Transportation Research Part F: Psychology and Behaviour 96 (2023) 185–199

Contents lists available at ScienceDirect

Transportation Research Part F: Psychology and Behaviour

journal homepage: www.elsevier.com/locate/trf

Trust in automated parking systems: A mixed methods evaluation

Ewart J. de Visser [a,b,c], Elizabeth Phillips [b], Nathan Tenhundfeld [c,*], Bianca Donadio [a], Christian Barentine [a], Boyoung Kim [b], Anna Madison [a], Anthony Ries [a], Chad C. Tossell [a]

[a] U.S. Air Force Academy, United States
[b] George Mason University, United States
[c] University of Alabama in Huntsville, United States

ARTICLE INFO

Keywords:
Automation
Autonomy
Trust
Human-machine teaming
Driving
Self-driving cars

ABSTRACT

In two studies, we evaluated the trust and usefulness of automated compared to manual parking using an experimental paradigm and also by surveying owners of vehicles with automated parking features. In Study 1, we compared participants' ability to manually park a Tesla Model X to their use of the Autopark feature to complete perpendicular and parallel parking maneuvers. We investigated differences in parking success and duration, intervention behavior, self-reported levels of trust in and workload associated with the automation, as well as eye and head movements related to monitoring the automation. We found higher levels of trust in the automated parallel parking maneuvers compared to perpendicular parking. The Tesla's automated perpendicular parking was found to be less efficient than manually executing this maneuver. Study 2 investigated the frequency with which owners of vehicles with automated parking features used those features and probed why they chose not to use them. Vehicle owners reported low use of any automated parking feature. Owners further reported using their vehicle's autonomous parking features in ways consistent with the empirical findings from Study 1: higher usage rates of autonomous parallel parking. The results from both studies revealed that 1) automated parking is error-prone, 2) drivers nonetheless have calibrated trust in the automated parking system, and 3) the benefits of automated parallel parking surpass those of automated perpendicular parking with the current state of the technology.

1. Introduction

1.1. A step towards autonomy: automated parking systems

To date, research on automated parking systems, a type of advanced driver assistance system (ADAS), spans varying degrees of parking assistance including attentional cueing (Hipp, Heuten, Löcken, & Boll, 2016), multimodal displays (Airaksinen et al., 2004; Eskandarian, 2012; Kidd et al., 2015; Tada and Wada, 2015), parking spot identification (Surpris, Liu, & Vincenzi, 2014), and fully autonomous parking (Reimer et al., 2010; Reimer et al., 2016; Suppé et al., 2010). Automated parking is a necessary partially automated safety feature for moving towards a high level of vehicle automation in the future (i.e., Level 4 or Level 5 automation)

* Corresponding author.
E-mail address: NLT0006@uah.edu (N. Tenhundfeld).

https://doi.org/10.1016/j.trf.2023.05.018
Received 19 September 2022; Received in revised form 19 April 2023; Accepted 31 May 2023
Available online 26 June 2023
1369-8478/

(Society for Automotive Engineers, 2018). The potential benefit of such automated parking for traffic systems is considerable (Green, 2006). To illustrate, one study has suggested that 30 % of traffic in cities is due to people cruising for parking alone (Shoup, 2007), which adds to congestion on city streets that are already crowded with pedestrians, cyclists, and a variety of other transit systems. If automated parking could be faster, more efficient, and autonomous, much of this traffic could be alleviated. Automated parking may also have additional benefits for the elderly (Yang & Coughlin, 2012), wheelchair-bound (Suppé, Navarro-Serment, & Steinfeld, 2010), and novice drivers (Tada & Wada, 2015). Studies have further shown that automated parking systems significantly reduce workload and stress for human drivers (Reimer et al., 2010; Reimer et al., 2016). Another benefit of these systems may be that they help to eliminate the inherent human variability in parking, which can prevent electric vehicles from efficiently charging themselves (Birrell, Wilson, Yang, Dhadyalla, & Jennings, 2015). Lastly, effective automation parking systems may reduce thousands of injuries that occur in parking facilities yearly (N. C. for S. and Analysis, 2015).

While the eventual benefits for ADAS might be large (de Winter, 2019), there may be automation “transition” costs related to the imperfect implementation of these systems as transportation systems evolve (Hancock et al., 2019; Hancock, 2019). Decades of previous research have established that automation is not always convenient or useful by default (Parasuraman and Wickens, 2008; Parasuraman et al., 2008; Kaber, 2018). Rather, the major insight of this body of work is that automation does not simply replace the human, but fundamentally changes the nature of the task, often in unexpected and unanticipated ways (Parasuraman & Riley, 1997). Disadvantages with automation have included mis-calibrated trust (Lee and See, 2004; Hoff and Bashir, 2015), reduced situation awareness (Kaber & Endsley, 2004), unbalanced mental workload, skill degradation (Bainbridge, 1983; Parasuraman et al., 2000), and complacency and automation bias (Parasuraman & Manzey, 2010).

Although much research has evaluated human performance issues related to driving or supervising a partially automated car (Basu and Singhal, 2016; Cunningham and Regan, 2015), few studies have investigated automated features for specific vehicle maneuvers, such as automated parking, in their own right, even though these features are now commonly included in many commercially available vehicles today. As vehicle manufacturers continue to build increasingly complex autonomous features, the need to critically evaluate these systems and their implications for users, owners, communities, and society, will grow in kind. Futurists and technologists often point to the future and what could be, and while we share their drive and optimism for creating a better tomorrow, we have a responsibility to evaluate the technology as it is available in its current form today.

1.2. *Trust in automated parking systems*

One critical factor for reliance, use, and adoption of automated parking systems may be a driver’s trust in the system, but, to date, there has been little work to thoroughly examine this factor in automated parking systems specifically. For this work, we use the following definition for trust: “the attitude that an agent will help achieve an individual’s goals in a situation characterized by uncertain and vulnerability” (Lee & See, 2004). Important to note is the distinction between trust and trustworthiness and how this relates to the calibration of trust. While trust refers to the attitude that a user has towards a system in terms of their intent to rely on a system, trustworthiness is a property of a system divided in the dimensions of performance, process and purpose (Lee & See, 2004). Trust calibration is the alignment of trust and trustworthiness such that the trust in the system matches the trustworthiness of the system (de Visser, Cohen, Freedy, & Parasuraman, 2014).

Research on human interactions with automated parking features is not new (Gadgil and Green, 2005; Nourinejad et al., 2018; Totzke et al., 2011; Edelmann et al., 2019), but only recently work has focused on evaluations of trust in these systems and several did not have access to real automated vehicles (Ma et al., Jun. 2020; Neuhaus et al., 2019; Raats et al., 2019; Dikmen et al., 2017). Prior work on trust in automated parking systems suggests that a user’s trust in the system increases quickly with repeated exposure, especially during initial acquaintance and use of the system (Tenhundfeld et al., 2019; Tenhundfeld et al., 2019; Trösterer et al., 2014). Trust appears to be further facilitated by greater transparency and knowledge about what the system is doing (Edelmann et al., 2019; Tenhundfeld et al., 2019; Tenhundfeld et al., 2019; Tomzcak, et al., 2019). Specifically, participants that were shown how the automated parking system worked intervened less, an indication of reduced distrust, compared to those that were only told about the system’s operation (Tenhundfeld et al., 2019).

Yet, some avenues regarding trust in automated parking systems remain unexplored. First, it is unclear how well these commercial systems are generally performing in the real-world. Performance is the largest determinant of trust in an automated system (Lee and See, 2004; Hoff and Bashir, 2015; Schaefer et al., 2016). Furthermore, previous work has not compared specific situations and contexts in which the automated parking system might have varying levels of performance (i.e. perpendicular versus parallel parking). For instance, if the performance of autonomous parking systems work best for parallel parking under most environmental conditions, but perform poorly when perpendicular parking into angled spaces (specific conditions), people may either adopt strategies where they only trust the vehicle to parallel park even though perpendicular may work well in some cases (situation specific trust) or may not trust any of the automated features (system-wide trust).

Comparing such situations may reveal whether drivers apply trust phenomena established in other domains, such as situation-specific (dis)trust (Cohen, Parasuraman, & Freeman, 1998), component-specific trust (Lopez and Pak, Dec. 2020; Bahner et al., 2008) or system-wide (dis)trust (Rice et al., 2016; Walliser et al., 2023), to automated parking systems, a topic that has not yet been explored. It is also not clear how initial impressions of the system might influence trust and use over an extended period for example the owner of the vehicle. Previous work has demonstrated, for example, that trust in the system generally increases over time for an owner, although this work was in fact with only one owner (Endsley, 2017). Would drivers become more calibrated to the specific behavior of the automated parking system or would they simply ignore it if it does not serve their needs? And does the attitude of an owner perhaps change from perceiving the car as a tool as opposed to an object that they have some sort of relationship with (de Visser, 2020)? Lastly, trust itself might be elicited and assessed more accurately in situations where there vulnerability to the participant by being in a car that performs an automated maneuver as opposed to the generally risk-free laboratory studies in which trust is typically evaluated. Laboratory studies are also rarely able to capture the complexity of real-world parking situations and a range of idiosyncrasies of those situations (e.g., lighting and weather conditions, crowding by other vehicles). Given these questions, more research needs to be conducted to understand how these factors influence trust with an automated parking system. Accordingly, we conducted two complementary studies which address this gap in the literature.

1.3. The current study

To explore the avenues of research outlined above, we report on two studies. One examined trust in and use of an automated parking system by evaluating human performance in an experimental study. The second assessed the attitudes of survey respondents who own a car with automated parking features. In Study 1, we compared manual and automation performance for both perpendicular and parallel parking with a Tesla Model X, along with participants' perceptions of trust in the automated parking system. Specifically, we assessed trust by examining intervention behaviors, self-reported attitudes, and verification behaviors as assessed by eye- and head movements (Kohn et al., 2021). Based on previous research (Tenhundfeld et al., 2019; Tenhundfeld et al., 2020), we predicted that participants would evaluate automated parking as more beneficial than manual parking in parallel, but not in perpendicular parking situations. Furthermore, Study 2 was designed to verify findings from Study 1 with owners of cars with automated features to evaluate how initial observations and experience with automation extrapolate to long-term use of such a vehicle.

2. Study 1 methods

2.1. Participants

Forty-five participants, consisting of both faculty and cadets at the U.S. Air Force Academy (USAFA) in Colorado, 28 males (M_{age} = 30.25, SD_{age} = 12.67), 17 females (M = 32.43, SD = 13.02), aged 18–54 years; (M = 31.08, SD = 12.70) participated in Study 1. None of the participants reported previous experience with automated parking features. All participants provided informed consent before starting the experiment. Cadets were compensated with course credit in return for their participation, and faculty members were not compensated. All procedures were reviewed and approved by the U.S. Air Force Academy's Institutional Review Board.

2.2. Experimental design

The experimental design consisted of two independent variables manipulated as within-subject factors: Parking Mode (Manual versus Auto) and Parking Situation (Perpendicular versus Parallel). For Parking Mode, participants either parked the Tesla themselves with no assistance (Manual) or were assisted by the Autopark system (Auto). The two parking situations included a perpendicular or parallel parking situation between two vehicles (see Fig. 1). All participants completed the study with the following order of parking conditions: Manual-Perpendicular, followed by Auto-Perpendicular, Manual-Parallel, and Auto-Parallel. This order was chosen to minimize biasing participants to the Autopark's behavior and approach to parking. Manual conditions were presented first to capture a baseline of how participants would normally park their own vehicle—for instance with the option to park nose-front, or back-in—before being exposed to the Auto conditions. Autopark maneuvers the Tesla by backing into the parking spot in both parking conditions, which is non-standard for perpendicular parking. Thus, we started with Manual Perpendicular Parking Situation to avoid biasing participants into mimicking the Tesla's behavior unnaturally on the perpendicular trials. Using this order, we could evaluate participants' parking strategy (backing-in or nose-front parking) for each parking situation in the way they normally park their cars before they learned how Tesla would complete the maneuver. Participants were asked to complete four parking trials in each condition for a total of 16 trials.

2.3. Parking setup and task paradigm

Participants used a USAFA outdoor parking lot to perform all parking maneuvers. The Tesla Autopark software (version 9.0)

Fig. 1. Layout of the experimental setup and sequence of Autopark maneuvers into each space. The width of the perpendicular parking spot used in the study was 134 in. The length of the parallel parking spot was 296 in. Tesla's Autopark (version 9.0) cannot park in angled parking spots.

requires parking spaces to be flanked by other vehicles. Thus, the target parking space was configured with two vehicles on either side of the space—to the left and right for perpendicular parking and to the front and back for parallel parking (see Fig. 1).

For the manual parking conditions, participants were instructed to park how they normally would for both Perpendicular and Parallel trials. This meant that participants were free to either back into the spot, or pull in nose first. For the Auto conditions, participants were verbally instructed on how to engage the Tesla's Autopark feature (Tenhundfeld et al., 2019; Tenhundfeld et al., 2019). To engage the Autopark feature, participants had to drive slowly past an empty parking space. Once the parking space was identified by the Tesla, the letter "P" inside a grey box would appear on the dashboard. The driver would then shift the vehicle into reverse, an "Autopark Ready" notification would appear on the center console, and the driver would tap a "Start" button to finish engaging the Autopark. Then, the driver would take their hands off of the wheel and release the brake to allow the Autopark to begin.

2.4. Autopark behavior

In the perpendicular parking situation, Autopark executed the parking maneuver by backing into the parking spot in three stages. For a typical trial, the Tesla first backed towards the outer corner of the parking spot. Then, it pulled forward once to align itself with the parking spot. In this stage, it was possible that the Tesla pulled forward more than once to adjust its alignment (Tenhundfeld et al., 2019; Tenhundfeld et al., 2020). The car then finished parking by backing straight into the space with the nose of the car facing out (see Fig. 1).

The parallel Autopark maneuver more closely resembled standard manual parallel parking than it does manual, nose-front, perpendicular parking (Tomzcak et al., 2019). Once engaged by the driver, the parallel Autopark backs toward a curb at a 45-degree angle, then gradually squared itself with the curb, and then completed around two to four gear shifts to center itself in the parking space between the two surrounding vehicles (see Fig. 1). In this context we use gear shifts to reference the shifting from forward to reverse (and vice versa). Although participants were informed of how to engage the Autopark, they were not informed of the parking stages in either Perpendicular or Parallel trials.

2.5. Parking performance and efficiency measures

Parking performance was characterized by several measures. *Success rate* was calculated by dividing the number of completed trials by the number of attempted trials. For Manual trials, completed trials were counted when the participant successfully parked in the spot. For Auto trials, completed trials were counted when the Autopark engaged *and* parked the car. *Engage rate* was calculated by dividing the number of trials in which the Autopark was successfully engaged divided by the number of attempted trials. *Parking rate* was calculated by dividing the number of successfully parked trials by the number of engaged trials. We further recorded errors in Auto conditions that caused unsuccessful trials. *Failure rate* was the inverse of success rate (*1-Succes rate*) and *Failure to engage* was the inverse of *Engage rate* (1-*Engage rate*). Vehicle-caused errors included identifying the wrong parking spot or unforeseen Autopark cancelation (i.e. the vehicle disengaged the Autoparking for reasons that were not communicated by the vehicle to the participant or experimenters). Driver-caused errors included accidentally canceling the Autopark due to not fully understanding how to engage the feature or intentionally intervening due to not trusting the system by taking over the steering wheel or hitting the brake.

To examine parking efficiency, we calculated parking duration and the number of gear shifts used. *Parking duration* was measured in seconds from the start of the parking attempt to its completion. To provide a point of comparison across the manual and auto conditions, the park duration in the Manual-Perpendicular condition began when the participant began turning the steering wheel toward the parking space if parking nose-forward, or away from the space if parking backward. In the Manual-Parallel condition, recording began when the participants shifted the vehicle into reverse to begin the park. For the Auto conditions, recording began when the participant hit the "Start" button on the center console. We further recorded the *Number of gear shifts* (e.g. drive, reverse) that were used to complete the park in either the manual or auto conditions. We judged more efficient parking as parking performed with fewer gear shifts.

2.6. Mental workload, trust, and self-confidence measures

Five subjective measures were also recorded including cognitive workload, perceived parking self-confidence, perceived trust in the Tesla, and preferences for and future likelihood of using Autopark. To measure cognitive workload during parking conditions, we used the NASA Task Load Index (NASA-TLX) a subjective measure of workload commonly used for assessing human–machine interfaces (Hart and Staveland, 1988; Hart, 2006). Workload scores were calculated as the average of its six sub-scales. We also asked participants to respond to two items about their self-confidence in their own parking, "To what extent are you self-confident about your ability to park?" and about their trust in the Autopark feature, "To what extent do you trust the Tesla's ability to park itself?" Participants responded to both items using a scale ranging from "Not at all" (0) to "Completely" (20) (Tomzcak, et al., 2019; Tenhundfeld et al., 2020). *Relative trust* measures were calculated for each participant, which was done by taking their trust in the vehicle, minus their self-confidence, for both Perpendicular and Parallel conditions. Positive values for this measure are predictive of reliance and use, while negative values for this measure are indicate of disuse (Lee & Moray, 1994). The following items were used to assess participant preferences for and future likelihood of using Autopark if that feature was available to them in a vehicle that they owned, "How likely would it be for you to use the Tesla's Autopark feature if it was available in your own car?" (0: Not at all – 20: Completely) and "If you had to choose between your own ability or the Tesla's Autopark ability to successfully park a car, which one would you choose? (Myself / Autopark)".

2.7. Eye-tracking measurement and analysis

Eye-tracking data were collected with Tobii Pro 2 eye tracking glasses (50 Hz sampling rate) using the standard calibration routine before recording eye movement data. Two Areas of Interest (AOIs) were established to record the amount of *monitoring of the automation* by each participant. The first AOI was the center console screen, and the second was the dashboard (see Fig. 4a). These AOIs were chosen because these displays show parking-related information, including whether the parking opportunity is detected on the dashboard, and a rear camera with a wide-angle view of the parking space on the center display to monitor any obstacles. Prior research (Tenhundfeld et al., 2019) has shown that as participants repeatedly complete Autopark trials their distrust in the automation is reflected in an increase of fixation durations on the center console display. In contrast, a switch from more fixation durations on the center display to more fixation durations on the dashboard display is an indication of less distrust / more trust.

We used iMotions software (version 7.2) to analyze fixation duration and fixation frequency for each AOI during parking. Total fixation time for these AOIs was calculated for each participant and split by each trial. Participants were included in the eye tracking analysis if at least 60 % of data samples were valid over the entire recording of the data and if they had at least two successful parks in each of the four conditions. This was to ensure that, at a minimum, we could analyze the first versus the last park for every participant across all of the conditions. Given these criteria, we excluded 14 participants from eye tracking analyses: one due to data quality (i.e. < 60 % valid data samples) and 13 due to less than two successful parking trials per condition. The remaining 31 participants included in the eye tracking analysis had an average data quality of 81 %.

2.8. Head-movement measurement and analysis

Head movement data were obtained from the gyroscope and accelerometer on the Tobii Pro 2 eye tracking glasses. Head movement data from participants' first and last successful parks were used for analyses. To analyze the head movements of the participants, we calculated each participant's head velocity data in degrees per second (deg/s) for the duration of the parking time period which was further divided into 5-second segments (see Fig. 2). We then derived a head movement algorithm which included groups of segments

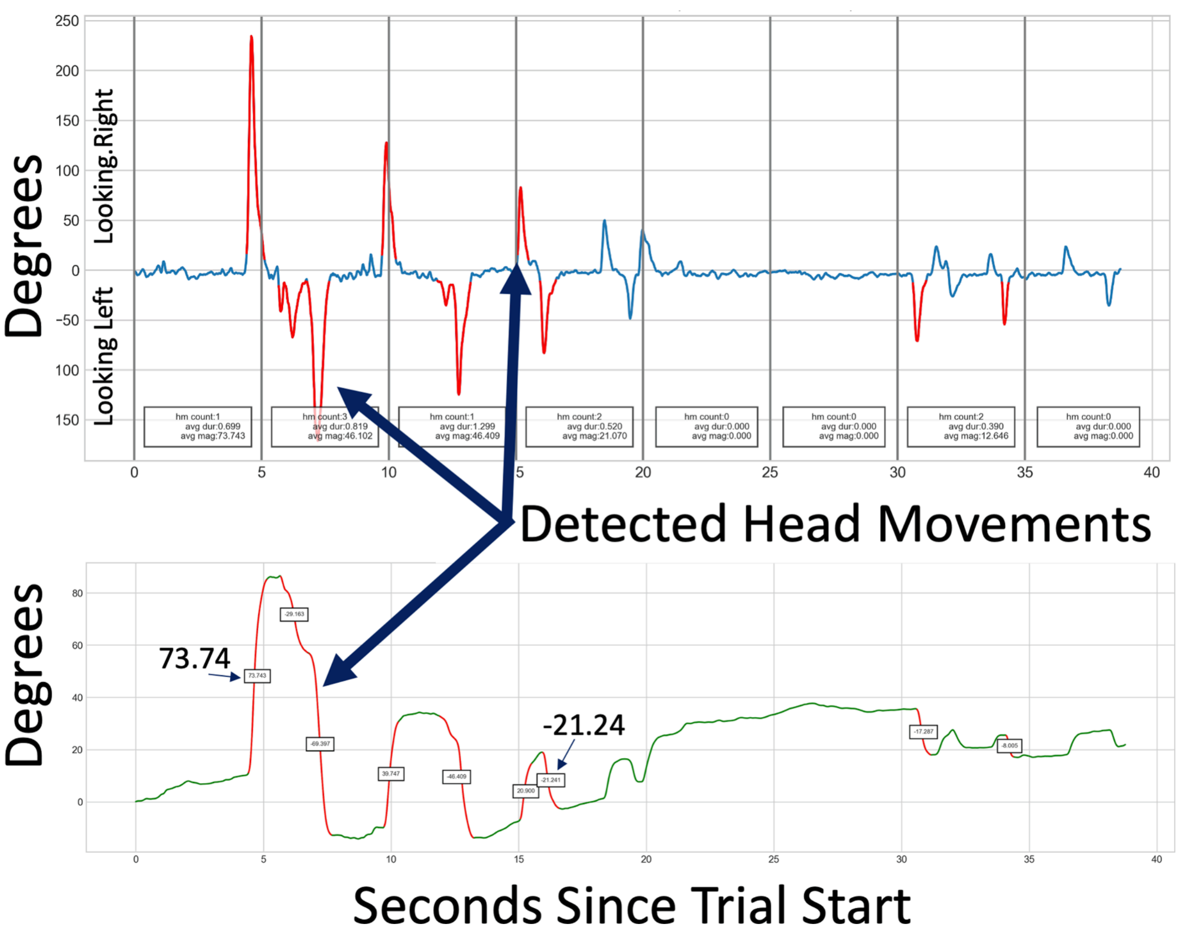

Fig. 2. Algorithm output to detect head movements. The top figure shows head movement velocity (degrees/second) over 5-second increments (x-axis. The lower figure shows the magnitude of head movements in degrees.

that met the following criteria: samples with absolute velocities above a low threshold, while also having at least one sample above a high threshold, and a minimum number of samples above the low threshold. To compute *Head turns* (horizontal or yaw head movements), we used a low threshold of 10 deg/s, a high threshold of 50 deg/s, and a minimum duration of 5 samples. To compute *Head nods* (vertical or pitch head movements), we used a low threshold of 10 deg/s, a high threshold of 20 deg/s, and the same minimum duration. Segments that met these criteria were marked as head movements, and the rest of the samples in the trial were marked as head fixations. In addition to isolating head movements using velocity, we also added up the velocities over time to calculate an approximate head angle throughout the trial. The participant's head orientation at the beginning of the parking maneuver was set as the "origin". To calculate the *Head angle*, a running sum of the velocity value of each sample was divided by the sample rate of the glasses. There was an inherent, but consistent drift in this calculation, which we eliminated by subtracting the drift divided by the sample rate for each sample.

2.9. Procedure

Participants entered the study by arriving in a parking garage where the Tesla was housed. Each participant first read and then signed an informed consent form and then showed their valid driver's license to the experimenter. The experimenter then drove them to the parking lot, outfitted the participant with the Tobii Pro 2 eye tracking glasses, and calibrated them. The participants then switched seats with the experimenter and adjusted the driver's seat as necessary for comfort. Next, the experimenter explained to the participants that their task was to complete 16 trials, four for each condition, of parking and explained how to park manually and with Autopark (Section C). After instructions were given, the experimenter began recording eye tracking data with the Tobii glasses. For consistency, each trial began with participants driving one lap around the parking area so they could approach the parking space from the same side in each trial. After driving the lap, participants would approach the parking space and attempt to complete the park by either manually pulling into the space or by attempting to engage the Autopark feature depending on the condition they were completing. In the two Auto conditions, if the participants were unsuccessful in their attempts to engage the Autopark feature or complete the parking maneuver in any way, they were instructed to go on to their next trial, by starting their next lap. Participants then completed the NASA-TLX and the parking self-confidence and trust in the Tesla's Autopark items after each set of four trials in each condition. After completing all the trials, the experimenter and the participant switched seats again, and the experimenter drove the participant back to the parking garage where the study began. Then, participants completed the remaining subjective measures as well as the parking self-confidence and trust in the Tesla's Autopark items for a final time. Participants were then debriefed, thanked for their time, and if applicable, provided course credit for their participation. The duration of the study was approximately 50 minutes.

3. Study I results

3.1. Parking performance

In Manual parking mode, all drivers parked perfectly with 100 % success in both the Perpendicular and Parallel parking conditions (see Table 1). As expected, all participants reverse-parked in the parallel parking situation by backing the Tesla into the spot, whereas most participants forward parked, nose-first, in the perpendicular parking situation. The exception to this strategy was six participants, who all backed in the Tesla to varying degrees in the Manual Perpendicular Parking Situation. Three participants backed in for all their Perpendicular-Manual trials, two participants did this for three of their trials, and one participant on only one trial.

In contrast with manual parking, performance in the Auto parking mode was considerably less successful with an average parking success of around 56 % for Perpendicular and 68 % for Parallel situations, although this difference was not statistically significant (see Table 1). The types of failure, however, occurred at different rates between the situations. Although the Autopark was engaged at a higher rate for perpendicular compared to parallel situations ($p < .05$), Autopark completed the parking maneuver at a much lower rate in Perpendicular compared to Parallel situations ($p < .001$). Causes for errors in Autopark engagement were the vehicle's inability to detect a parking opportunity or participants driving above 5 mph. Other causes of failure could be traced to the vehicle or driver specifically, and occurred at higher rates in Perpendicular compared to Parallel parking situations. Specifically, vehicles identified the wrong spot or spontaneously canceled in the middle of a parking attempt more often in Perpendicular compared to Parallel parking situations. Additionally, drivers accidentally canceled Autopark by not removing their hands from the wheel or feet from the brake pedal quickly enough or intentionally intervened in the parking attempt at higher rates in Perpendicular compared to Parallel parking situations. Lastly, we did not observe any re-alignment or adjustment in the third stage of automated parking beyond the first attempt to park the car (Tenhundfeld et al., 2019; Tenhundfeld et al., 2020). In summary, Manual performance far outperformed Auto performance and there was slightly better performance in the Parallel compared to the Perpendicular parking situations.

Table 1a
Manual parking performance.

Performance Measure	Perpendicular	Parallel	*p*	*d*
Success Rate	**100 (0)**	**100 (0)**	***na***	***na***

Table 1b
Auto parking performance: success rates by category.

Performance Measure	Category	Perpendicular	Parallel	*p*	*d*
Success Rate		**56 (5)**	**68 (6)**	***ns***	**.2**
	Engage Rate	85 (3)	69 (6)	*	.4
	Parking Rate	66 (5)	97 (2)	***	.9

Table 1c
Auto parking performance: failure rates by cause.

Performance Measure	Cause	Perpendicular	Parallel	*p*	*d*
Failure Rate		**44 (5)**	**32 (6)**	***ns***	**.2**
Failed to Engage		16 (3)	31 (6)	*	.4
Vehicle-caused		10 (2)	1 (1)	***	.6
	Wrong Spot	4 (1)	1 (1)	*	.3
	Cancellation	6 (2)	0 (0)	**	.5
Driver-caused		18 (4)	1 (1)	***	.7
	Intervention	10 (3)	0 (0)	**	.5
	Cancellation	9 (2)	1 (1)	***	.5

*p<.05, **p<.01,***p<.001
Note: All numbers are percentages. Numbers in the parentheses represent standard error of the mean. Cohen's d was calculated.

3.2. Parking efficiency

Parallel parking ($M = 42.2$, $SE = 2.3$) took longer than Perpendicular parking ($M = 33.7$, SE = 1.49), $F(1, 20) = 6.7$, $p = .017$, $\eta_p^2 = 0.25$ and Manual trials ($M = 27.9$, $SE = 1.81$) were faster than Auto trials ($M = 48$, $SE = 1.27$), $F(1, 20) = 72.3$, $p < .001$, $\eta_p^2 = 0.78$. Parking Situation and Parking Mode interreacted such that participants were much faster to park the car in Manual compared to Automated mode in Perpendicular trials, but parked the car with similar duration in Manual and Auto conditions, $F(1, 20) = 233.3$, $p < .001$, $\eta_p^2 = 0.92$ (see Fig. 3). Parallel parking required more gear shifts ($M = 2.7$, $SE = 0.1$) than Perpendicular parking ($M = 2.2$, SE = 0.04), $F(1, 31) = 25.3$, p <.001, $\eta_p^2 = 0.45$ and Parking with Auto ($M = 2.8$, $SE = 0.1$) required more gear shifts than in Manual ($M = 2.0$, $SE = 0.10$), $F(1, 31) = 46.1$, p <.001, $\eta_p^2 = 0.6$. In a similar pattern compared to parking duration, Parking Situation and Parking Mode interacted such that participants experienced more gear shifts with Auto compared to Manual during Perpendicular parking, but experienced equivalent gear shifts in the Parallel trials, $F(1, 31) = 74.94$, p <.001, $\eta_p^2 = 0.707$ (see Fig. 3).

3.3. Mental workload

Workload was higher in Manual ($M = 28.9$, $SE = 1.5$) compared to Auto conditions ($M = 20.5$, $SE = 1.9$), $F(1, 40) = 15.7$, $p < .001$, $\eta_p^2 = 0.28$, but statistically equivalent for Parking Situation, $p = .32$. Parking Situation and Parking Mode interacted such that, compared to Manual parking, workload was reduced by the Auto parking feature for Parallel parking, but not for Perpendicular parking, $F(1, 40) = 38.04$, $p < .001$, $\eta_p^2 = 0.49$.

3.4. Trust and self-confidence

Participants were more self-confident in their ability to park perpendicularly compared to their ability to park parallel, $t(40) = 3.39$, $p = .002$, $d = 0.53$ (Fig. 3). Trust in Automated parking was higher in Parallel parking compared to Perpendicular situations, $t(40) = 2.60$, $p = .013$, $d = 0.41$. Relative trust scores were lower and negative in Perpendicular ($M = -3.23$, $SE = 0.95$) compared to the positive scores for Parallel parking ($M = 1.67$, $SE = 0.89$), $t(40) = 3.66$, $p = .001$, $d = 0.57$.

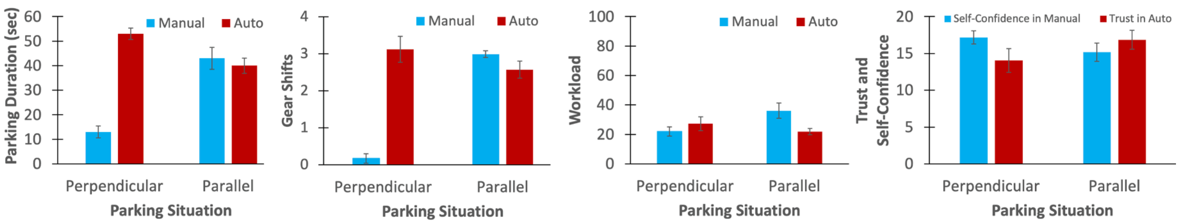

Fig. 3. Parking efficiency (duration in seconds, gear shifts) and self-report measures (workload, trust/self-confidence) for Parking Mode by Parking Situation. The range for workload (0–100) and trust and self-confidence (0–20) are indicated by the scales. Error bars are 95 % confidence intervals.

3.5. Fixation duration

There was a significant three-way interaction between Parking Situation, Parking Mode and AOI (Center versus Dash), $F(1, 17) = 32.22$, $p < .001$, $\eta^2 = 0.66$ on fixation duration (see Fig. 4a-c). Fixation duration increased in Auto compared to Manual conditions, $F(1, 17) = 102.2$, $p < .001$, $\eta^2 = 0.86$ and was higher for the Center display compared to the Dashboard, $F(1, 17) = 62.5$, $p < .001$, $\eta^2 = 0.79$. Parking Situation and Parking Mode interacted, $F(1, 17) = 27.9$, $p < .001$, $\eta^2 = 0.62$, such that fixation duration increased much more from Manual to Auto during Perpendicular parking compared to a similar increase from Manual to Auto in Parallel parking situations, $t(17) = 5.3$, $p < .001$. Parking Mode and AOI interacted, $F(1, 17) = 60.92$, $p < .001$, $\eta^2 = 0.78$, such that fixation duration increased much more for Auto compared to Manual in the Center display compared to the Dash display, $t(17) = 7.81$, $p < .001$.

3.6. Head turn frequency and magnitudes

Head turn frequency was higher in the First ($M = 0.47$, SE $= 0.03$) versus the Last ($M = 0.42$, SE $= 0.03$) park, $F(1,17) = 5.52$, $p = .031$, $\eta^2 = 0.25$, in Perpendicular ($M = 0.47$, SE $= 0.03$) compared to Parallel ($M = 0.41$, SE $= 0.02$) conditions, $F(1,17) = 5.16$, $p = .036$, $\eta^2 = 0.23$, and in Manual ($M = 0.6$, SE $= 0.03$) versus Auto ($M = 0.28$, SE $= 0.03$) conditions, $F(1,17) = 150.9$, $p < .001$, $\eta^2 = 0.9$. No interactions were significant for head turn frequency, $p > 0.05$. For head turn magnitude, Parking Situation and Park Mode interacted, $F(1,17) = 48.6$, $p < .001$, $\eta^2 = 0.74$, such that larger head turn movements were made in Manual compared to Auto during Parallel parking trials. This pattern reversed for Perpendicular conditions, with larger head turn movements found in the Auto compared to Manual trials (Fig. 4d). No other interactions were significant, $p > .1$.

3.7. Head nod frequency and magnitudes

More head nods were made in the First ($M = 0.38$, $SE = 0.06$) versus Last ($M = 0.29$, $SE = 0.022$) park, $F(1,17) = 8.56$, $p = .009$, $\eta^2 = 0.34$, in Parallel ($M = 0.4$, $SE = 0.032$) compared to Perpendicular ($M = 0.269$, $SE = 0.024$) conditions, $F(1,17) = 30.12$, $p < .001$, $\eta^2 = 0.64$, and in Manual ($M = 0.47$, $SE = 0.038$) versus Auto ($M = 0.2$, $SE = 0.025$) conditions, $F(1,17) = 46.7$, $p < .001$, $\eta^2 = 0.73$. The only significant interaction for vertical head movement frequency was between Parking Situation and Park Mode, $F(1,17) = 40.9$, $p < .001$, $\eta^2 = 0.7$, indicating the difference between Auto and Manual was larger for Parallel parking with respect to Perpendicular parking $t(17) = 6.4$, $p < .001$ (see Fig. 4e). For head nod magnitude, there was a three-way interaction between Park Sequence, Parking Situation and Park Mode, $F(1,17) = 5.21$, $p = .036$, $\eta^2 = 0.23$ (see Fig. 4f-g). During the First Parallel park trial, larger head nod movements were made in the Manual compared to the Auto conditions, but during the Last Parallel park trial this pattern reversed and larger head nods were made in the Auto compared to the Manual conditions.

4. Study 1 discussion

4.1. Summary

The goal of this study was to examine human performance and trust in an automated parking system, using behavior, self-report, and physiological measures. Results showed that while automated parking was less successful and more error-prone than manual parking, it was most beneficial, efficient, and trustworthy in parallel parking situations compared to perpendicular parking situations.

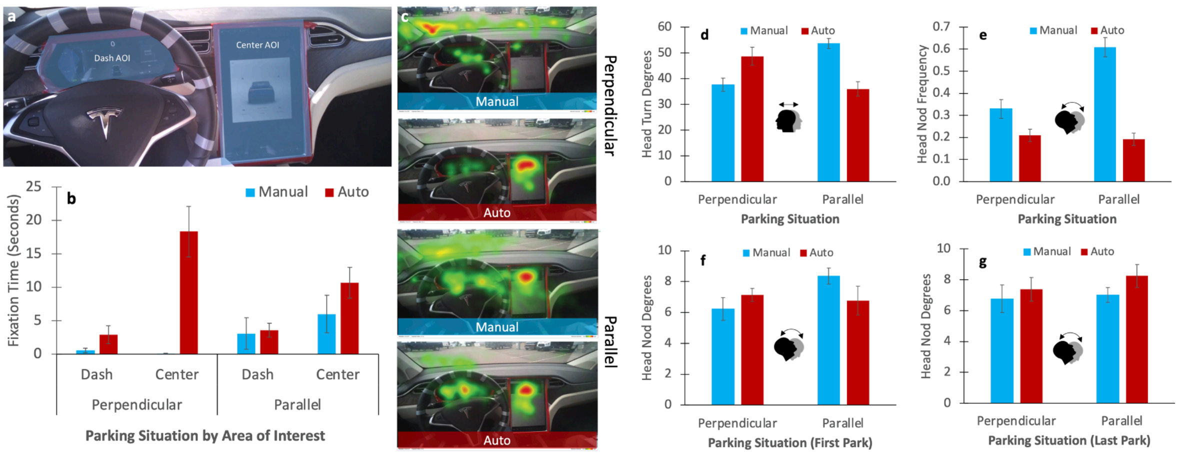

Fig. 4. a-g. a) Areas of Interest for eye-movements including Dash Board and the Center Display, b) Fixation duration in seconds shown for Parking Mode by Parking Situation, c) example heat maps of a single participant for Parking Mode by Parking Situation, d-g) Head turns magnitude, Head nod frequency, Head nod magnitude (first park) and Head nod magnitude (last park) for Parking Mode by Parking Situation. All error bars are 1 standard error.

The center display was monitored more in auto conditions to keep an eye on the rear camera, reflecting a change in how the task was performed compared to manual (Parasuraman and Riley, 1997; Parasuraman et al., 2000), and perpendicular parking with automation required more monitoring than parallel parking, reflecting a higher degree of distrust in the system (Parasuraman and Wickens, 2008; Parasuraman and Manzey, 2010; Tenhundfeld et al., 2019; Tenhundfeld et al., 2020). Consistent with eye-monitoring patterns, participants turned their heads more to check their surroundings in the auto versus the manual condition in the perpendicular situation, but this pattern reversed in the parallel situation, likely because automated parallel parking performed better. Lastly, participants head nodded more in manual compared to auto conditions, most likely because participants checked the gear shift more often in manual operation. Head movement data thus provided important additional context and information about automation monitoring and verification behaviors as well as parking task performance. Head movements could therefore be added as an unobtrusive physiological measure of trust in automation (Kohn et al., 2021; Krausman, May 2022; de Visser, 2018).

One reason why perpendicular parking was not trusted as much as parallel parking could be because there was a mismatch between the human parking approach and the automation parking approach. Most drivers in our experiment chose to front park the car in the perpendicular parking situation but the automation, perhaps unexpectedly, backed into the parking space instead. Additional distrust may have been caused by the short clearance distance of the Tesla while parking. One study has indicated that, on average, drivers prefer about 21 in. of clearance behind their vehicle (Gadgil & Green, 2005), yet the Tesla starts pulling forward at 11 in. from a car with drivers generally intervening at 15 in. from a car (Tenhundfeld et al., 2019). Shorter margins may be possible for automation but should be clearly communicated to the driver through transparent design (Endsley, 2023; Chen et al., 2018).

While our results are clear about the performance, use and trust in the automated parking feature of a Tesla car with drivers who have limited experience with ADAS features, there may be limitations to the generalizability of this study. For example, our experimental paradigm involved repeated parking, which may have forced drivers to use the system more than they normally would. It is possible that in more realistic parking situations (i.e. high traffic, difficult spots, nighttime), drivers would not even try the parking function. Alternatively, vehicle owners may have had more time to experiment and try out their car's parking features and may be more acclimated to its idiosyncrasies and thus trust it more We conducted a survey to address these concerns by examining whether the trust and use attitudes observed in this study extended to drivers that own a Tesla.

4.2. Study II

The goal of Study 2 was to address some of the limitations of Study 1 and to investigate whether issues of trust, use, and error were similarly observed by owners of Tesla cars. By examining the attitudes of Tesla car owners, who would have had more time to experience its ADAS features, we could better assess how imperfections of the parking system affect use and trust over longer periods of time. This would allow us to better contextualize the results observed in Study 1 and assess which results were unique to our method and which ones have been experienced by a relevant population such as car owners.

4.3. Method

One hundred and thirteen participants ($N = 113$, $M_{age} = 41.50$, $SD_{\mathrm{age}} = 15.70$) were recruited from online forums, Facebook groups, and various subreddits on Reddit to complete an online survey on automated parking. The recruitment statement indicated that researchers were interested in owners of vehicles with automated parking features and were informed that the survey would take about three minutes to complete. Participants who completed the survey were asked to forward the survey to anyone else who would be interested in participating (i.e., snowball sampling). The online survey consisted of 12 questions that asked about the participant's age, vehicle, the autonomous features included on their vehicle, their use of those autonomous features, and their overall trust in technology. Twenty-two respondents indicated that their vehicle did not have an automated parking feature, and thus no other data was collected from them, which left 91 respondents for data analyses. Of those 91 remaining respondents, 81 owned a Tesla, two owned a Volvo, and the remaining respondents owned a Mercedes, Ford, BMW, Volkswagen, Jeep, and Toyota, respectively. Two respondents did not indicate what type of car they owned.

Table 2
% Participants who have each feature.

Automated Parking	96
Adaptive Cruise Control	94
Automated Steering	92
Blind Spot Warning/Alert	92
Forward Collision Warning	88
Automatic Lane Change	86
Automatic High Beams	84
Rear Cross Traffic Warning	84
Automatic Emergency Braking	78
Lane Keeping Assist	35
Automated Door Opening	22
Automated Pull Forward/Backwards*	5
Automatic Sign Recognition	0

* This feature automatically pulls a car out of a parking spot.

4.4. Results

Results showed that out of the 91 respondents, 88 indicated that their vehicle could autonomously parallel park, while 80 respondents indicated that their vehicle could autonomously perpendicular park. Participants were also asked to indicate which features their vehicle did or did not have (see Table 2).

Among the 91 respondents, 18 had never used the automated parking feature in their vehicle before. The 73 remaining participants were asked to indicate how often they used the automated parking feature to parallel and perpendicular park, each on a Likert scale, ranging from one (Never) to seven (Always). Across parking situations, respondents on average did not use the automated parking often ($M = 2.8$, $SD = 1.9$), and were significantly less likely to use the automated parking for perpendicular ($M = 2.4$, $SD = 1.9$) than parallel ($M = 3.3$, $SD = 2.3$) parking, as indicated by a Wilcoxon Signed Ranks Test, $Z = 4.3$, $p < .001$ (see Fig. 5). Participants also rated their overall trust in technology on a sliding scale from one to ten as high ($M = 7.6$, $SD = 2$).

When respondents were asked why they had not used their automated parking features, responses fell into two categories (see Table 3). The first was imperfect detection: the system simply had never presented the option to them, rarely detects a spot, or detects the spot too late. The second category: the system is inherently faulty, being either too slow or unreliable. This does, however, beg the question as to how the user knows this if they have truly never used the automated parking feature before. Perhaps there is a bias against the use of automated parking from the online forums used by these respondents.

Respondents were asked if they used the automated parallel park feature, and if not, why not. The most common reason given for not using automated parallel parking was that it is too slow and may be an "inconvenience" to others. Participants also indicated that they either lived in an area where it is not necessary, or they have other options. Finally, respondents were asked if they used the automated perpendicular park feature, and if not, why not. The most common theme for not using the perpendicular park feature was that it was too slow and that it is easier to park the vehicle themselves. For both parallel and perpendicular parking, respondents also indicated that the system is relatively imperfect (e.g., "finicky"). Common responses can be found in Table 3.

The final question asked was for participants to indicate anything else they thought the researchers should know about the automated features in their vehicle. Most participants indicated that they "love" the automated features in their vehicles. However, most who indicated this love did so about the autosteer or adaptive cruise control rather than the Autopark. Many of the participants also indicated that they were excited about the future of the technology, saying things like they "can't wait" or that "[full self-driving] is coming".

4.5. Discussion

Respondents of the online survey who owned vehicles with autonomous parking were significantly less likely to use the perpendicular automated parking feature than they were to use the parallel automated parking feature, largely driven by the fact that they believed they were better and faster at perpendicular parking than their vehicle. Similarly, the frequency of responses indicated that those who do not use the parallel parking system refrain because the system is too slow, they believe they are better than automated parking, and they simply do not need to parallel park frequently.

The results of Study 2 are consistent with Study 1 in which participants were able to park significantly faster than the Autopark feature in the Perpendicular trials. The difference in the present study between the frequency of use of the parallel versus perpendicular capabilities may represent a real-world manifestation of different levels of self-confidence with and workload resulting from parallel parking. Previous research has suggested that self-confidence is a predictor of whether participants would be willing to use Autopark features (Tenhundfeld, de Visser, Ries, Finomore, & Tossell, 2020).

While there was no temporal benefit in Study 1 for parallel parking when using the Autopark, there was a benefit for workload. While workload was not evaluated here, it would stand to reason that individual differences in workload associated with parallel parking may influence the frequency of use, especially for those who live in places where parallel parking that are both necessary and

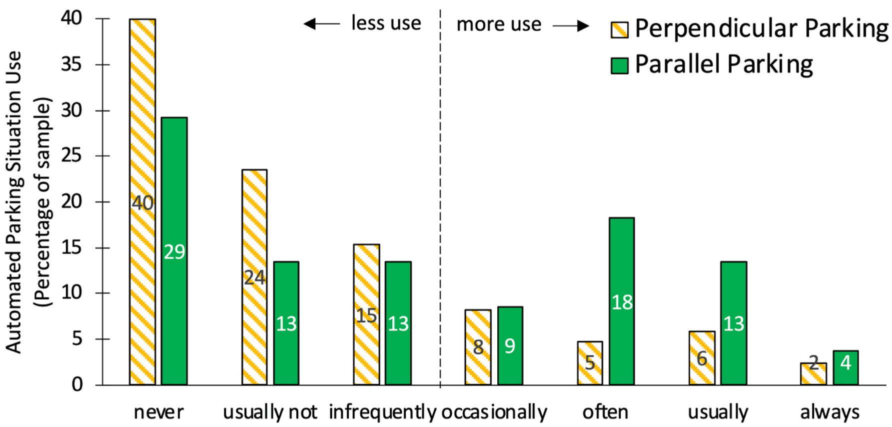

Fig. 5. Use of perpendicular and parallel parking features.

Table 3
% Participants who stated these reasons for **not** using the parking features.

	Perpendicular	Parallel
The system is too slow	60	51
The system is faulty / I am better	55	35
I do not need this feature	6	24
I do not feel comfortable using the system	4	3

difficult (e.g., crowded cities with small parking spaces, one-way streets).

Finally, the open-ended responses indicated that while participants in the present study love automated features of their vehicles, they tended to appreciate features other than automated parking. This seems to further suggest that although the automated parking feature is ‘impressive’ and ‘a neat thing to have’, it serves as a luxury, rather than a true benefit to our participants.

5. General discussion

5.1. Summary of two studies

In Study 1, we explored human and vehicle performance for both perpendicular and parallel parking with a Tesla Model X (Tesla), along with participants’ perceptions of trust in the automated parking system. We compared participants’ ability to park in both perpendicular and parallel parking spots while using Tesla’s Autopark and while manual parking. We found the main benefits of automated parking, both for the vehicle’s performance and for human drivers, emerged for parallel parking as opposed to perpendicular parking. Motivated by Study 1′s findings, in Study 2, we surveyed owners of vehicles with automated parking capabilities to understand how frequently they use those features and why. Vehicle owner preferences for automated parallel parking were consistent with Study 1′s findings that automated perpendicular parking tends to be less reliable and slower than both human drivers and automated parallel parking. Together, these studies provide some of the first empirical evidence describing the relative utility of autonomous vehicle features.

Furthermore, this paper makes several contributions that may benefit the human-automation, human-robot, human–machine, and human-systems interaction communities at large and manufacturers of vehicles with ADAS. First, we provide guidance on real-world costs and benefits of using a commercially available automated parking systems as compared to human manual parking. Second, we provide design guidelines to promote the situation-specific trust that may help address the unique nature of trusting automated parking systems and other future autonomous vehicle features. Lastly, we present some novel measures that may serve as benchmarks to evaluate current automated parking systems, future fully autonomous valets, and other automated driving features.

5.2. Autopark and other automated features may be fault tolerant for now in the context of a human–machine system

Even though the automated parking systems examined in this set of studies were not particularly good (observed empirically and reported by owners), the consequences of this “clumsy” automation (Wiener, 1989) in this case may not be very severe. The reason for this is that drivers are still mostly manually operating the vehicle even with this specific set of ADAS features and can easily catch automation errors because they are obvious (Madhavan, Wiegmann, & Lacson, 2006). The low level of automation provided by the Autopark is value-added, if it works, and not an essential requirement for operating the Tesla vehicle overall. Legally, and according to the Tesla owner’s manual, drivers are still responsible for always maintaining their focus on the driving task. This makes it likely that if the automated parking makes mistakes, the owner of the vehicle will catch them and compensate for them. This is in fact what happened in Study 1. Our results further showed that both the drivers in our study and the owners surveyed were well calibrated to the shortcomings of the automated parking system.

It is worth noting, however, that although users are technically required to monitor the automation at all times, we know from decades of research in human interactions with autonomous systems that a monitoring paradigm is not a perfect solution for imperfect automation (Parasuraman & Manzey, 2010). Errors in automation monitoring can often be worse than errors in manual execution (Parasuraman et al., 1993; Bailey and Scerbo, 2007). Long periods of vigilant monitoring stress human perceptual and cognitive systems in ways that often make performance much worse overall for both traditional vigilance tasks (Warm, Parasuraman, & Matthews, 2008) as well as those specific to monitoring automated vehicles (Greenlee, DeLucia, & Newton, 2018). Asking drivers to closely monitor the automation for long periods may thus be an efficient legal solution for risk mitigation, but not an appropriate strategy for mitigating human performance problems associated with the automation.

5.3. Imperfect automation may have a cost for initial adoption and long-term trust development

When it comes to automation adoption and trust, it is important to understand the consequences of automation failures. An abundance of research has shown that easily observable errors tend to degrade trust significantly more than errors that may not be as easily observed (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003). These failures of an unreliable automated system can lead to system disuse, which in turn can impact the performance of the human–machine team (Parasuraman and Riley, 1997; Dzindolet et al., 2003). However, not all errors are treated the same. Errors that occur early in the interaction between the user and the system have a significantly greater impact on the trust in the system than do errors that come later (Rossi, Dautenhahn, Koay, & Walter, 2017). Even if the reliability of a system improves following these early errors, trust may be slow to catch up (Moray, Inagaki, & Itoh, 2000).

One concern for manufacturers of automated systems, especially self-driving vehicles, is system-wide trust (Rice, Winter, Deaton, & Cremer, 2016). System-wide trust occurs when poor performance in one component of a system results in the degradation of trust across all parts of the system (Keller and Rice, 2009; Walliser et al., 2016). As such, failures in perpendicular parking could impact whether a user trusts the vehicle to drive itself on the highway. While these tasks are somewhat unrelated, this 'bleed-over' presents a potential real barrier to the adoption and acceptance of automation (Matsuyama, et al., 2021).

Alternatively, owners might be resilient to trust decline that comes as a result of imperfect automation (de Visser, 2016; Chiou and Lee, 2021) due to emotional ties built (purposefully or otherwise) with brands like Tesla. It is possible that for brands that have fiercely loyal consumers (i.e. Tesla, Apple, etc.), failures may be downplayed and thus less impactful because of the relationship users have with the product as well as the brand overall (Norman, 2004). Our participants certainly made comments to this effect. A different type of theoretical model might be needed to explain how such trust relationships are built, developed, and repaired over time (de Visser, 2020; Chiou and Lee, 2021), especially as they account for trust in the trust that is placed in the companies and brands that create automation as opposed to the automation itself. However, this idea needs to be explored further in the context of self-driving vehicles and other high-risk environments.

5.4. Improvements in training, certification, and design adjustments are essential

Several improvements could be made to enhance the overall human–machine system in this context. First, the reliability of Autopark should be improved particularly when it comes to the detection of a parking spot, and the variety of different parking situations that could be encountered. Second, one way in which users could be made to feel more comfortable is to either increase the distance at which the vehicle pulls forward to 21 in., which would make it consistent with the average manual parking behavior observed in prior empirical studies, or communicate to the driver the distance at which point the vehicle will pull forward. This could lead to greater acceptance and adoption of the feature. Previous research has indeed demonstrated this to be true by showing the importance of legibility in robot behavior (Dragan, Lee, & Srinivasa, 2013) as well as incorporating the clarity and preference of automated driving behaviors (Basu, Yang, Hungerman, Singhal, & Dragan, 2017). Third, new drivers should undergo training about the specific automation features including Autopark, and obtain appropriate certification in their knowledge of those features (see (Cummings, 2019). Lastly, physiological measures as demonstrated in this work could be used as an input to adaptive automation approaches (Taylor et al., 2013; Grier, et al., 2008; Parasuraman et al., 2009). Such adaptations could further allow the system to better anticipate the needs of the driver by providing additional warnings, information, or context when certain automated behaviors are unanticipated or where they deviate from what humans would like to do.

5.5. A long way from autonomous valets

Automated driving features have the potential to impact society beyond the immediate improvements in roadway safety by reducing pollution and changing transportation and parking infrastructures to have a smaller land-use footprint. On-street parking can result in 30 min of cruise time per parking spot, producing unnecessary pollution (Shoup, 2007). Automated parking features and autonomous valets could potentially eliminate or minimize cruise time for parking spots and lead to an overall decrease in vehicle emissions. Currently, roadway and parking lot infrastructure is engineered for manual vehicles and can be a barrier to the accurate functioning of automated parking features. For example, Tesla's Autopark feature is incompatible with parking lots with diagonal parking spots. A step towards automated parking and autonomous valet services would require an overhaul of parking infrastructures to support automated vehicle technology capabilities. With the rise of vehicle automation and driverless vehicles, parking lots no longer need to allocate space for drivers (and passengers) to enter and leave the vehicle or the parking structure. Parking structures could have smaller land-use footprints since parking spots for automated vehicles could be smaller and denser, allowing for multi-row layouts (Nourinejad, Bahrami, & Roorda, 2018). Additionally, roadway infrastructures can reduce land use and increase lane capacity since automated vehicles can travel with shorter headways and within narrower lanes (Chen, Balieu, & Kringos, 2016).

6. Conclusion

This work presents an evaluation of trust in automated parking systems. While automated parking is currently only moderately useful, with improved reliability of the system trust and use of these systems can increase. This development may further establish long-term trust in automated features and the emergence of autonomous valets.

CRediT authorship contribution statement

Ewart J. de Visser: Conceptualization, Methodology, Writing – original draft, Project administration, Supervision. **Elizabeth Phillips:** Writing – original draft. **Nathan Tenhundfeld:** Conceptualization, Methodology, Writing – original draft, Formal analysis, Investigation. **Bianca Donadio:** Investigation, Writing – review & editing. **Christian Barentine:** Software, Data curation. **Boyoung Kim:** Writing – review & editing. **Anna Madison:** Conceptualization, Methodology, Investigation, Writing – original draft, Supervision. **Anthony Ries:** Methodology, Formal analysis, Visualization. **Chad C. Tossell:** Funding acquisition, Conceptualization, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Acknowledgments

This work was supported by the Air Force Office of Scientific Research Grant 16RT0881f and 21USCOR004. The authors would like to thank Reagan B. Batson, Jofree T. Hunter, Alexander J. LaVille, Kayla B. Simmons, and Ashey M. Wright for their help in data coding.

References

Airaksinen, T., Aminoff, H., Byström, E., Eimar, G., Mata, I., & Schmidt, D. (2004). Automatic Parallel Parking Assistance System User Interface Design – Easier Said Than Done? *Human Factors, no. June*, 1–6.
Bahner, J. E. E., Hüper, A. D. A. D., & Manzey, D. H. (2008). Misuse of automated decision aids: Complacency, automation bias and the impact of training experience. *International Journal of Human Computer Studies, 66*(9), 688–699. https://doi.org/10.1016/j.ijhcs.2008.06.001
Bailey, N. R., & Scerbo, M. W. (2007). Automation-induced complacency for monitoring highly reliable systems: The role of task complexity, system experience, and operator trust. *Theoretical Issues in Ergonomics Science, 8*(4), 321–348.
Bainbridge, L. (1983). Ironies of automation. *Automatica, 19*(6), 775–779. https://doi.org/10.1016/0005-1098(83)90046-8
Basu, C., Singhal, M. (2016). "Trust dynamics in human autonomous vehicle interaction: A review of trust models," in *AAAI Spring Symposium - Technical Report*, 2016, pp. 85–91.
Basu, C., Yang, Q., Hungerman, D., Singhal, M., Dragan, A. D. (2017). "Do You Want Your Autonomous Car To Drive Like You?," *Proceedings of the 2017 ACM/IEEE International Conference on Human-Robot Interaction - HRI '17*, pp. 417–425, 2017, doi: 10.1145/2909824.3020250.
Birrell, S. A., Wilson, D., Yang, C. P., Dhadyalla, G., & Jennings, P. (2015). How driver behaviour and parking alignment affects inductive charging systems for electric vehicles. *Transportation Research Part C: Emerging Technologies* (vol. 58, no. PD,, 721–731. https://doi.org/10.1016/j.trc.2015.04.011
Chen, F., Balieu, R., & Kringos, N. (2016). Potential influences on long-term service performance of road infrastructure by automated vehicles. *Transportation Research Record, 2550*, 72–79. https://doi.org/10.3141/2550-10
Chen, J. Y. C., Lakhmani, S. G., Stowers, K., Selkowitz, A. R., Wright, J. L., & Barnes, M. (2018). Situation awareness-based agent transparency and human-autonomy teaming effectiveness. *Theoretical Issues in Ergonomics Science, 19*(3), 259–282.
Chiou, E. K., & Lee, J. D. (2021). Trusting automation: Designing for responsivity and resilience. *Human Factors*, 1–29. https://doi.org/10.1177/00187208211009995
Cohen, M., Parasuraman, R., Freeman, J. (1998). "Trust in decision aids: A model and its training implications," In *Proceedings of the 1998 Command and Control Research and Technology Symposium*, Monterey, CA: International Command and Control Institute, 1998, pp. 1–37.
Cummings, M. L. (2019). "Adaptation of Human Licensing Examinations to the Certification of Autonomous Systems", in *Safe, Autonomous and Intelligent Vehicles*, 145–162.
Cunningham, M., Regan, M. A. (2015). "Autonomous Vehicles: Human Factors Issues and Future Research," in *Proceedings of the 2015 Australasian Road Safety Conference*, 2015.
de Visser, E. J., et al. (2016). "Almost Human: Anthropomorphism Increases Trust Resilience in Cognitive Agents". *Journal of Experimental Psychology: Applied Advance online publication*. https://doi.org/10.1037/xap0000092
de Visser, E. J., et al. (2018). Learning From the Slips of Others: Neural Correlates of Trust in Automated Agents. *Frontiers in Human Neuroscience, 12*(309), 1–15. https://doi.org/10.3389/fnhum.2018.00309
de Visser, E. J., et al. (2020). Towards a Theory of Longitudinal Trust Calibration in Human-Robot Teams. *International Journal of Social Robotics, 12*, 459–478. https://doi.org/10.1007/s12369-019-00596-x
de Visser, E.J., Cohen, M., Freedy, A., Parasuraman, R. (2014). "A Design Methodology for Trust Cue Calibration," in *Virtual Augmented and Mixed Reality. Designing and Developing Virtual and Augmented Environments Lecure Notes in Computer Science*, 2014, pp. 251–262.
de Winter, J. C. F. (2019). Pitfalls of automation: A faulty narrative? *Ergonomics, 62*(4), 505–508. https://doi.org/10.1080/00140139.2019.1563334
Dikmen, M., Burns, C. (2017). "Trust in autonomous vehicles: The case of Tesla Autopilot and Summon," presented at the 2017 IEEE International conference on systems, man, and cybernetics (SMC), IEEE, 2017, pp. 1093–1098.
Dragan, A. D., Lee, K. C. T., & Srinivasa, S. S. (2013). Legibility and predictability of robot motion. In *ACM/IEEE International Conference on Human-Robot Interaction* (pp. 301–308). IEEE. https://doi.org/10.1109/HRI.2013.6483603.
Dzindolet, M. T., Peterson, S. A., Pomranky, R. A., Pierce, L. G., & Beck, H. P. (2003). The role of trust in automation reliance. *International Journal of Human Computer Studies, 58*(6), 697–718. https://doi.org/10.1016/S1071-5819(03)00038-7
Edelmann, A., Stumper, S., Petzoldt, T. (2019). "Specific Feedback Matters - The Role of Specific Feedback in the Development of Trust in Automated Driving Systems," in *Proceedings of the 30th IEEE Intelligent Vehicles Symposium*, Paris, 2019.
Endsley, M. R. (2017). Autonomous Driving Systems: A Preliminary Naturalistic Study of the Tesla Model S. *Journal of Cognitive Engineering and Decision Making, 11*(3), 225–238. https://doi.org/10.1177/1555343417695197
Endsley, M. R. (2023). Supporting Human-AI Teams: Transparency, explainability, and situation awareness. *Computers in Human Behavior, 140*, Article 107574.
Eskandarian, A. (2012). *Handbook of intelligent vehicles*, vol. 1–2. 2012. doi: 10.1007/978-0-85729-085-4.
Gadgil, S., & Green, P. (2005). How much clearance drivers want while parking: Data to guide the design of parking assistance systems. *Proceedings of the Human Factors and Ergonomics Society, 2004*, 1935–1939. https://doi.org/10.1177/154193120504902211
Green, P. (2006). *Parking crashes and parking assistance system design: Evidence from crash databases, the literature, and insurance agent interviews*. SAE.
Greenlee, E. T., DeLucia, P. R., & Newton, D. C. (2018). Driver Vigilance in Automated Vehicles: Hazard Detection Failures Are a Matter of Time. *Human Factors, 60*(4), 465–476. https://doi.org/10.1177/0018720818761711
Grier, R., *et* al. (2008). "The red-line of workload: Theory, research, and design," in *Proceedings of the Human Factors and Ergonomics Society*, 2008, pp. 1204–1208. doi: 10.1177/154193120805201811.
Hancock, P. A. (2019). Some promises in the pitfalls of automated and autonomous vehicles: A response to commentators. *Ergonomics, 62*(4), 514–520. https://doi.org/10.1080/00140139.2019.1586103
Hancock, P. A., Nourbakhsh, I., & Stewart, J. (2019). On the future of transportation in an era of automated and autonomous vehicles. *Proceedings of the National Academy of Sciences, 116*(16), 7684–7691. https://doi.org/10.1073/pnas.1805770115

Hart, S. G. (2006). Nasa-Task Load Index (NASA-TLX); 20 Years Later. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 50*(9), 904–908. https://doi.org/10.1177/154193120605000909
Hart, S. G., & Staveland, L. E. (1988). Development of NASA-TLX (Task Load Index): Results of Empirical and Theoretical Research. *Advances in Psychology* (vol. 52, no. C,, 139–183. https://doi.org/10.1016/S0166-4115(08)62386-9
Hipp, M., Heuten, W., Löcken, A., Boll, S. (2016). "Ambient park assist: Supporting reverse parking maneuvers with ambient light". In *AutomotiveUI 2016 - 8th International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Adjunct Proceedings*, pp. 45–50, 2016, doi: 10.1145/3004323.3004327.
Hoff, K. A., & Bashir, M. (2015). Trust in Automation : Integrating Empirical Evidence on Factors That Influence Trust. *Human Factors, 57*(3), 407–434. https://doi.org/10.1177/0018720814547570
Kaber, D. B. (2018). Issues in Human-Automation Interaction Modeling: Presumptive Aspects of Frameworks of Types and Levels of Automation. *Journal of Cognitive Engineering and Decision Making, 12*(1), 7–24.
Kaber, D.B., Endsley, M.R. (2004). The effects of level of automation and adaptive automation on human performance, situation awareness and workload in a dynamic control task, vol. 5, no. 2. 2004. doi: 10.1080/1463922021000054335.
Keller, D., & Rice, S. (2009). System-wide versus component-specific trust using multiple aids. *Journal of General Psychology, 137*(1), 114–128. https://doi.org/10.1080/00221300903266713
Kidd, D. G., Hagoski, B. K., Tucker, T. G., & Chiang, D. P. (2015). The effectiveness of a rearview camera and parking sensor system alone and combined for preventing a collision with an unexpected stationary or moving object. *Human Factors, 57*(4), 689–700. https://doi.org/10.1177/0018720814553028
Kohn, S. C., de Visser, E. J., Wiese, E., Lee, Y.-C., & Shaw, T. H. (2021). Measurement of Trust in Automation: A Narrative Review & Reference Guide. *Frontiers in Psychology, no. October*, 85. https://doi.org/10.3389/fpsyg.2021.604977
Krausman, A., et al. (May 2022). Trust Measurement in Human-Autonomy Teams: Development of a Conceptual Toolkit. *J. Hum.-Robot Interact.*, 3530874. https://doi.org/10.1145/3530874
Lee, J. D., & Moray, N. (1994). Trust, self-confidence, and operators' adaptation to automation. *International Journal of Human-Computer Studies, 40*, 153–184.
Lee, J. D., & See, K. A. (2004). Trust in Automation: Designing for Appropriate Reliance. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 46*(1), 50–80. https://doi.org/10.1518/hfes.46.1.50_30392
Lopez, J., & Pak, R. (Dec. 2020). Does One Bad Machine Spoil the Bunch?: A Review of Trust in Multiple-Component Systems. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting, 64*(1). https://doi.org/10.1177/1071181320641370
Ma, J., Feng, X., Gong, Z., & Zhang, Q. (Jun. 2020). Creating Appropriate Trust in Automated Valet Parking System. *Journal of Physics: Conference Series, 1549*(5), Article 052059. https://doi.org/10.1088/1742-6596/1549/5/052059
Madhavan, P., Wiegmann, D. A., & Lacson, F. C. (Jun. 2006). Automation Failures on Tasks Easily Performed by Operators Undermine Trust in Automated Aids. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 48*(2), 241–256. https://doi.org/10.1518/001872006777724408
Matsuyama, L.,*et al.* (2021). "Determinants that influence the acceptance and adoption of mission critical autonomous systems," in *Proceedings of the AIAA SciTech Forum*, 2021. doi: 10.2514/6.2021-1156.
Moray, N., Inagaki, T., & Itoh, M. (2000). Adaptive automation, trust, and self-confidence in fault management of time-critical tasks. *Journal of Experimental Psychology: Applied, 6*(1), 44–58. https://doi.org/10.1037/1076-898X.6.1.44
Neuhaus, R., Lenz, E., Borojeni, S.S., Hassenzahl, M. (2019). "Exploring the Future Experience of Automated 'Valet Parking' - a User Enactment." In *Proceedings of the 11th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, Utrecht Netherlands: ACM, Sep. 2019, pp. 24–34. doi: 10.1145/3342197.3344518.
N. C. for S. and Analysis, "Non-Traffic Surveillance: Fatality and Injury Statistics in Non-Traffic Crashes in 2015," National Highway Traffic Safety Administration, 2018. [Online]. Available: www.nhtsa.gov/research-data/special-crash-investiga-.
Norman, D. A. (2004). Emotional design: Why we love (or hate) everyday things. *Basic Civitas Books*. https://doi.org/10.5860/choice.41-6846
Nourinejad, M., Bahrami, S., & Roorda, M. J. (2018). Designing parking facilities for autonomous vehicles. *Transportation Research Part B: Methodological, 109*, 110–127. https://doi.org/10.1016/j.trb.2017.12.017
Parasuraman, R., Cosenzo, K. A., & de Visser, E. J. (2009). Adaptive automation for human supervision of multiple uninhabited vehicles: Effects on change detection, situation awareness, and mental workload. *Military Psychology, 21*(2), 270–297. https://doi.org/10.1080/08995600902768800
Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors, 52*(3), 381–410. https://doi.org/10.1177/0018720810376055.Copyright
Parasuraman, R., Molloy, R., & Singh, I. L. (1993). Performance Consequences of Automation Induced Complacency. *The International Journal of Aviation Psychology, 3*(1), 1–23. https://doi.org/10.1207/s15327108ijap0301
Parasuraman, R., & Riley, V. (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 39*(2), 230–253. https://doi.org/10.1518/001872097778543886
Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2000). A Model for Types and Levels of Human Interaction with Automation. *IEEE Transactions on Systems, Man, and Cybernetics, 30*(3), 286–297.
Parasuraman, R., Sheridan, T. B. T. B., & Wickens, C. D. C. D. (May 2000). A Model for Types and Levels of Human Interaction with Automation. *IEEE Transactions on Systems, Man, and Cybernetics, 30*(3), 286–297. https://doi.org/10.1109/3468.844354
Parasuraman, R., Sheridan, T. B., & Wickens, C. D. (2008). Situation Awareness, Mental Workload, and Trust in Automation: Viable, Empirically Supported Cognitive Engineering Constructs. *Journal of Cognitive Engineering and Decision Making, 2*(2), 140–160. https://doi.org/10.1518/155534308X284417
Parasuraman, R., & Wickens, C. D. (2008). Humans: Still Vital After All These Years of Automation. *Human Factors, 50*(3), 511–520. https://doi.org/10.4324/9781315095080-14
Raats, K., Fors, V., Pink, S. (2019). "Understanding trust in automated vehicles," presented at the Proceedings of the 31st Australian Conference on Human-Computer-Interaction, 2019, pp. 352–358.
Reimer, B., Mehler, B., & Coughlin, J. F. (2010). An Evaluation of Driver Reactions to New Vehicle Parking Assist Technologies Developed to Reduce Driver Stress. *New England University Transportation Center, no. November*, 1–26. https://doi.org/10.13140/RG.2.1.3317.3361
Reimer, B., Mehler, B., & Coughlin, J. F. (2016). Reductions in self-reported stress and anticipatory heart rate with the use of a semi-automated parallel parking system. *Applied Ergonomics, 52*, 120–127. https://doi.org/10.1016/j.apergo.2015.07.008
Rice, S., Winter, S. R., Deaton, J. E., & Cremer, I. (2016). What Are the Predictors of System-Wide Trust Loss in Transportation Automation? *Journal of Aviation Technology and Engineering, 6*(1), pp. https://doi.org/10.7771/2159-6670.1120
Rossi, A., Dautenhahn, K., Koay, K. L., Walter, M. L. (2017). "How the Timing and Magnitude of Robot Errors Influence Peoples' Trust of Robots in an Emergency Scenario," in *International Conference on Social Robotics*, 2017, pp. 526–535. doi: 10.1007/978-3-319-70022-9.
Schaefer, K. E., Chen, J. Y. C., Szalma, J. L., & Hancock, P. A. (2016). A Meta-Analysis of Factors Influencing the Development of Trust in Automation : Implications for Understanding Autonomy in Future Systems. *Human Factors, 58*(3), pp. https://doi.org/10.1177/0018720816634228
Shoup, D. (2007). Cruising for Parking. *ACCESS Magazine, 1*(30), pp. https://doi.org/10.11436/mssj.15.250
Society for Automotive Engineers, "Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor Vehicles," Society for Automotive Engineers, 2018. [Online]. Available: https://www.sae.org/standards/content/j3016_201806/.
Suppé, A., Navarro-Serment, L. E., Steinfeld, A. (2010). "Semi-autonomous virtual valet parking," *AutomotiveUI 2010 - 2nd International Conference on Automotive User Interfaces and Interactive Vehicular Applications, Conference Proceedings*, no. AutomotiveUI, pp. 139–142, 2010, doi: 10.1145/1969773.1969798.
Surpris, G., Liu, D., & Vincenzi, D. (2014). How much can a smart parking system save you? *Ergonomics in Design, 22*(4), 15–20. https://doi.org/10.1177/1064804614526202
Tada, S., Wada, T. (2015). "Effect of skill development of haptic shared control in backward parking assist". In *2015 IEEE International Conference on Vehicular Electronics and Safety, ICVES 2015*, pp. 164–169, 2016, doi: 10.1109/ICVES.2015.7396912.

Taylor, G. S., Reinerman-Jones, L. E., Szalma, J. L., Mouloua, M., & Hancock, P. A. (2013). What to automate: Addressing the multidimensionality of cognitive resources through system design. *Journal of Cognitive Engineering and Decision Making, 7*(4), 311–329. https://doi.org/10.1177/1555343413495396

Tenhundfeld, N. L., de Visser, E. J., Haring, K. S., Ries, A. J., Finomore, V. S., & Tossell, C. C. (2019). Calibrating Trust in Automation Through Familiarity With the Autoparking Feature of a Tesla Model X. *Journal of Cognitive Engineering and Decision Making, 13*(4), pp. https://doi.org/10.1177/1555343419869083

Tenhundfeld, N. L., de Visser, E. J.., Haring, K. S., Ries, A. J., Finomore, V. S., & Tossell, C. C. (2019). Calibrating trust in automation through familiarity with the autoparking feature of a Tesla Model X. *Journal of Cognitive Engineering and Decision Making, 13*(4), 279–294. https://doi.org/10.1177/1555343419869083

Tenhundfeld, N. L., de Visser, E. J., Ries, A. J., Finomore, V. S., & Tossell, C. C. (2020). Trust and Distrust of Automated Parking in a Tesla Model X. *Human Factors, 62* (2), 194–210. https://doi.org/10.1177/0018720819865412

Tomzcak, K., *et al.*, "Let Tesla Park Your Tesla: Driver Trust in a Semi-Automated Car," in *Proceedings of the annual Systems and Information Engineering Design Symposium (SIEDS) Conference.*, 2019. doi: 10.1109/SIEDS.2019.8735647.

Totzke, I., Jessberger, S., Mühlbacher, D., & Krüger, H. P. (2011). Semi-autonomous advanced parking assistants: Do they really have to be learned if steering is automated? *IET Intelligent Transport Systems, 5*(2), 141–147. https://doi.org/10.1049/iet-its.2010.0112

Trösterer, S., Wurhofer, D., Rödel, C., Tscheligi, M. (2014). "Using a Parking Assist System Over Time," in *6th International Conference on Automotive User Interfaces and Interactive Vehicular Applications*, 2014, pp. 1–8. doi: 10.1145/2667317.2667327.

Walliser, J. C., de Visser, E. J., & Shaw, T. H. (2023). Exploring system wide trust prevalence and mitigation strategies with multiple autonomous agents. *Computers in Human Behavior, 143*, Article 107671.

Walliser, J.C., De Visser, E.J., Shaw, T. H. (2016). "Application of a system-wide trust strategy when supervising multiple autonomous agents," in *Proceedings of the Human Factors and Ergonomics Society*, 2016, pp. 133–137. doi: 10.1177/1541931213601031.

Warm, J. S., Parasuraman, R., & Matthews, G. (2008). Vigilance Requires Hard Mental Work and Is Stressful. *Human Factors: The Journal of the Human Factors and Ergonomics Society, 50*(3), 433–441. https://doi.org/10.1518/001872008X312152

Wiener, E.L. (1989). "Human factors of advanced technology (glass cockpit) transport aircraft," National Aeronautics and Space Administration, 1989. [Online]. Available: http://ntrs.nasa.gov/search.jsp?R=19890016609.

Yang, J., & Coughlin, J. F. (2012). In-vehicle technology for self-driving cars: Advantages and challenges for aging drivers. *International Journal of, 13*(2), 293–300. https://doi.org/10.1007/s12239