# Speeding behavior while using adaptive cruise control and lane centering

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# Contents

## ABSTRACT

**Objective:** Adaptive cruise control (ACC) and lane centering are usually marketed as convenience features but may also serve a safety purpose. However, given that speeding is associated with increased crash risk and worse crash outcomes, the extent to which drivers speed using ACC may reduce the maximum safety benefit they can obtain from this system. The current study was conducted to characterize speeding behavior among drivers using adaptive cruise control and a similar system with added lane centering.

**Methods:** We recruited 40 licensed adult drivers from the Boston, Massachusetts, metro area. These drivers were given either a 2017 Volvo S90 or a 2016 Land Rover Range Rover Evoque to use for about 4 weeks.

**Results:** Drivers were significantly more likely to speed while they used ACC (95%) relative to periods of manual control (77%). A similar pattern arose for drivers using ACC with added lane centering (96% vs. 77%). Drivers who traveled over the posted limit with these systems engaged also sped slightly faster than drivers controlling their vehicle manually. Finally, we found that these differences were the most pronounced on limited-access roads with a lower speed limit (55 mph).

**Conclusions:** These findings point to a possible obstacle to obtaining the full safety potential from this advanced vehicle technology. Any consideration of the net safety effect of ACC and lane centering should account for the effects of more frequent and elevated speeding.

# INTRODUCTION

Manual tasks are often automated out of a desire to improve performance. There are a great number of success stories in this regard, from commercial aviation (e.g., Wiener & Curry, 1980) and mass transit (e.g., Longo & Bramani, 2015), to maritime shipping (e.g., Hetherington, Flin, & Mearns, 2006). However, far from removing human responsibility altogether, automation has largely altered the responsibilities of operators who now must assume managerial positions over automated elements of the system. Even for tasks that are entirely automated, a human operator is typically placed in a supervisory role. The assumption of supervisory duties introduces the potential for errors related to the failure to attend or respond to the automation's mistakes (Bagheri & Jamieson, 2004; Parasuraman & Riley, 1997). Poor outcomes can also result when automation is used at inappropriate times or in ways outside the bounds of its intended design.

Of particular interest to the current study, cruise control allows the user to specify a speed that exceeds the legal limit. Cruise control maintains a speed selected by the driver; adaptive cruise control (ACC) is a more advanced variant that dynamically adjusts vehicle speed to match pace with a leading vehicle. In both cases, a task that was previously controlled manually by the driver is now automated. There is some evidence to suggest that drivers may drive faster when they have access to ACC (National Highway Traffic Safety Administration [NHTSA], 1998), but the extent to which they exceed the speed limit with this system engaged is unknown. The current study was conducted to quantify driver speeding behaviors while using ACC and a more advanced variant with added lane centering. Lane centering automates the steering process by keeping the vehicle centered in the lane (with driver supervision).

Although ACC is typically marketed as a convenience rather than a safety feature, it can also serve a safety purpose. At default settings, the system tends to maintain a greater lead compared with manual driving (Xiong & Boyle, 2011), allowing more time for braking in response to a critical event. Research also suggests that ACC may reduce crash risk by reducing passing maneuvers and lane changes (Crump, 1984; Garber & Ehrhart, 2000). A recent analysis of insurance claims support this notion, finding that the presence of ACC on certain BMW vehicles was associated with greater reductions in claim rates than what was seen for vehicles with other crash avoidance systems (Highway Loss Data Institute, 2019a). The safety benefit of the lane-centering functionality is less clear, however. The same analysis found that adding lane centering to BMW's ACC system did not provide an additional safety benefit (HLDI, 2019a), although it remains to be seen whether this feature improves safety outcomes in other vehicles.

The safety benefit of ACC and lane centering will be reduced to the extent that drivers using these systems engage in more frequent risky speeding behavior than drivers controlling their vehicles manually. All else being equal, faster speeds increase the distance that a vehicle travels before the driver can respond to an emergency, increase the distance needed to stop, and increase the risk that an evasive steering maneuver will result in a loss of control (Elvik, 2005). Speeding is known to reduce drivers' ability to avoid a crash if they are faced with a critical event, and even small increases in speed can substantially worsen crash outcomes (Elvik, 2009; Kloeden, McLean, & Glonek, 2002). ACC may help manage some conflict scenarios (e.g., lead vehicle decelerations within the ACCs limits) but leaves the driver responsible in others (e.g., vehicle cut-ins). Much like conventional control, a driver's ability to react to emergent events remains more impaired at higher speeds. Overall, speeding has long been known as a major factor in traffic safety. The latest estimates suggest that speeding is a contributing factor in 26% of motor vehicle fatalities (IIHS, 2020), and federal data place the cost of speed-related crashes at $52 billion each year (NHTSA, 2015). As such, the mitigation of speeding through the appropriate use of automation could enhance road safety.

ACC and lane centering are relatively rare in today's fleet—just 17% of model year 2020 vehicle series are equipped with ACC as standard (Highway Loss Data Institute, 2019b), and lane centering is even less prevalent. It is reasonable to expect that these systems will become more common in the future. The way drivers use (or misuse) these systems will have a significant impact on highway safety. Driver speeding behavior with today's technology can be used to anticipate the effects that these systems might have when they are more widespread (NHTSA, 2006).

# METHOD

## Participants

Licensed adult drivers (*N* = 40; 55% male) were recruited from the Boston, Massachusetts, metro area. As part of the recruitment process, background and driving record checks were performed to meet risk-minimizing standards associated with the Massachusetts Institute of Technology's (MIT's) policy for driving MIT-owned vehicles. To be eligible, participants must not have been involved in a police-reported crash, must not have received two or more moving-traffic-violation convictions in the past year, and must not have had other high-risk behaviors on their record (e.g., driving under the influence, license suspension, etc.). Drivers were on average 43.9 years old (*SD* = 14.1) and reported commuting at least 30 miles a day along a consistent route.

## Vehicles and systems

All participants were provided either a 2017 Volvo S90 (*n* = 20) or a 2016 Land Rover Range Rover Evoque (*n* = 20) for their personal use for approximately 4 weeks (*M* = 4.1 weeks, *SD* = 0.94). Both the S90 and the Evoque were equipped with ACC, which provided consistent headway and speed control. The Volvo S90 was also equipped with a second system—Pilot Assist—which provided lane centering in addition to the base functionality of ACC.

The vehicles were instrumented with the MIT Advanced Vehicle Technology (MIT-AVT) RIDER (Real-time Intelligent Driving Environment Recording) data acquisition system (Fridman et al., 2019). Video cameras were installed facing the instrument panel, and computer vision was used to determine the status of the advanced driver assistance systems. Vehicle speed and location were recorded using a GPS chip. GPS data were also used to obtain functional class (Federal Highway Administration, 2013) and posted speed limits of the roads where the travel occurred. Speed limits for approximately 1% of the data could not be identified; these segments were discarded. The current dataset was restricted to interstates, freeways, and other expressways.

## Procedure

Participants were trained for 90 minutes upon receipt of the vehicle. The first 30 minutes took place inside the stationary vehicle and focused on basic vehicle functions and instrumentation. The remainder of the training (60 minutes) took place on the road, where participants went through the process of activating and deactivating the driver assistance systems, including ACC and lane centering. After training, participants responded to demographic and individual differences questionnaires.

## Analysis

Speeding behavior was analyzed in two ways. First, a binary variable was created to indicate whether or not the driver was speeding. This variable assumed a value of 1 if the vehicle's current speed exceeded the posted limit of the road, else it assumed a value of 0. Second, the posted limit was subtracted from participants' speed values to produce a value for the degree of speeding: the vehicle's speed relative to the current limit. The latter analysis was restricted to periods where the drivers were speeding so as to get an estimate for speeding severity by control type. Only periods of "free-flow" driving were retained for analysis; free-flow was defined as traveling 5 mph below the speed limit or faster, which was the approach used by NHTSA in its examination of speeding behavior that occurred during a large naturalistic driving study (Richard, Joonbum, Brown, Landgraf, 2020).

The binary speeding variable was used in a logistic model to predict the probability of speeding. Odds ratios were converted to risk ratios for this analysis (Zhang & Yu, 1998). The continuous speeding variable was then used in a linear model to predict the amount over the speed limit that speeding drivers were traveling. Both outcomes were predicted by control type (ACC, Pilot Assist, manual driving) and speed limit (55 mph, 60 mph, 65 mph). Vehicle type (S90 vs. Evoque) and trip number (number of free-flow trips since onset) were included as covariates.

A follow-up analysis was conducted to determine whether the effect of control type on speeding behavior varied by the speed limit of the road. This interaction was calculated using a binary control type variable (ACC/Pilot Assist vs. manual) and speed limit (55 mph, 60 mph, 65 mph). Control type was converted to a binary variable for the interaction term to ensure sufficient representation in each cell. Elvik's (2009) Power Model was then used to convert these speed values into more concrete terms: estimated percentage change in fatal, injury, and property-damage-only crash risk. Finally, to assess the degree to which speeding is consistent within drivers, we correlated participants' probability and magnitude of speeding during manual driving with that during ACC/Pilot Assist use.

All regression analyses were conducted using linear mixed-effects models (Bates, Mächler, Bolker, & Walker, 2015), and Sattherwaite approximations (1946) were used to determine denominator degrees of freedom for *t*- and *p*-values. Mixed-effects models are appropriate for repeated measures designs where participants provide numerous nonindependent responses. In the case of the current study, for example, speed was recorded every second. Vehicle speed at one second is necessarily correlated with vehicle speed in the next. Similarly, drivers who speed during one trip may be more likely to speed in a subsequent trip. Using an ordinary regression model in the current study would mistakenly assume these measurements to be independent, which would overestimate degrees of freedom and inflate the Type 1 error rate. All the mixed-effects models in the current study used a three-level structure with trips nested within drivers, as well as a random slopes term for control state.

## RESULTS

The 40 participants undertook an average of 25 trips each on limited-access roads (*SD* = 14), totaling approximately 20,000 miles traveled (*M* = 516 miles each, *SD* = 409). The majority of these miles were traveled under manual control (60%), followed by ACC (32%) and Pilot Assist (7.3%). We first examined a density plot of vehicle speed relative to the speed limit by control state. This plot shows density spikes close to each 5-mph interval around the speed limit for ACC and Pilot Assist use (Figure 1).

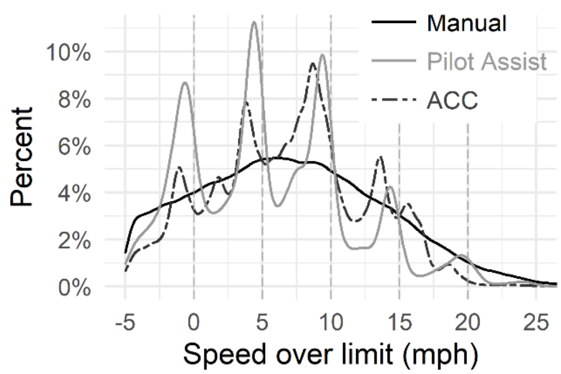


**Figure 1.** Distribution of vehicle speed over limit by control state.

Drivers were significantly more likely to speed while they used ACC (95%) relative to periods of manual driving (77%), RR=1.24, 95% CI [1.20, 1.26], $p <. 001$. A similar pattern arose for drivers using Pilot Assist (96% vs. 77%), RR=1.24, 95% CI [1.18, 1.27], $p < .001$ (Figure 2). There were no significant differences by vehicle type (S90 vs. Evoque), and trip number did not significantly predict the probability of speeding.

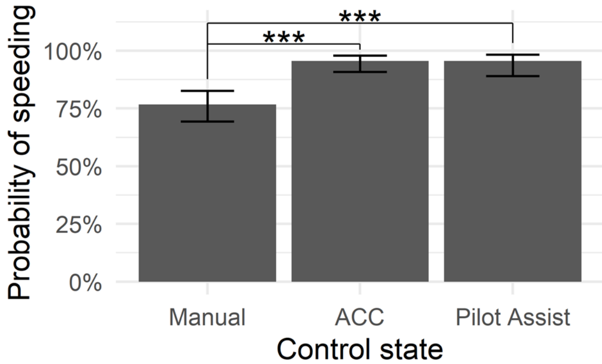


**Figure 2.** Probability of speeding by control state. Error bars represent 95% confidence interval (CI). *** $p < .001$.

There were also statistically significant differences in the magnitude of speeding between manual, ACC, and Pilot Assist travel (Figure 3). While speeding, drivers controlling their vehicles manually traveled 6.1 mph over the speed limit, compared with 7.0 mph over during ACC travel (B = .91, $SE$ = 0.27, $t(32.0)=3.40$, $p = .002$) and 7.1 mph over during Pilot Assist travel (B=1.03, $SE$ = 0.44, $t(19.0)=2.36$, $p = .029$). Thus, although there were rather large differences in the probability of speeding by control state, the differences in the magnitude of speeding were comparatively small. There were no significant differences by vehicle type (S90 vs. Evoque), and trip number did not significantly predict the magnitude of speeding.

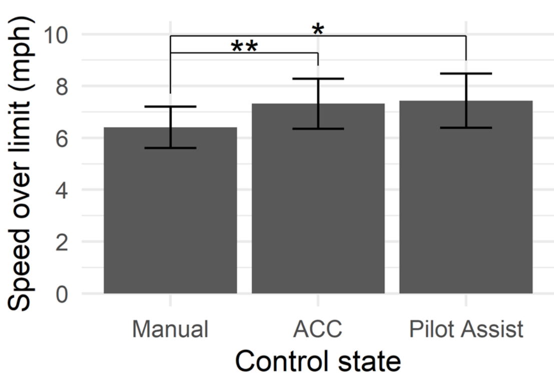


**Figure 3.** Miles per hour over the speed limit by control state. Error bars represent 95% confidence interval (CI). ** = $p < .01$, * = $p < .05$.

Overall, the magnitude of speeding behavior decreased as the speed limit increased, B = −1.41, $SE = 0.11$, $t(1483) = -12.5$, $p < .001$. On average, speeding drivers traveled about 8 mph over the limit on 55-mph and 60-mph roads, but only about 5 mph over on 65-mph roads. The interaction between control state and speed limit was also significant, B = −.51, $SE = .14$, $t(668.6) = -3.65$, $p < .001$, such that the effect of control state on speeding was more pronounced on roads with a lower speed limit (Figure 4). The largest difference in the magnitude of speeding behavior between manual control and ACC/Pilot Assist occurred on 55-mph roads (Δ 1.4 mph); the difference was negligible for 60-mph roads (Δ 0.26 mph) and 65-mph roads (Δ 0.41 mph). In sum, the data suggest that ACC and Pilot Assist increase speeding the most when the speed limit is relatively low.

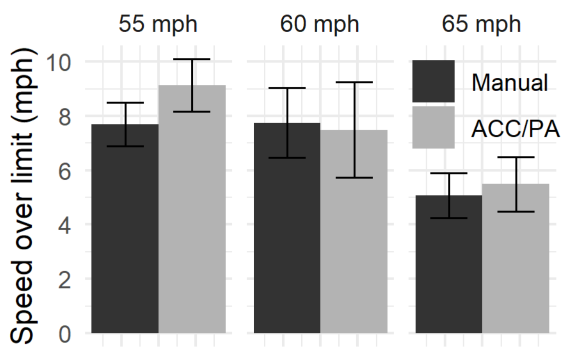


**Figure 4.** Miles per hour over the speed limit by control state and speed limit. Error bars represent 95% confidence interval (CI). PA = Pilot Assist.

Elvik (2009) provides an equation for converting change in speed to the probability of various crash outcomes. Briefly, this equation consists of *speed after* divided by *speed before* raised to an exponent. The exponent varies depending on outcome (fatal, injury, property damage only) and road type (rural, urban, overall) and includes bounds for calculating a 95% confidence interval. Assuming that the automation associated with ACC/Pilot Assist does not significantly impact this calculation, the equation can be used to estimate the change in crash risk associated with the increase in speed observed for ACC/Pilot Assist use. We estimated the projected change in fatal, injury, and property-damage-only crash risk using the speed values from 55-mph roads because the largest increase in speeding behavior was observed there. Compared with manual driving, the increase in speed associated with ACC/Pilot Assist use was estimated to increase crash risk by 10% for fatal crashes, by 4% for injury crashes, and by 3% for property-damage-only crashes (Figure 5).

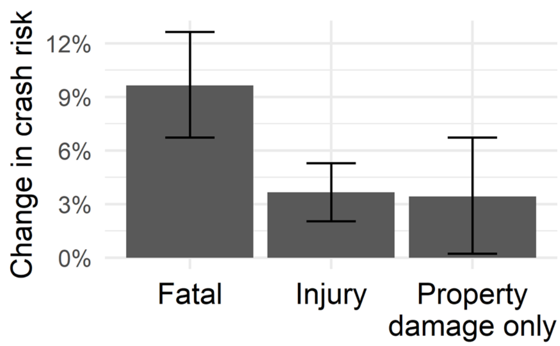


**Figure 5.** Estimated change in fatal, injury, and property-damage-only crashes associated with increased speed during ACC/Pilot Assist use compared with manual driving on freeways with 55-mph speed limits. Error bars represent 95% confidence interval (CI).

The tendency to drive over the speed limit was relatively stable within participants across control types. That is, if a driver were predisposed toward speeding while manually controlling the vehicle, the same could be said for their tendency to speed while using ACC/Pilot Assist. This was true for both probability of speeding ($r$ = .63) and magnitude of speeding ($r$ = .66) (Figure 6).

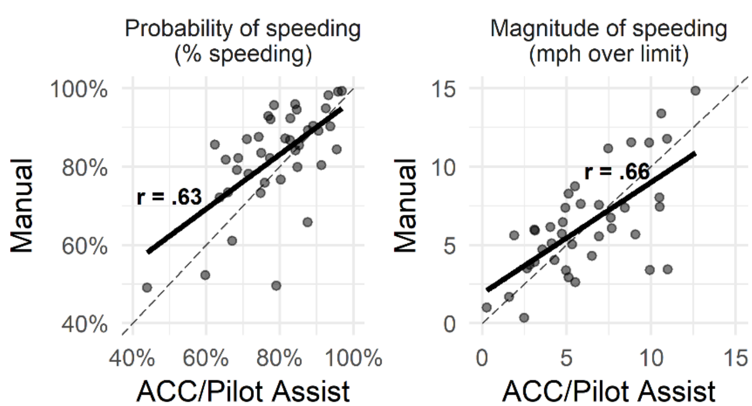


**Figure 6.** Correlation of speeding behaviors between manual driving and ACC/Pilot Assist driving by participant.

## DISCUSSION

We found that ACC and Pilot Assist use were associated with more frequent speeding and speeding that was greater in magnitude compared with manual driving. When drivers employed these systems, they were 24% more likely to speed and the amount over the limit they sped was slightly higher compared with when they were controlling their vehicles manually. Although the raw increase in speed associated with ACC and Pilot Assist use was only about 1 mph, it should be interpreted in light of the crash estimates derived from the Elvik (2009) equation. The speed differences observed in the current study were associated with a potentially substantial increase in fatal crashes (+10%), injury crashes (+4%), and property-damage-only crashes (+3%). These estimates are consistent with past research. For example, an IIHS analysis of speed limits found that the small average speed increase that results from raising the speed limit by 5 mph on interstates and freeways increased fatality rates on those roads by 8.5% (Farmer, 2019).

More frequent and severe speeding behavior while using ACC and lane centering may at least partially offset the safety benefits associated with these systems. Speed at impact is a primary predictor of crash severity, and so all else being equal, drivers using ACC would be at a greater risk of injury than drivers operating their vehicles manually. However, the current study did not measure a number of aspects related to ACC use that past research has linked with positive safety outcomes. For example, it is possible that drivers in the current study who set ACC to higher speeds also set a greater following distance. The control system automation involved with ACC is also designed to respond better than drivers to certain risky scenarios such as lead vehicle deceleration. Future research should consider the combined effect of excess speeding and greater following distance (among others: Crump, 1984; Garber & Ehrhart, 2000; Xiong and Boyle, 2011) to calculate the net effect that ACC has on safety.

Driver inattention can exacerbate the ill effects of excessive speed, and inattention is more common among drivers aided by automation—like ACC and lane centering—compared with those operating their vehicle manually (De Winter, Happee, Martens, & Stanton, 2014; Llaneras, Salinger, &

Green, 2013; Reagan et al., 2020; Wickens, 1994). Inattentiveness is a powerful predictor of crash risk (Dingus et al., 2016; Klauer, Dingus, Neale, Sudweeks, & Ramsey, 2006; Monk, Boehm-Davis, & Trafton, 2004), especially when attention is directed toward a secondary, non-driving task (Atchley, Tran, & Salehinejad, 2017; Caird, Willness, Steel, & Scialfa, 2008; Guo et al., 2017). Being distracted by secondary tasks also makes reclaiming control of the vehicle more difficult (see Cunningham & Regan, 2017 for a review). Thus, ACC and lane centering may not only increase the likelihood that drivers speed but may also reduce their ability to effectively reengage with manual driving. The dual consequences of driver inattention and excess vehicle speed represent obstacles to achieving the full safety potential of ACC and lane-centering technology. Understanding how automation can benefit the driver experience without triggering undesirable secondary behaviors will be a key challenge for highway safety research as ACC and other automated systems become more common in the years to come.

There has been some discussion about whether vehicles should disallow or limit drivers' ability to speed while using ACC and similar, more extensive automation. Although setting limits on vehicle speed has the potential to reduce speeding behavior, it is also possible that a more limited system would redirect risky drivers back to manual control. We found that drivers who speed while using ACC also tended to speed while controlling the vehicle manually, and so it is possible that a driver who is prevented from speeding by vehicle automation will not ultimately be deterred. If automated speed and headway control has a net positive effect on crash risk, a return to manual control may (ironically) increase crash risk compared to a less restrictive system. However, speed-limiting systems have been used successfully in the past to influence driver behavior. Intelligent Speed Adaptation (ISA)—an in-vehicle system that supports driver compliance with the speed limit—provides a useful analogue to the question of what might result from speed-restrictive ACC/partial automation. Studies on this system have found generally positive results, with slower and more homogenous driving speeds under ISA than not (Besseling & van Boxtel, 2001; Biding & Lind, 2002), even when the system was set up to merely warn the driver that the speed limit was being exceeded (Carsten & Tate, 2005). Future research should consider the data on ISA efficacy when trying to understand how speed-limited automation might affect driver behavior.

ACC use was associated with speeding behavior that was more closely clustered around 5-mph intervals compared with manual driving. These clusters are likely the manifestation of individual differences in how drivers perceive the balance between exceeding the speed limit and avoiding detection by law enforcement. Past research has shown that drivers commonly perceive enforcement tolerances of anywhere between 5–10 miles per hour over the posted speed limit (Soole, Watson, & Fleiter, 2013), and ACC makes it easier to maintain a specified speed over the limit than it would be under manual control. The study vehicles also allowed ACC/Pilot Assist users to modify their speed upward or downward by 5 mph by activating a toggle; this convenience likely contributed to the clustered distribution of speeds. Future research may seek to assess the influence of multi-mph toggling on speeding behavior.

The current study only examined ACC use on limited-access roads. Inappropriate use on surface streets—if it is common enough—may serve to further increase crash risk. Past research suggests that up to 10% of total ACC engagement takes place on surface streets, typically principal and minor arterials (NHTSA, 1998; Reagan et al., 2020). Although arterials are high-capacity roads, they contain relatively frequent stops and intersections that might increase crash risk for drivers misusing ACC. Future research should consider how ACC use on arterials might differ from its use on freeways or interstates.

Our data were restricted to roads in Massachusetts. Although limited-access roads tend to share similar characteristics across the United States (e.g., long, straight, and uninterrupted), it is possible that ACC has a different effect on speeding in other states—in those with more rural areas, for example (Enriquez & Pickrell, 2019). Similarly, the state-wide maximum speed limit in Massachusetts (65 mph) is lower than the maximum in other states. Our findings suggest that ACC increases the magnitude of speeding more when the speed limit is relatively low. Thus, it is possible that speeding caused by (mis)use of these systems will be less common in states where a greater proportion of interstates have a high speed limit.

## SUMMARY

The current study found that drivers tended to speed 24% more often and about 1 mph over the limit while using ACC and a similar system with added lane centering, relative to periods of manual driving. Heightened speeding behavior was most common with these systems while on limited-access roads with a lower speed limit (i.e., 55 mph). These findings point to a possible obstacle to obtaining the full safety potential from this advanced vehicle technology; any consideration of the net safety effect of automated speed and headway control should account for the effects of more frequent and elevated speeding.

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