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# The role of alternative fuel vehicles: Using behavioral and sensor data to model hierarchies in travel

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ABSTRACT

Greater adoption and use of alternative fuel vehicles (AFVs) can be environmentally beneficial and reduce dependence on gasoline. The use of AFVs vis-à-vis conventional gasoline vehicles is not well understood, especially when it comes to travel choices and short-term driving decisions. Using data that contains a sufficiently large number of early AFV adopters (who have overcome obstacles to adoption), this study explores differences in use of AFVs and conventional gasoline vehicles (and hybrid vehicles). The study analyzes large-scale behavioral data integrated with sensor data from global positioning system devices, representing advances in large-scale data analytics. Specifically, it makes sense of data containing 54,043,889 s of speed observations, and 65,652 trips made by 2908 drivers in 5 regions of California. The study answers important research questions about AFV use patterns (e.g., trip frequency and daily vehicle miles traveled) and driving practices. Driving volatility, as one measure of driving practice, is used as a key metric in this study to capture acceleration, and vehicular jerk decisions that exceed certain thresholds during a trip. The results show that AFVs cannot be viewed as monolithic; there are important differences within AFV use, i.e., between plug-in hybrids, battery electric, or compressed natural gas vehicles. Multi-level models are particularly appropriate for analysis, given that the data are nested, i.e., multiple trips are made by different drivers who reside in various regions. Using such models, the study also found that driving volatility varies significantly between trips, driver groups, and regions in California. Some alternative fuel vehicles are associated with calmer driving compared with conventional vehicles. The implications of the results for safety, informed consumer choices and large-scale data analytics are discussed.



## 1. Introduction

Automobiles are the dominant mode of personal travel in the United States. While they are associated with economic development, automobiles also have adverse impacts on the environment, generate greenhouse gases, and result in dependence on petroleum. One solution to lowering petroleum dependence and reducing emissions is the wider adoption and use of alternative fuel vehicles (AFVs). They are generally more fuel-efficient and environmentally-friendly compared with conventional fuel vehicles (gasoline and diesel) and fulfill expanding individual travel demands of the future (Lavrenz and Gkritza, 2013; Ji et al., 2012). Driving behavior in alternative fuel vehicles is of particular interest, if they are to be purchased

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and used widely. AFVs include plug-in hybrid electric vehicles (PHEVs), battery electric vehicles (BEVs), and compressed natural gas (CNG). While most hybrid electric vehicles are not necessarily AFVs (i.e., are gasoline-based), they are more fuel efficient making use of a smaller engine coupled with electric battery. The key research questions are:

- Whether alternative fuel vehicles and hybrid vehicles have similar use characteristics (trip frequency, vehicle miles traveled, etc.) as conventional vehicles?
- Whether drivers of alternative fuel vehicles are more or less prone to abrupt maneuvers, e.g., aggressive accelerations or vehicular jerk?

The main motivation for the study comes from the potential to learn important lessons from examining the behaviors of early AFV adopters who typically have to overcome adoption barriers such as higher vehicle acquisition costs, shorter driving ranges, scarcity of refueling stations, and potential safety and reliability issues. The study provides a stronger behavioral basis for future tools that can be developed to potentially increase the adoption, diffusion, and use of AFVs and ultimately a large-scale energy transition to alternative fuels. There is an added sense of urgency to examine the use of AFVs as they are gaining greater acceptance and popularity.

Behavioral data used in this study are hierarchical, i.e., they are nested with multiple trips made by different drivers who reside in various regions. Multi-level models have been used for analysis of such data, but not widely in the travel behavior field. This study uses multi-level modeling in a novel way to study whether driving volatility (a key measure of driving performance) varies significantly between trips, driver groups, and regions in California. Relatively new and unique large-scale behavioral data integrated with sensor data from global positioning system devices are used to estimate models and learn from expanded data that has only recently become available (Lohr, 2012; Siripirote et al., 2014; Byon and Liang, 2013).

## 2. Literature review

Vehicle miles/hours traveled, trip frequency, and travel times/distances are often used as measures of performance in transportation. Increasingly, speed and acceleration data are the becoming available and these measures are increasingly used to characterize the driving behavior. Wang et al. used the average speed, average acceleration and the percentage of time in acceleration mode to capture the driving behavior in Chinese cities (Wang et al., 2008). Hung et al. viewed the driving characteristics in a similar way and pointed out the associated factors, including land use, flow density, road width and road network (Hung et al., 2005). Sciarretta et al. investigated the driving behavior of hybrid electric vehicle by collecting their speeds and accelerations. They pointed out that the driving conditions, driver characteristics and vehicle performance are important for understanding the driving experience of hybrid electric vehicle users (Sciarretta and Guzzella, 2007). Johannesson et al. also used the speed and acceleration to quantify driving behavior of hybrid vehicles (Johannesson et al., 2007). Furthermore, the rates of fuel consumption and emissions were used to characterize the driving behavior of internal combustion engine vehicles (Murphey et al., 2009). Generally, hybrid vehicles have higher fuel economy than conventional vehicles (Musardo et al., 2005; Fontaras et al., 2008) and also there are zero-emission electric vehicles in use (Lam and Louey, 2006). In order to be somewhat consistent with previous studies, this study uses measures related to the vehicle movement (speed) to characterize the driving behavior.

To understand driving behavior, researchers have defined driving styles, e.g., aggressive driving or calm driving. Typically, cut-off thresholds are used to demarcate driving behavior. Kim et al. gave 1.47 m/s$^2$ (4.82 ft/s$^2$) and 2.28 m/s$^2$ (7.47 ft/s$^2$) as thresholds for aggressive and extremely aggressive accelerations (Kim and Choi, 2013). While De Vlieger et al. pointed out 0.45–0.65 m/s$^2$ for calm driving, 0.65–0.80 m/s$^2$ (2.13–2.62 ft/s$^2$) for normal driving and 0.85–1.10 m/s$^2$ (2.79–3.61 ft/s$^2$) for aggressive driving (De Vlieger et al., 2000). Thresholds suggested in literature are summarized in Table 1. The somewhat arbitrary cut-off points ignore the heterogeneity of driving behavior under different speeds, which has been found in some of the previous studies by the authors (Wang et al., 2015; Liu et al., 2014). The results showed that at lower speeds on local/collector roads large acceleration/deceleration values are frequent but at higher speeds (typically on freeways with a good level of service) drivers often do not (or cannot) accelerate and decelerate abruptly. Notably, alternative fuel vehicles may have different performance outcomes because of their different power systems compared with conventional gasoline vehicles (Hori et al., 1998; Moreno et al., 2006).

This study uses the term driving "volatility" instead of "aggressiveness" to measure abrupt accelerations and decelerations, as mentioned in some of our previous studies (Wang et al., 2015; Liu et al., 2014). The difference between "aggressiveness" and "volatility" is similar to the terms "accident" and "crash" (Stewart and Lord, 2002). Using the term "volatility" is neutral and describes the driving behavior in a more objective and impersonal way. The method for measuring driving volatility is discussed in the next section.

A variety of statistical models have been used to explore links between driving behavior and associated factors, based on the data structure and research purposes. Analysis of variance (ANOVA), Chi-square test and *t*-tests are the most commonly used methods comparing various groups (Subhashini and Arumugam, 1981; Simons-Morton et al., 2005). Ordinary Least Square (OLS) models including linear and logistic regressions are frequently applied to find the relationships between outcomes and associated factors (Khattak et al., 1995; McElroy, 1967; Dissanayake and Perera, 2011; Khattak and Rocha, 2003). Some studies have noted the hierarchical nature of behavioral data and applied multi-level models to explain relationships