, clusters 2 and 3 in quadrants 1 and 3, respectively, are clustered with two driver aggressiveness categories (speeding_trip_freq_Rarely/Sometimes) and are worth discussion.

Cluster 1 shows that unemployed (drivers_employment_unemployment), females (drivers_sex_Female), and the least aggressive drivers (speeding_tri_freq_Not_at_all) are strongly associated with non-speeding trips. We expect to observe that the least aggressive drivers are strongly associated with non-speeding trips, even for trips without child occupancy. Cluster 2 presents the general pattern for trips of parent drivers (have_child_yes) without child occupancy. White/Caucasian drivers from age group 30 to 39 years and without any passengers (trip_occupancy_type_0) rarely have speeding trips (speeding_trip_freq_Rarely). In cluster 3, which shows trips without the presence of children, moderate speeding behavior (speeding_trip_freq_Sometimes) is strongly associated with drivers in an older age group from 40 to 55 years old without children under 15 years old and from the Black/African American or Hispanic communities.

Cluster 4 shows the dominant categories that are associated with speeding trips without children present in the

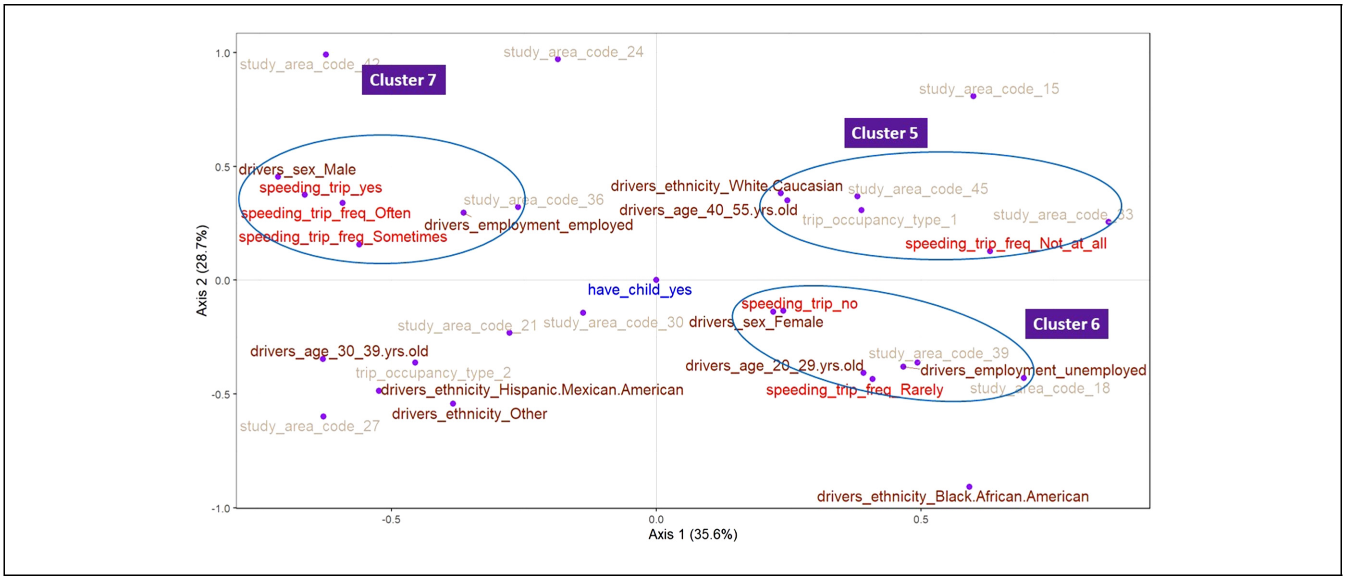

Figure 3. Driving speeding pattern with child occupancy.

trips. Speeding trips are often associated with frequently speeding drivers (speeding_trip_freq_Often). Moreover, speeding trips are also highly associated with employed and male drivers from the younger age group (drivers_age_20_29.yrs.old). Younger and male drivers are more likely to speed and drive aggressively compared with older or female drivers, which is consistent with existing studies (*13*). This cluster also shows that speeding trips are highly associated with the study area with area code 30, which refers to the Houston area. Houston, Texas, is a metropolitan area with a population of 2.31 million in 2019. This association suggests that drivers from highly populated areas are more likely to speed, which is also shown in some previous studies (*44*).

Speeding Pattern with Child Occupancy

Clusters 5, 6, and 7 are three clusters showing the association between the drivers' speeding patterns and demographic/driver features in trips with child occupancy (see Figure 3). Two categories of the speeding pattern, speeding trip (speeding_trip_no) and non-speeding trip (speeding_tri_yes), are clustered into cluster 6 and cluster 7 in the fourth and second quadrants, respectively. Cluster 5 presents a pattern associated with the least driver aggression (speeding_trip_freq_Not_at_all) which will be covered in the following discussion. Cluster 5 demonstrates that parent drivers from the 40 to 55 age group with White/Caucasian ethnicity are defensive drivers with the least aggression during driving. In cluster 6, non-speeding trips are highly associated with unemployed, young, female drivers from the age group 20 to 29 years old. These drivers are often defensive drivers who rarely have speeding trips (speeding_trip_freq_Rarely). Cluster 7 associates the speeding trips (speeding_trip_yes) with employed male drivers that often display speeding behaviors (speeding_tri_freq_Sometimes/Often).

The TCA analyses demonstrate seven speeding-related clusters. Seven clusters present the patterns for trips with or without child occupancy from two perspectives: speeding patterns of individual trips and drivers' general aggression. The speeding pattern is categorized by if the trip is a speeding trip or not. Drivers' aggression has four categories: *Not at all*, *Rarely*, *Sometimes*, and *Often*. The aggression category is measured by the percentage of speeding trips out of all trips recorded in the dataset.

- In general, female and unemployed drivers are associated with low driving aggression as regards speeding behavior, even without child presence in the trips. The defensive driving behavior remains similar for trips with child occupancy. Because of the design of the survey, female drivers may be stay-at-home parents, which is classified as unemployed in this dataset. However, the descriptive statistics in Table 6 have the distribution of employed and unemployed status for female drivers. The employed and unemployed drivers are 60% and 40% for the female driver population. Therefore, the female sex and unemployment could both be strong indicators of defensive driving trips with or without child presence. Female and unemployed drivers are often less aggressive in driving in multiple studies.
- Within the 40 to 55 age group, drivers exhibit occasional speeding behavior when they do not

have children under the age of fifteen in their trips. However, interestingly, when these drivers have children under the age of fifteen present, they demonstrate the highest level of defensive driving behavior and refrain from any instances of speeding. This indicates a notable disparity in driving behavior among drivers from the same age group, depending on the presence or absence of children during their trips.

- As shown in cluster 4, drivers from the youngest age group in the dataset, 20 to 29 years old, are the most aggressive drivers (speeding_trip_freq_Often) if there is no child present in their trips. Younger drivers are more likely to be aggressive and reckless during driving. This finding has been documented in multiple studies (*5*, *13*). However, these young parents drive very defensively when children are present on their trips. It is interesting to observe that young parent drivers, especially female drivers, changed their reckless driving behavior and become defensive. This finding reinforces the conclusions in Kelley-Baker and Romano's study (*27*).
- Male and employed drivers exhibit a predominant association with frequent speeding behavior and speeding trips in both trips without children occupancy and trips with children present, reinforcing the existing evidence that male drivers, in comparison with their female counterparts, tend to display a higher inclination toward aggressive driving and speeding (*45*). This research found that male drivers continue driving aggressively and recklessly even with the presence of children in their trips.
- Ethnicity appears to have a role in influencing driving patterns. When considering trips without child occupancy, White/Caucasian drivers tend to exhibit slightly more defensive driving behavior (speeding_trip_freq_Rarely) compared with Hispanic or African American drivers (speeding_trip_freq_Sometimes). However, it is important to note that these associations based on ethnicity do not imply causation. Further research is needed to explore additional factors, such as economic status, educational background, and other relevant aspects that may be associated with ethnicity, potentially contributing to these observed differences in driving behavior.
- The metropolitan area of Houston exhibits a strong correlation with the highest levels of driver aggression in trips without children present, as indicated by the frequency of speeding and the occurrence of speeding trips. However, interestingly, this metropolitan area does not show any significant associations with speeding-related clusters for trips with child occupancy. Furthermore, other study areas display varying associations with different factors in trips involving or not involving children. This highlights that, similar to frequent speeding behavior, these driving behaviors can exhibit spatial variations even among drivers with similar demographic characteristics (*46*). This result requires further investigation into spatial effects on speeding behavior for trips with or without child occupancy.

Based on the findings from the study, some recommendations are described below:

- **Promote defensive driving education and awareness:** Given that female and unemployed drivers exhibited lower driving aggression and engaged in defensive driving behavior, educational programs and campaigns emphasizing defensive driving techniques could be developed and targeted toward all drivers, with a particular focus on promoting safe driving practices to male and employed drivers.
- **Tailored interventions for different age groups:** Recognizing the differences in driving behavior among age groups, it is important to design age-specific interventions. For instance, drivers in the 40 to 55 age group may benefit from targeted programs that reinforce defensive driving when traveling with children, whereas younger drivers in the 20 to 29 age group could benefit from interventions that address their tendency for aggressive driving when children are not present.
- **Addressing male driver aggression:** Given that male and employed drivers tend to exhibit frequent speeding behavior and aggression, interventions should focus on reducing aggressive driving tendencies. This could include targeted campaigns promoting safe driving practices, highlighting the risks associated with speeding, and promoting responsible driving behaviors, particularly when children are present in the vehicle.
- **Explore the role of ethnicity and associated factors:** The study suggests that ethnicity may have some association with driving patterns. Further investigation is needed to understand the underlying factors contributing to these differences. This could involve examining socioeconomic, educational, and cultural factors to identify potential areas for targeted interventions or educational initiatives.
- **Spatial considerations for interventions:** The study highlights spatial differences in speeding behavior and driver aggression across different study areas. Understanding spatial effects on speeding behavior, particularly with and without child

occupancy, can help inform the development of location-specific interventions, such as targeted enforcement strategies, road infrastructure improvements, or public awareness campaigns tailored to specific areas.

Conclusions

Speeding leads to a higher collision rate and a higher probability of casualties. The likelihood of driver's mistakes resulting from the high speed compounds with loss of control of the vehicle and failure to anticipate and avoid risk in a timely manner. Although many studies have examined the speed–crash association and the association between driver behavior and the presence of passengers (*47–55*), examination of the presence of child occupants has not been explored as extensively. The unique contribution of this paper is that it explores the patterns of speeding behavior with child occupancy by utilizing household travel survey data from multiple study areas in Texas. The study employs a dimension reduction algorithm called TCA to process the data, allowing for a comprehensive analysis of the relationship between speeding behavior, driver aggression, and various demographic factors such as age, gender, employment, locality, and ethnicity. By uncovering multiple dimensions and using new data sources, the study provides a more in-depth understanding of the factors influencing speeding behavior with child occupancy. The results, presented through clusters with multiple aspects, can aid in the development of targeted countermeasures, such as tailored education for driver groups with children.

The analysis explores the association among speeding behavior, the driver's aggression, and the driver's demographic factors in trips with or without the occupancy of children. Patterns in trips without children present and patterns in trips with children present are recognized and compared. Many findings are not documented when using a CA perspective. For example, for trips without children occupancy, drivers from the youngest group 20 to 29 are likely to be more aggressive drivers and often have speeding trips. However, with the presence of children in their trips, parent drivers from this age group become the most defensive driver. The results also found unemployed drivers tend to drive more defensively compared with employed drivers during trips with child occupancy. Drivers with different ethnicities tend to have different speeding patterns with child presence. However, this association does not suggest causation. The economic factors, demographical factors, and even characteristics of the living area could have a significant effect on the ethnicity presentation.

There are several potential countermeasures that could be used to address aggressive speeding behaviors. Public awareness is an effective tool for communicating information about the risks of speeding to society and promoting current law enforcement activities that are enforcing speed compliance. In addition, a range of low and mid-cost engineering tools have proven safety benefits by addressing speed hazards on these roadways. Finally, new technologies in vehicles can help maintain the posted speed limit in an automatic fashion. Action should be encouraged in the industrial sector to develop more of these tools.

This study is unique because of its study design and analysis, but it still has several limitations. One limitation is that the data are not balanced by driver age, gender, or ethnicity. There is a need for an extension of this study with the use of balanced data. Second, many other influential factors are not considered in this analysis as data concerning these variables are not readily available. Some findings can be associated with the demographic characteristics of some areas. Future studies can explore this issue. Additionally, usage of the real study areas along with some key demographic information may be intuitive in future studies. However, information in such detail is rarely present. The use of the current data is still able to identify some of the key insights. This study acknowledges the validity of exploring the differential behavior of drivers when considering children versus teenagers. Future research could explore deeper into this aspect, specifically comparing the driving behaviors, risk perceptions, and decision-making processes of drivers in these distinct age groups. By conducting targeted studies that specifically differentiate between children and teenagers, valuable insights can be gained about the nuances of driver behavior and how they relate to speeding tendencies in the presence of passengers within these age brackets.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Subasish Das; data collection: Subasish Das and Xiaoqiang Kong; analysis and interpretation of results: Subasish Das, Xiaoqiang Kong, Zihang Wei, and Xiao Xiao; draft manuscript preparation: Subasish Das, Xiaoqiang Kong, Zihang Wei, Xiao Xiao, David Mills, and Ahmed Hossain. All authors reviewed the results and approved the final version of the manuscript.

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