Turing in the driver's seat: Can people distinguish between automated and manually driven vehicles?

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Abstract
As the number of automated vehicles is increasing on our roads, we wanted to know if people could detect if a car was being driven by a human driver or automation in a lane change task. This is particularly relevant, as most of the road collisions involve automated vehicles being struck from behind by manually driven vehicles. To address the detection of automated vehicles, an online survey presented videos of lane change maneuvers on multi-lane carriageways from behind the automated vehicle. We reasoned that, on such roads, the behavior of the vehicles in front would have more of an effect on drivers than those of the vehicles behind. To this end, an online survey was conducted with 769 people judging 60 video clips, classifying the lane change either being performed by Autopilot software or a human driver. Over 34,000 responses were recorded. It was found that automated and manual lane changes were virtually indistinguishable from the rear of the vehicle. The main conclusion of the research was that vehicles in automated mode should display this fact to other road users all around the vehicle as this may have an effect on other road users in anticipating the behavior of the other vehicle.

KEYWORDS
automation, Autopilot, road user interaction, self-driving, Turing test

1 | INTRODUCTION

Automated, self-driving, automobiles have moved from being science fiction to the simple fact (Stanton, 2015). This is, no doubt, driven by perceived consumer desire to be chauffeured from origin to destination, allowing them to get on with, putatively, more interesting activities than driving per se (Banks, Eriksson, O’Donoghue, & Stanton, 2018; Carsten, Lai, Barnard, Jamson, & Merat, 2012). The utility of automated driving has been much discussed in the academic (De Winter, Happee, Martens, & Stanton, 2014; Hancock, 2018, 2019) and more general public literature (Stanton, 2015). There are those that argue that human drivers need to be in charge of vehicle automation; that automated driving systems in the intermediary levels need to be designed for appropriate reliance, keeping the driver in the control "loop" (Banks & Stanton, 2016), and those that argue that the driver needs to be removed altogether (Alessandrini, Campagna, Delle Site, Filippi, & Persia, 2015). Most motor vehicle manufacturers are working on producing the former in the short to medium term, whilst retaining an eye on the latter for developments in the longer term.

Currently, the electric motor vehicle manufacturer Tesla is offering an Autopilot system as a downloadable software option (with...
the promise of regular updates) when customers buy their cars. This software claims to steer within a lane, change lanes with the simple tap of a turn signal, and manage speed by using active, traffic-aware, cruise control (Tesla Motors, 2016). Driving is, however, in fact, a very demanding activity, comprising over 1600 subtasks (Walker, Stanton, & Salmon, 2015). Learning to drive is effortful and takes some considerable amount of time to master successfully (Stanton, Walker, Young, Kazi, & Salmon, 2007). Currently, over 1.35 million people a year die in traffic collisions around the world (World Health Organization, 2018). Furthermore, it has been suggested that drivers blamed for over 90% of collisions, whether it is their fault or not (Singh, 2015; Stanton & Salmon, 2009; Thorpe, Jochem, & Pomerleau, 1997). Automated driving holds the potential to reduce this figure substantially (Musk, Stanton & Marsden, 1996). Elon Musk (Musk, 2016) has gone so far to say: “The probability of having an accident is 50% lower if you have Autopilot on. Even with our first version. So we can see basically what’s the average number of kilometers to an accident – accident defined by airbag deployment. Even with this early version, it’s almost twice as good as a person.” Whilst this claim is not based on any scientific studies, driver assistance systems could not only save many hundreds of thousands of lives worldwide but also would have helped the European Commission reach its goal of reducing road traffic deaths by 50% by 2030 (European Commission, 2019). It must be noted that consumer adoption of automated vehicles cannot happen overnight even if this was desired. Consequently, a transition period must be expected in which automated and manually driven vehicles share the same infrastructure (Ioannou, 1998). This has raised some safety concerns, as automated vehicles will have to be able to predict the behavior of somewhat unpredictable human drivers, whilst drivers of manual vehicles must anticipate and adapt to the driving style of automated vehicles seeking to improve their performance (van Loon & Martens, 2015). What is not yet known is how drivers of other, manually driven, vehicles will react to the presence of automated vehicles on the road in front of them. There is some suggestion that automated vehicles do not necessarily behave like manually driven vehicles and that drivers following such vehicles might not anticipate their behavior correctly (Wang & Li, 2019). This is important, as their perception of a car driven by an autopilot, rather than one driven by a human, may change the way in which they interact with it on the road (Thompson, Read, Wijnands, & Salmon, 2020). For example, Millard-Ball (2016) suggests that drivers may “play a game of chicken” with automated vehicles, as such vehicles are, in their nature, cautious to ensure safety. Indeed, Chris Urmson at Google has stated that “We make the cars as paranoid as possible, because there are some things they won’t be able to avoid” (quoted by Rogers, 2016).

Normally, pedestrians and drivers alike use certain strategies to negotiate traffic. For example, research has indicated that pedestrians tend to look directly at drivers before crossing the road (Evans & Norman, 1998), and often provide signals of gratitude (e.g., hand gestures, nodding, or smiling). However, such cues are not currently available when automation is involved, especially if there is no “driver” to communicate with (Lundgren et al., 2017). Similarly, Rodriguez (2017) found that cyclists feel less safe when interacting with pod-like automated vehicles in intersections. Thompson et al. (2020) suggest that automated vehicles could create conflicts with other road users, particularly with cyclists and pedestrians. One way of resolving this was proposed via “the smiling car” (Semcon, 2017), which shows a pedestrian that they have been detected, and that the vehicle will yield through a means of “humanlike” communication, something that has been previously suggested by Eriksson and Stanton (2017a) and Norman (1993).

The question remains, however, are human road users able to detect a vehicle being driven by a set of computer algorithms rather than by another human driver in moving traffic? Whilst for some vehicles, this differentiation is relatively simple (e.g., Waymo vehicles, previously known as Google Car, are equipped with a large LIDAR scanner on the roof of the vehicle), vehicles equipped with automated functionality enabling periods of “hands and feet free driving” (Banks, Stanton, & Harvey, 2014) are increasingly resembling normal cars. The Tesla Model S, for example, looks like any other medium-sized saloon vehicle. Even if the driver following an automated vehicle recognizes it as such (from the vehicle shape and/or badge), it does not necessarily mean that it is being driven in automated mode. This adds an additional layer of complexity to the driving task (Walker, Stanton, & Salmon, 2018) as road users will not be able to distinguish what is an automated vehicle simply from the make and model. The concern here is that automated and manual driving might be quite different in terms of setting appropriate expectations about their future behavior for drivers of manually drive vehicles following them. Reports on collisions with self-driving vehicles suggest that the majority are being rear-ended by drivers of manual vehicles (Wang & Li, 2019). Being able to differentiate between a vehicle being driven by an automated algorithm and a manually driven vehicle essentially represents the on-road equivalent of the “Turing test.” In 1950, Alan Turing (Turing, 1950) argued that to pass his test, a machine would need to exhibit intelligent behavior equivalent to, or at least indistinguishable from, that of a human. This is the much-discussed “imitation game.” We are not suggesting that the Autopilot “thinks” like a human driver, rather that people will be unable to distinguish between the external, observable behavior of the Autopilot and human drivers in our lane-change test specified below, much like Searle’s Chinese room experiment (Searle, 1980). Searle (1980) argued that whilst computer following rules set out in a set algorithm might be able to mimic the behavior of a human (in Searle’s thought experiment it was the exchanging of Chinese symbols following as a set of rules does not mean that you understand Chinese), it does not necessarily follow that the machine is thinking like the human, nor that human thinking is like that of machine computation. We chose a lane-changing task as our referent, as weaving crashes (which are comparable to the lane change manoeuvres; Pande & Abdel-Aty, 2006) is the cause of more than 20% of collisions on US freeways (motorways; Golob & Recker, 2004). Such maneuvers are one of the most challenging on multi-lane carriageways (Heesen, Baumann, Kelsch, Nause, & Friedrich, 2012; Young, Lenné, & Williamson, 2011). Performance
variability in human perception and decision making has been shown to be one of the causes of such collisions (Stanton & Salmon, 2009; Treat et al., 1979). For road users, in the target lane for the lane change, drivers need approximately 8–14 s to anticipate and react to an entering vehicle (Heesen et al., 2012; Zheng, Ahn, Chen, & Laval, 2013). We anticipated that the study of the lane change maneuvers should reveal differences in manual and automated driving behavior if they are to be found, and (much more so than simple lane-keeping or longitudinal car following) would. To do this, our plan was to present video clips of lane change maneuvers to drivers and ask them to classify them as either manual or automated.

2 | METHOD

To submit the Tesla Model S P90D (with the first generation of Autopilot) to the Turing test (Turing, 1950), we video-recorded a number of lane changes on multi-lane carriageways (the A46, M40, and M42 between Coventry and Birmingham in the United Kingdom). The video recordings were from the following vehicle using a GoPro camera with a standard lens capturing the leading vehicle as well as all three-lane of the full road view in front of the camera. The filming was from behind the target vehicle to represent the view a vehicle following would have, as the lane change would most likely to affect this vehicle (a lane change is unlikely to affect a vehicle in front of the target vehicle). This camera angle was chosen because the vehicle was on British motorways and dual carriageways (aka Freeway) where all the traffic flows in the same direction (oncoming traffic is separated by a central median and collision barrier) and there were no vulnerable road users (VRUs; such as pedestrians and cyclists). All lane changes were successful. Clips were limited to around 5 s due to image size constraints, and to ensure that the participants focused on the lane change rather than other traffic information. Examples stills for one video clip showing a vehicle changing lanes can be seen in Figures 1 (before), 2 (during), and 3 (after). Finnegan and Green (1990) estimate that it takes 1.5 s on average to change lanes. This estimate does not include the preparatory activities, which as glancing around and making judgments about the traffic, which raises the lane change time to 6.6 s on average. All of the video clips had completed lane changes within them. No information was provided on the other traffic and the image sequences were randomized. Half of these lane change maneuvers were performed by the Autopilot software whilst the other half was completed by a human driver (half of the lane changes in both manual and automated conditions were to the left-hand lane). The automated lane changes were initiated by the driver moving the indicator stalk in the intended direction of the move. No other driver interaction was performed.

The videos were then processed in a generic video editing software to select lane changes that fulfilled the following requirements: good visibility and no identifiers visible (e.g., license plate numbers). The videos were further processed using a bespoke C# program that utilized the Open Source tool FFMPEG to batch-convert the files to .GIF and compress the resulting files into a size suitable for web use. A total of 60 lane change maneuvers were chosen for inclusion in an online survey (30 manual and 30 automated). This survey was designed using an online survey tool (iSurvey), which is owned by the University of Southampton. The primary aim was to explore whether people could correctly identify whether Tesla was being driven by the Autopilot software or by the human driver.

2.1 | Participants

A total of seven hundred and sixty-nine \((n = 769)\) people responded to the online survey (of which 156 were female), with an average age of
39 years (standard deviation: 14 years). They self-declared 20 years of driving experience (standard deviation: 14 years), of which 331 said they had some previous experience of advanced driver assistance systems (such as adaptive cruise control and lane-keeping assist systems). Permission for the study was provided by the University of Southampton Ethics and Research Governance Office (ERGO number 24961).

2.2 Procedure

Upon providing consent, the participants filled out a short demographics questionnaire, including responses to a question regarding their familiarity with advanced driver assistance systems. They were then invited to view two example graphics interchange format clips of lane change manoeuvres. One of these manoeuvres was conducted by a human driver and the other was conducted by the Autopilot software, which was explained to them in the text accompanying the video clip. After viewing the two test items, they completed the classification task of categorizing the lane change as performed by a human driver or Autopilot software for the 60 clips presented to them. The classification was undertaken using a drop-down menu below each video. The total time of the survey was approximately 20 min from entering the questionnaire until its completion.

FIGURE 2 Still image from a video clip showing a white vehicle during the lane change

FIGURE 3 Still image from a video clip showing a white vehicle after the lane change had been completed
2.3 | Analysis

The data were partitioned into TP = true positives (classified as Autopilot and it was Autopilot), TN = true negatives (classified as a human driver and it was a human driver), FP = false positives (classified as Autopilot and it was a human driver), and FN = false negatives (classified as a human driver and it was Autopilot). From this Matthews correlation coefficient (MCC) was computed as described in the equation below (Matthews, 1975):

\[
MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}.
\]

The MCC is essentially a correlation coefficient between the observed data actual data in binary classification. As such, it reveals peoples’ (in)ability to discriminate between the Autopilot software and human driver, as described below.

3 | RESULTS

Overall, participants had significant difficulty in distinguishing the difference between the lane changes performed by the Autopilot software and those performed by a human driver. The data show that \( \phi = 0.01 \), where a coefficient of +1 represents a perfect positive prediction, 0 a random prediction, and −1 a perfect negative prediction. As Table 1 shows, the weak positive prediction means that people were only very marginally more likely to identify the Autopilot when it was driving but, at the same time, more likely to ascribe the Autopilot as driving when in fact it was a human driver in control. With over 34,000 individual lane changes classified in this survey, the findings appear to be determinative.

4 | DISCUSSION

What does this outcome mean? In essence, it determines that even at the current time, people find it very difficult to distinguish between a vehicle driven by a human driver and that driven by the Autopilot system in the context of the present lane-change test, when the vehicle is viewed from behind. This is a very specific set of circumstances and the research needs to be extended to other viewing angles. For the present study, however, one could go so far as to say that, based on the reported data, the two are virtually indistinguishable, and driving automation features are likely to become even more difficult to discern in the future. We, therefore, need to consider the possible implications this can have on the safety of other road users who are unable to determine “who” is in control of other vehicles (Banks & Stanton, 2016). This is particularly important when we consider the safety of VRUs, especially given the recent fatality involving the Uber vehicle and a cyclist crossing the road (Stanton, Salmon, Walker, & Stanton, 2019). This unfortunate event is likely to further exacerbate the feeling of unease surrounding the use of automated vehicles on our roads.

Seventy years after Turing (1950) set-up his challenge, machines, namely the Tesla Model S, are beginning to imitate human behavior in a convincing manner. We suggest that over the coming years, more vehicle manufacturers will release vehicles capable of passing the Turing test. However, much like in Searle’s (1980) thought experiment, these vehicles may seem intelligent, but they are still controlled by computer algorithms, without any full understanding of the traffic system around them. This is likely to create a number of issues, especially when we consider that technical systems are vulnerable to the onset of failure (Goodall, 2014; Stanton & Marsden, 1996; Stanton, Young, & McCaulder, 1997). This means that they may still not function in a satisfactory manner all of the time, especially when they reach the limits of their operational design domain, or experience sudden changes in the driving environment (Eriksson & Stanton, 2017a; Hancock, 2018). In such cases, at least for the intermediary stages of automation, we anticipate that the driver will have to step in as a fallback, resuming manual vehicle control. Depending on the level of automation, and the time frame to resume control afforded by the vehicle, it is likely that these vehicles will, from an external perspective, express puzzling behaviors. This is because drivers will find themselves being entered back into the main control-feedback loop despite external conditions have changed. This may result in over and undershoot in the steering input (Russell et al., 2016). Furthermore, Desmond, Hancock, and Monette (1998) found larger heading errors and poorer lateral control in the first 20 s after resuming control from automated driving following a failure. Also, it takes up to 40 s for the driver to regain control stability after a transition to manual driving (Eriksson & Stanton, 2017c; Merat, Jamson, Lai, Daly, & Carsten, 2014). In the worst-case scenario, the driver may be forced to conduct harsh braking, rapid lane changes and unnecessary stopping of the vehicle (Gold, Damböck, Lorenz, & Bengler, 2013). In the best-case scenario, with ample time to resume control, almost no detrimental effects on lateral behaviors may be evident (Eriksson & Stanton, 2017b). This means that, if drivers cannot distinguish automatically driven vehicles from those who are driven by human drivers, a sudden change in control authority in one of these vehicles, with sudden and severe lateral movements, may pose significant safety risks as drivers of manual vehicles either fail to react or overreact (Young & Stanton, 2002). Such an event may well propagate through the traffic stream.

| TABLE 1 | Responses to our online survey of video clips of lane changes conducted in the Tesla Model S P90D |
|-----------------|-----------------|-----------------|-----------------|
| Who was actually driving the car | Autopilot software | Human driver |
| Who people thought was driving the car | Autopilot software | 8889 (TP) | 8241 (FP) |
| | Human driver | 8804 (FN) | 8391 (TN) |

Abbreviations: FN, false negatives; TN, true negatives; TP, true positives.
(Young & Stanton, 2007), and potentially lead to fatal collisions, such as vehicles leaving the roadway. These events may spark an overall distrust in automated driving systems (Hancock et al., 2011; Schaefer, Chen, Szalma, & Hancock, 2016; Walker, Stanton, & Salmon, 2016), despite the potential safety improvements and accident reductions that they bring when functioning safely within their operational parameters (Stanton & Marsden, 1996). Thus, the status of the automation, and potentially whether a vehicle is automated or not, should not only be communicated through the human–machine interface (HMI) to a driver of such a vehicle, but also to other road users through external communication channels (in the cases where it is not obvious that a vehicle possesses such features, by, e.g., being with a salient LIDAR scanner), so that behavioral change may be anticipated.

In recent years, external HMIs for autonomous vehicles have been explored (e.g., Böckle, Brenden, Klingegård, Habibovic, & Bout, 2017; Lundgren et al., 2017; Matthews, Chowdhary, & Kieson, 2017). Such literature mostly covers VRUs. There are a number of ways a vehicle can communicate its intentions to a VRU, for example, through vehicle kinematics (such as slowing down and stopping, see Lundgren et al., 2017) or through the use of external human–machine interfaces (eHMI). eHMIs may utilize different design patterns, such as icons (Fridman et al., 2017), textual information (Matthews et al., 2017), a simulated smile/frown (Semcon, 2017), or patterns of light (Böckle et al., 2017; de Clercq, Dietrich, Núñez Velasco, de Winter, & Happee, 2019).

Amongst these eHMI variations, textually based interfaces have shown evident promise. For example, in an Amazon Mechanical Turk survey, Fridman et al. (2017) found that participants preferred the textual eHMI over icon-based alternatives. This has been further corroborated by de Clercq et al. (2019) who reported that participants found that the textual HMI was less ambiguous than other eHMI types and that eHMIs increase the time participants felt safe to cross in front of an approaching vehicle. Indeed, utilizing an eHMI may increase the resolution of potentially dangerous and inefficient vehicle-pedestrian deadlock situations by up to 38% (Matthews et al., 2017). One obvious conclusion of this study is the eHMI should communicate the driving mode all around the vehicle, such as the rear and sides, and not just from the front, which is where most of the research is focused. More research into the 360° eHMI is needed for the effectiveness of this strategy can be ascertained. It also remains uncertain whether or not eHMIs, targeted at facilitating driver–vehicle interaction in traffic could be of practical use. Volvo Cars stated that they will not mark their automated driving prototype vehicles as “automated” to avoid automation abuse (Parasuraman, Molloy, & Singh, 1993) resulting from divulging such information (Connor, 2016). A recent example of such abuse was seen by Waymo, whose vehicle was held up at an on-ramp as other road users would not give berth to merge for their “self-driving” prototype vehicle (Gupta, 2017). Therefore, were commended that eHMIs should be further researched in an effort to facilitate interaction between road users in the traffic environment.

There are some limitations with this study however, and future work should replicate with a camera directed at the driver of the automated vehicle. Arguably, people might perform this detection task if the vehicle is being viewed from the front, the side, or any other angle. Also, the lane change task, swapping lane from left to right, or vice versa, is only one aspect of vehicle control. Changes of speed were not considered, only changes of direction (although this is quite a frequent task performed on British motorways). Clearly then, other driving tasks need to be considered. Extending the study to a wider variety of driving tasks and different road types, as well as interactions with VRUs remains an important goal for future research. A final limitation of the study was the gender imbalance in the participants, with approximately 20% females, whereas in the UK driving population the balance is roughly equal. Any future study should address this gender imbalance with a more representative sample of participants.

5 | CONCLUSION

In this study, we queried 769 people on 60 video clips of a Tesla Model S carrying out a lane-change under the control of a driver, or the Autopilot software in an online survey. In essence, the process was subjecting them to the Turing test (Turing, 1950) using partially automated vehicles. The results revealed that our participants were unable to distinguish between the human driver, or the autopilot manoeuvering the vehicle, in a total of 34,325 classifications. This has significant implications for traffic safety, as drivers tend to use nonverbal, nonsymbolic, cues to negotiate interactions with other drivers and VRUs. If a vehicle is not able to indicate whether it is in automated mode to other road users, then they may mistake it for a manually driven vehicle, which could then lead to inappropriate interaction. A solution to this problem would be eHMI all around the vehicle that communicates that the vehicle is in automated driving mode to other road users. If the vehicle does communicate it is the automated driving mode, however, then it might be bullied by drivers of manually driven vehicles. There seems to be no simple solution to this problem, and new rules of the road may be required.

PRACTITIONER SUMMARY

We wanted to know if people could detect if a car was being driven by a human driver or automation in a lane change task. An online survey was conducted with people judging video clips. It was found that automated and manual lane changes were virtually indistinguishable.

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Semcon. (2017). The smiling car. Retrieved from https://semcon.com/sv/smilingcar

Singh, S. (2015). Critical reasons for crashes investigated in the national motor vehicle crash causation survey.

Stanton, N. A. (2015, March). Responses to autonomous vehicles. Ingenia, pp. 9, 11.

Stanton, N. A., & Marsden, P. (1996). From fly-by-wire to drive-by-wire: Safety implications of automation in vehicles. Safety Science, 24(1), 35–49. https://doi.org/10.1016/S0925-7535(96)00067-7

Stanton, N. A., & Salmon, P. M. (2009). Human error taxonomies applied to driving: A generic driver error taxonomy and its implications for intelligent transport systems. Safety Science, 47(2), 227–237.

Stanton, N. A., Salmon, P. M., Walker, G. H., & Stanton, M. (2019). Models and methods for collision analysis: A comparison study based on the Uber collision with a pedestrian. Safety Science, 120, 117–128.

Stanton, N. A., Walker, G. H., Young, M. S., Kazi, T., & Salmon, P. M. (2007). Changing drivers’ minds: The evaluation of an advanced driver coaching system. Ergonomics, 50(8), 1209–1234.

Stanton, N. A., Young, M., & McCaulder, B. (1997). Drive-by-wire: The case of mental workload and the ability of the driver to reclaim control. Safety Science, 27(2-3), 149–159.

Tesla Motors. (2016). Model S Software Version 7.0. Retrieved from https://www.tesla.com/en_GB/presskit/autopilot

Thompson, J., Read, G. J., Wijnands, J. S., & Salmon, P. M. (2020). The perils of perfect performance; considering the effects of introducing autonomous vehicles on rates of car vs cyclist conflict. Ergonomics, 63, 981–996.

Thorpe, C., Jochem, T., & Pomerleau, D. (1997). The 1997 automated highway free agent demonstration, Proceedings of conference on intelligent transportation systems (pp. 496–501). Boston, MA: IEEE.

Treat, J. R., Tumbas, N. S., McDonald, S. T., Shimar, D., Hume, R. D., Mayer, R. E., Stansier, R. L., & Castellan, N. J. (1979). Tri-level study of the causes of traffic collisions: final report. Executive summary. Bloomington, IN: Institute for Research in Public Safety, Indiana University.

Turing, A. M. (1950). Computing machinery and intelligence. Mind, 59(236), 433–460.

Walker, G. H., Stanton, N. A., & Salmon, P. M. (2015). Human factors in automotive engineering and technology. Farnham, UK: Ashgate Publishing Ltd.

Walker, G. H., Stanton, N. A., & Salmon, P. M. (2016). Trust in vehicle technology. International Journal of Vehicle Design, 70(2), 157–182.

Walker, G. H., Stanton, N. A., & Salmon, P. M. (2018). Vehicle feedback and driver situation awareness. Boca Raton, FL: CRC Press.

Wang, S., & Li, Z. (2019). Exploring the mechanism of crashes with automated vehicles using statistical modeling approaches. PLoS One, 14(3), e0214550.

World Health Organization. (2018). Global status report on road safety 2018: Summary (No. WHO/NMH/NVI/18.20). Geneva, Switzerland: World Health Organization.

Young, K. L., Lenné, M. G., & Williamson, A. R. (2011). Sensitivity of the lane change test as a measure of in-vehicle system demand. Applied Ergonomics, 42(4), 611–618.

Young, M. S., & Stanton, N. A. (2002). Malleable attentional resources theory: A new explanation for the effects of mental underload on performance. Human Factors, 44(3), 365–375.

Young, M. S., & Stanton, N. A. (2007). Back to the future: Brake reaction times for manual and automated vehicles. Ergonomics, 50(1), 46–58.

Zheng, Z., Ahn, S., Chen, D., & Laval, J. (2013). The effects of lane-changing on the immediate follower: Anticipation, relaxation, and change in driver characteristics. Transportation Research Part C: Emerging Technologies, 26, 367–379.

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