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Once a driver, always a driver — Manual driving style persists in automated driving takeover

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ABSTRACT

As automated vehicles require human drivers to resume control in critical situations, predicting driver takeover behaviour could be beneficial for safe transitions of control. While previous research has explored predicting takeover behaviour in relation to driver state and traits, little work has examined the predictive value of manual driving style. We hypothesised that drivers' behaviour during manual driving is predictive of their takeover behaviour when resuming control from an automated vehicle. We assessed 38 drivers with varying experience in a high-fidelity driving simulator. After completing manual driving sessions to assess their driving style, participants performed an automated driving task, typically on a subsequent date. Measures of driving style from manual driving sessions, including headway and lane change speed, were found to be predictive of takeover behaviour. The level of driving experience was associated with the behavioural measures, but correlations between measures of manual driving style and takeover behaviour remained after controlling for driver experience. Our findings demonstrate that how drivers reclaim control from their automated vehicle is not an isolated phenomenon but is associated with manual driving behaviour and driving experience. Strategies to improve takeover safety and comfort could be based on driving style measures, for example by the automated vehicle adapting its behaviour to match a driver's driving style.

1. Introduction

Recent decades have witnessed substantial advancements in sensor technology, artificial intelligence, and control systems, leading to a marked increase in vehicle automation. However, for the near future, humans will continue to be responsible for assuming control during critical situations because automated driving systems are limited to specific operational design domains.

A number of studies have shown that disengagement from the driving process can result in diminished situational awareness and low mental workload (De Winter et al., 2014; Young and Stanton, 2007), whereas high mental workload may occur when human intervention becomes necessary (Hancock, 2021). The susceptibility of automated vehicle drivers to these adverse effects has inspired considerable research on transitions from automated to manual control (Eriksson and Stanton, 2017; Lu et al., 2016; Naujoks et al., 2019; Ruscio et al., 2017). Much of this research focuses on examining the impact of warning systems (Forster et al., 2017; Lu et al., 2019; Petermeijer et al., 2017), environmental factors like traffic density (Doubek et al., 2020; Gold et al., 2016), and the engagement in cognitively (Radlmayr et al., 2019; Wandtner et al., 2018) or physically (Radhakrishnan et al., 2022; Zeeb et al., 2017) distracting non-driving activities prior to takeover.

The current study aims to predict the manner in which drivers regain control from an automated driving system. Accurate prediction of the quality of takeovers could allow for the design of feedback and interventions that intend to improve driver readiness before resuming control (as also suggested by Ayoub et al., 2022; Zhang et al., 2019b). Such predictions may be derived from the driver's state immediately before takeover while the automated driving system is still engaged, as well as from more enduring individual traits such as one's manual driving style.

Several studies have previously explored predicting takeover behaviour based on driver state. Braunagel et al. (2017) proposed a method for predicting takeover behaviour based on eyes-off-road time, secondary task engagement, and complexity of the traffic situation. Their study showed that in 63% of low-quality driver takeovers,

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warnings could have been given beforehand (i.e., true positives), while in 87% of adequate takeovers, the system would not have disturbed the driver (i.e., true negatives). Du et al. (2020) used physiological and environmental data to predict driver takeover performance. Inputs to a random forest algorithm included gaze, galvanic skin response, heart rate, traffic density, and takeover time budget. For a 3-s window, their method distinguished between good and poor takeover behaviour with 84% accuracy. Other proposed methods for predicting driver's readiness to take over include in-vehicle vision observations obtained from cameras, depth sensors, and an infrared camera pointed at the driver's feet (Deo and Trivedi, 2020). Additionally, physiological measures such as eye tracking and body posture have been used to predict takeover times (Lotz and Weissenberger, 2019).

The second approach to predicting takeover behaviour examines the influence of driver traits. Previous research has explored factors like age, gender, personality, and other attributes to determine their potential for predicting takeover behaviour. A driving simulator study by Matsumuro et al. (2020) evaluated drivers' propensity to override adaptive cruise control (ACC) for different deceleration rates of the preceding car. They assessed driving styles, including being 'methodical' (i.e., a tendency towards cautious and rule-adherent driving), through a questionnaire and manual driving without ACC. The findings revealed that methodical drivers intervened with ACC more frequently, especially in less hazardous scenarios. Körber et al. (2015) found that takeover time in automated driving could be predicted by multitasking test performance, with worse multitaskers taking longer to retake control. Although it might be intuitively thought that taking over control of an automated vehicle would be highly influenced by driving skill (such as can be described by a quick reaction time and skilful evasive manoeuvring), Körber et al. found that basic reaction time was not a strong predictor of takeover time, and noted that further research is needed to investigate the influence of age as a moderating factor. A later meta-analysis found no strong age effect on takeover times, potentially due to motivational processes, as older drivers may show greater caution in order to compensate for their slower response times (Zhang et al., 2019a). Li et al. (2019) found that older drivers took significantly more time than younger drivers to react, take over, and initiate an overtaking manoeuvre, which may reflect age-related declines in cognition, psychomotor ability, and increased caution. However, when given 20 s to take over, older drivers could take over as successfully as younger drivers, with no collisions or critical events. In summary, research indicates that certain personal characteristics have predictive value for driving behaviour in takeover situations.

Some of the above research (e.g., Matsumuro et al., 2020; Zhang et al., 2019a) suggests that the takeover process is affected by the driver's driving style, that is, whether the driver *chooses* to operate cautiously or riskily. The distinction between driving skill and driving style is a fundamental concept in traffic psychology (Blaauw et al., 1977; De Groot et al., 2012; Elander et al., 1993). Research has differentiated between driving skill (errors) and driving style (violations) by performing factor analysis or principal component analysis on objective driving measures (e.g., De Winter et al., 2007) and responses to questionnaires, such as the Driver Behaviour Questionnaire and Driving Skill Inventory (e.g., De Winter et al., 2015; Lajunen and Summala, 1995; Reason et al., 1990). Recordings of driving speed (e.g., exceeding the speed limit), following distance (e.g., tailgating), and degree of activity (e.g., frequent lane changes) have been found to correlate with each other and are statistically distinct from driving skill measures such as deviations in road position, incorrect lane positioning, or pressing the wrong pedals.

Literature surveys by McDonald et al. (2019) and De Winter et al. (2021) have concluded that responses during the takeover of control from an automated vehicle show similarities with previous findings on how drivers of manually operated cars respond in emergency scenarios. This suggests that driving measures obtained during manual driving are predictive of behaviour during takeover situations. A simulator study by Chen et al. (2020) provides some evidence for this assertion. Based on maximal longitudinal acceleration data gathered during a car-following experiment, the authors classified the participants into two groups: 12 'regular' drivers and 8 more 'aggressive' drivers. Contrary to their expectations, the authors found that those categorised as aggressive drivers during manual driving exhibited less severe braking in the takeover scenario. A subsequent experiment involving a larger number of participants showed that more experienced drivers exhibited a lower maximum deceleration when taking over control from the automated vehicle, suggesting they braked less abruptly or less unnecessarily than less experienced drivers (Chen et al., 2021). These findings point to an interplay between driving experience and driving style, where it appears that driving experience does not manifest through rapid responses, but rather through smooth driving when possible. It may also be the case that individuals who exhibit a brisk or more aggressive driving style during manual driving are better able to handle emergency situations, such as in a takeover scenario, and therefore handle such situations more smoothly (Chen et al., 2020).

The current study builds on the premise that past behaviour is a strong predictor of future behaviour (Ouellette and Wood, 1998). Rather than relying on distal measures such as psychometric test results or demographic indicators (e.g., age, gender), we hypothesise that drivers' behaviour during manual driving can be used to predict their behaviour while reclaiming control from an automated vehicle. It is not evident from the literature how strong these predictive relationships are, the manner in which these relationships are structured, and to what extent they correlate with drivers' levels of driving experience. Investigating these correlations is important, especially since much of the research to date has focused solely on analysing how quickly drivers take control after a takeover request (Zhang et al., 2019a), and much less on their behaviour during subsequent manoeuvring or the relationships with manual driving behaviour. A strong correlation with driving behaviour during manual driving would suggest that much of the takeover research is redundant with research into manual driving, and therefore occupies a less unique position than one might think.

In this study, we designed a series of driving scenarios to measure manual driving style. We created three scenarios: (1) a lane-change scenario to evaluate the timing and quickness of lane changes, (2) a car-following scenario to assess headway, and (3) a circular drive with road narrowings to assess the speed of drivers. These scenarios were expected to capture driving style measures likely to recur in takeover situations. Specifically, lane changes are relevant during takeovers, where obstacles, such as roadworks (Doubek et al., 2020), must be avoided by means of a lane change. Following distance provides insight into the temporal margins the driver maintains and is potentially predictive of safety margins in a takeover scenario. The last scenario aimed to capture the general risk-related driving style of the driver. We then assessed the associations between these measures and takeover behaviour during a subsequent driving simulator session. Our hypothesis was that manual driving measures are predictive of takeover behaviour.

An additional question is whether driving style measured during manual driving is predictive of takeover behaviour, or if this prediction could be equally well made based on the driver's self-reported driving experience and related variables. This was investigated by calculating the correlations between driving style during manual driving and behaviour during the takeover scenario, both without and with partialling out a driving experience construct.

2. Methods

2.1. Participants

In this study, conducted in November and December 2020, we enlisted a total of 38 employees from Porsche AG, of which 15 were females and 23 were males. Each participant held a valid driver's licence and had normal or corrected-to-normal vision. We included drivers with varying experience levels based on years of licensure and estimated lifetime mileage. However, to minimise the potential confounding effects of age-related factors, we limited the age range to a maximum of 40 years. Among the 38 participants, 19 were 20 years old or younger, 9 were between 21 and 30 years old, and 10 were between 31 and 40 years old.

In terms of driving frequency over the past 12 months, 19 participants reported driving daily, 9 drove 4–6 days per week, 5 drove 1–3 days per week, and 5 drove 1–4 days per month. As for annual mileage over the same period, 3 participants reported driving 1–1000 km, 7 reported 1001–5000 km, 5 reported 5001–10,000 km, 11 reported 10,001–20,000 km, 11 reported 20,001–50,000 km, and 1 reported more than 50,000 km.

Of the original set of 38 participants, data for some sessions were available for a smaller number of participants (between 34 and 37 participants, e.g., due to technical problems or dropout).

2.2. Simulator

The study was conducted in a high-fidelity hexapod driving simulator at the Porsche Research and Development Facility in Weissach, Germany. The 6-DOF moving base platform (eMove eM6-640-1800) was equipped with a fully functional vehicle cockpit. The platform featured an actuator stroke of 640 mm, and the motion cueing adhered to a classical washout algorithm. A 180-degree testing environment was achieved through projectors displaying 3840 × 2160 pixels on all three sides, with a refresh rate of 60 Hz. Only the left mirror was operational and integrated into the projected image. The vehicle dynamics simulation was based on an electric Porsche Taycan Turbo. Surrounding speakers generated wind, tyre, and vehicle sounds. Performance data were recorded at a frequency of 10 Hz.

2.3. Manual driving session 1: overtaking slow-driving trucks

The first scenario took place on a three-lane highway, with each lane measuring 3.6 m in width. Participants were instructed to follow a lead vehicle, which maintained an average speed of 130 km/h to reflect the recommended Autobahn speed, and exhibited minor speed fluctuations for realism. Participants were told to execute a lane change whenever the lead vehicle did so. During the drive, participants performed eight double-lane changes to overtake a slow-moving truck travelling at 80 km/h in the rightmost lane (Fig. 1). The lead vehicle overtook the truck when the distance between the lead vehicle and the truck was 59 m. The double lane change manoeuvres were interspersed with short sections featuring mild curves. Additional traffic was added to create a realistic environment and encourage environmental scanning. During the double lane changes, traffic occupied the leftmost lane only to avoid interfering with the participant's actions.

In manual driving session 1, each participant made eight lane changes. We extracted the following variables per lane change:

- The distance headway (in metres) relative to the lead vehicle at the moment the lead vehicle initiated its lane change. This following distance is seen as an indicator of driving style (e.g., Boyce and Geller, 2002; Itkonen et al., 2017; Sagberg et al., 2015).
- The time difference (in seconds) between the initiation of the lane change by the lead vehicle and the initiation by a lane change of the ego vehicle. This measure can be seen as indicative of driving style, where a later response can be afforded when the headway is longer. The time difference also depends on the driver's choice about when to change lanes.
- The duration of a lane change (in seconds) of the ego-vehicle. The lane change duration was defined as the time difference from the last moment that the lateral position relative to the centre of the right lane of the ego-vehicle was less than 0.75 m and the first moment it was greater than 3.125 m. Quickly changing lanes can be seen as indicative of a fast, confident driving style. However, it can also represent poor vehicle control skill, where the driver gives too rapid steering input in the driving simulator.

The eight values for the repeated lane changes were averaged to obtain a score per participant.

2.4. Manual driving session 2: car-following

The second drive took place on a single-lane rural road with a width of 3.6 m. Participants were instructed to follow a lead vehicle (Fig. 2). The lead vehicle had a mean speed of 100 km/h and featured small speed fluctuations to mimic naturalistic driving conditions. Furthermore, it was programmed to reduce speed if the following distance became too large. During the scenario, participants encountered six merging road sections. In each merging section, high-density traffic lanes merged into the initial single lane from the left and right simultaneously. Different vehicles were programmed to change lanes in front of the lead vehicle at each merging section. This traffic interaction should give drivers the impression that traffic might interfere, potentially influencing their following distance. Manual driving session 2 had a fairly stationary character, since participants only had to follow a lead vehicle. The following measure was extracted for each participant:

- The mean distance headway (in metres), a measure of driving style.

2.5. Manual driving session 3: curves and road narrowings

The third driving assessment drew upon the experimental designs of Van Winsum and Godthelp (1996), pertaining to curve driving, as well as Melman et al. (2020), pertaining to lane narrowings. Participants drove 30.7 km (seven laps) on a single-lane course with a width of 3.6 m. They encountered, per lap, four 90-degree curves with internal radii of 40, 80, 120, and 160 m, interspersed with straight sections. The curves did not include clothoid segments. Road signs after each curve specified a maximum speed of 100 km/h, and indicated the curves and narrowings. Participants faced two road narrowings per lap, starting from the second lap. The narrowings were presented on two of the four straight segments, with different pairs each lap to avoid repetition and predictability. More specifically, during Lap 2, it was: no road narrowing (N),

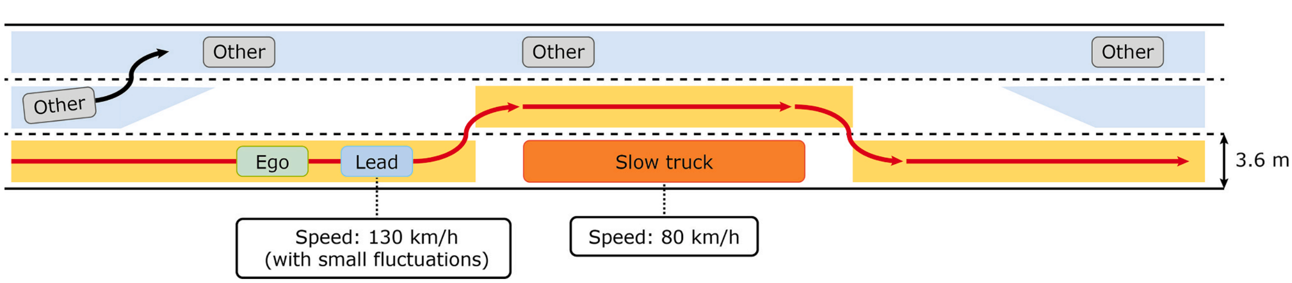

Fig. 1. Schematic visualisation of manual driving session 1: overtaking a slow truck on the highway.

Fig. 2. Car-following on a single-lane road in manual driving session 2. The image was obtained from the eye-tracking camera.

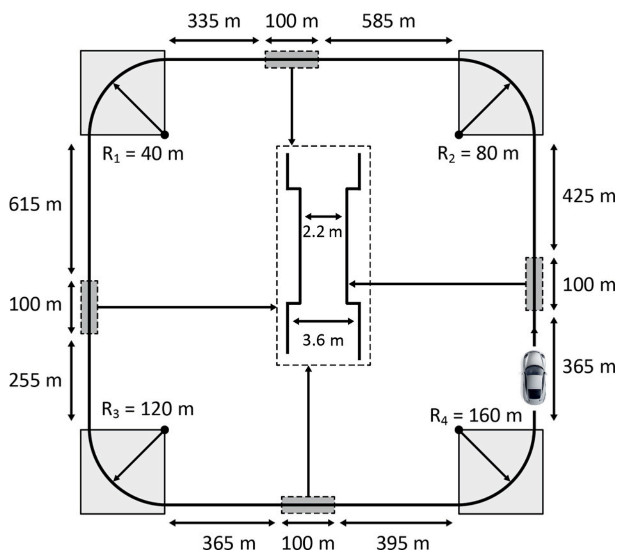

Fig. 3. Schematic of manual driving session 3. Dark grey rectangles indicate potential regions for road narrowings (2 of 4 were activated in a given lap); light grey squares indicate curves. Driving direction was counterclockwise.

road narrowing (Y), no road narrowing (N), road narrowing (Y), followed by Lap 3: YNYN, Lap 4: YYNN, Lap 5: NNYY, Lap 6: YNYN, and Lap 7: NYNY. During the narrowings, the road width was 2.2 m, decreasing the available lateral movement from 0.82 m to 0.12 m. Fig. 3 shows a schematic of the course, while Fig. 4 provides a photographic illustration. Participants started from a standstill, and the first 15 s were excluded from the analysis.

For manual driving session 3, we extracted:

- The mean speed over road segments (in km/h). This was first calculated per road segment, and then averaged over the road segments, per road segment type (Straight, Narrowing, and Curves with 40, 80, 120, and 160 m radius). Since all speeds of road segment types correlated positively with each other (between $r = 0.27$ for straight segments vs. curves with a radius of 80 m, to $r = 0.96$ for curves with a radius of 120 m vs. curves with a radius of 160 m, $n = 37$), it was decided to take the average of the six speeds per participant, in order to obtain one speed value per participant. As pointed out above, driving speed is indicative of driving style.

2.6. Automated driving session

The car drove on a two-lane highway at 130 km/h, each lane being 3.88 m wide. Six takeovers occurred during the drive, accompanied by 361 m long roadworks on the right lane, on a straight road without a hard shoulder. The automation was engaged via a steering wheel button, indicating hands-off driving via a green icon. Participants watched a video of a comedy TV series on a 10.9-inch central display during automated driving. The video automatically started playing when the automated driving function was enabled. Prior to their drive, participants were instructed to watch the video and not be occupied with checking the automated driving system. During the experiment, one experimenter monitored the participant via a live camera feed and could communicate through the intercom to ensure they were paying attention to the video, so that all participants would experience a similar level of distraction from the road. Participants received an audio-visual warning to take manual control during takeover scenarios (for details, see Doubek et al., 2020).

A 3 × 2 within-subject design was used with time budget (5, 7, and 20 s) and traffic density (low and medium) as independent variables. Each participant underwent all six takeover scenarios, with the order counterbalanced using a Latin square method. Medium traffic density scenarios involved a trailing vehicle on the adjacent left lane, making immediate lane changes unsafe. In the low traffic density scenarios, an immediate lane change was possible and safe. After each takeover, participants answered four questions (perceived criticality, discomfort, complexity, time budget; these data were not used in the present study). After the takeover, participants returned to the right lane and reactivated the automation, which continued the video.

The following dependent measures were calculated for each of the six takeover scenarios. With the exception of the minimum speed, the measures below were adopted from the takeover study by Doubek et al. (2020), of which the current automated driving session is a replication:

- The hands-on-wheel time (in seconds), measured by detecting the first steering wheel movement since the presentation of the takeover request. This measure is indicative of driving skill. That is, the hands-on-wheel time can be seen as representing a reflexive action or reaction time; after the driver has their hands on the wheel, they can decide to take further action, such as braking or changing lanes.
- Minimum time to collision (TTC) (in seconds). TTC was defined as the distance to the roadworks divided by current vehicle speed. The minimum TTC represents the lowest TTC while the vehicle was still driving in the right lane (lateral position smaller 1.94 m). This measure represents how quickly participants changed lanes, and how much time margin they left with respect to the stationary roadworks (Doubek et al., 2020). This measure is thus indicative of driving style, meaning that it represents the driver's choice to change lanes early or late; it does not necessarily represent the skill in how well the vehicle can be controlled.
- Minimum speed (in km/h). A lower minimum speed is indicative of caution. In comparison, a high minimum speed indicates that participants avoided the roadworks without braking. This measure is

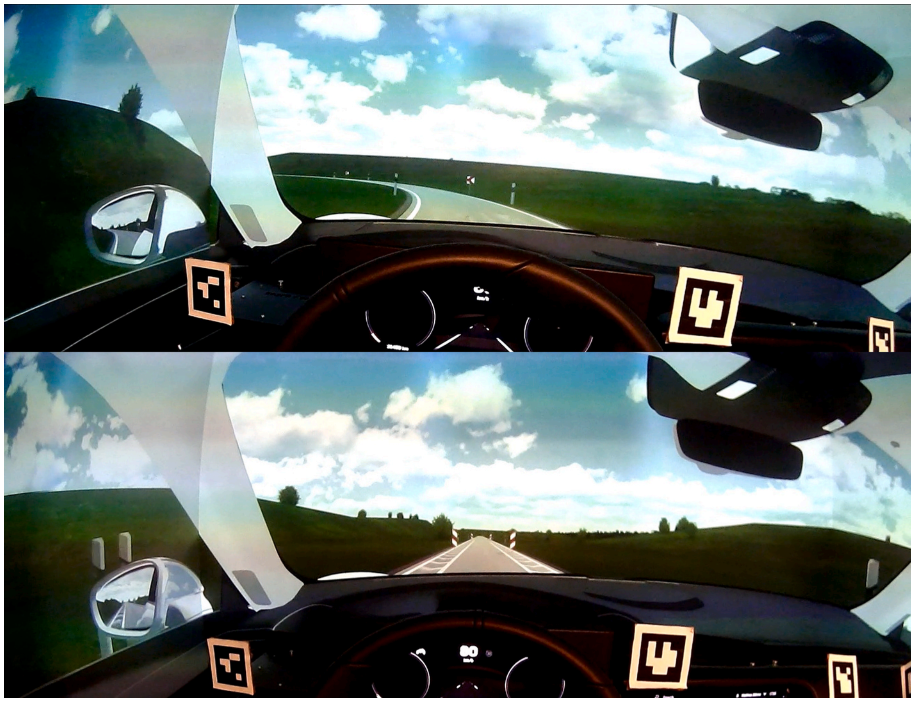

Fig. 4. Top: Curve with an inner radius of 120 m. Bottom: 100-m-long road narrowing. Both images were obtained from the eye-tracking camera.

indicative of driving style, because it represents the caution or uncertainty of the driver (Matsumuro et al., 2020).

- Lane change duration (in seconds), defined as in manual driving session 1. As explained, this is a measure of driving style, but it also captures elements of driving skill because the car responded quite sensitively to steering due to the sporty nature of the vehicle model.

Our initial presumption was that short time budgets primarily test driving skill, and long time budgets reflect driving style. More specifically, a time budget of 5 s requires a relatively quick evasive manoeuvre, whereas with a time budget of 20 s, there is ample time to respond, and it depends on the driver's voluntary choice when to switch from the right lane to the left lane. However, we decided to average the scores for the six takeovers into one score per participant, after first standardising the results for each of the six takeover scenarios, so that across participants, the mean for that takeover scenario was 0 and the standard deviations was 1. In this way, the six takeover scenarios received equal weight in determining the total score, and it is not the case that, for example, the long time budget scenarios dominate the overall minimum TTC value. Averaging of the six takeover scenarios was done for three more reasons. First, averaging increases statistical reliability. Second, even though the six takeover scenarios differed substantially in terms of time budgets, they shared similarities in the required lane change manoeuvre and the decision whether or not to brake. Third, an exploratory analysis showed that, after applying the aforementioned standardisation, the effect of the time budget on the predictive correlations was neither strong nor consistent. For example, the Spearman rank-order correlation coefficient (ρ) between the mean headway in manual driving session 2 and the minimum speed driven by participants in the takeover scenarios was -0.44 for the two takeovers with a time budget of 5 s, -0.48 for the two takeovers with a time budget of 7 s, and -0.45 for the two takeovers with a time budget of 20 s.

2.7. Procedure

Before driving, participants read and signed a consent form, completed a demographic questionnaire, and received a sheet with instructions for the upcoming manual driving tasks. They were informed to drive normally, stay on the road, and adjust speed for conditions. Once in the car, participants were equipped with eye-tracking glasses, calibrated using D-Lab software (version 3.5). Note that the eye-tracking data were not used in this study because our focus was on driver behaviour; however, an additional analysis using eye-tracking data is included in the Appendix.

Participants were told they would drive a Porsche Taycan Turbo simulation and that the simulation might differ from actual driving. They could use the intercom for questions. After each session, drivers rated motion sickness (where 0 is 'no problems', 1 is 'some discomfort, but no specific symptoms', 2 is 'vague symptoms', etc.; Bos et al., 2005) and mental workload (from 1: very low to 20: very high; Hart, 2006), and had a short break. The room and simulator were then cleaned and disinfected before the next experiment. All participants wore face masks. The driving time in manual driving session 1, 2, and 3 was approximately 9, 7, and 20 min, respectively.

In a later driving simulator session, participants first performed a manual car-following task, accompanied by the N-Back task, to introduce cognitive load. These data were not used in the present study. Next, participants completed the automated driving task, which was identical to the automated driving study by Doubek et al. (2020). In detail, participants were welcomed and first trained on the N-Back task, followed by a short break and eye-tracker calibration, and then a short drive without and with the N-Back task. Next, participants performed a familiarisation drive with the automated driving system. Finally, participants completed the aforementioned automated driving session, consisting of six takeovers.

Of the 36 participants who partook in the automated driving session, 8 participated the same day as the aforementioned manual driving session 1–3, 12 participants on the day after, and 14 participants two or more days after. The average interval between the start of manual driving session 1 and the start of the automated driving session was 2.38 days (median: 1 day, standard deviation: 2.65 days).

3. Results

3.1. Manual driving sessions

Fig. 5 shows the lateral position of all individual lane changes in manual driving session 1.

Fig. 6 shows boxplots with the mean speed per participant, split by type of road segment. An increasing trend of mean speed with increasing curve radius can be seen. At the road narrowings, most participants maintained their speed of approximately 100 km/h while some slowed down to below 90 km/h.

3.2. Automated driving session

For the automated driving session, data were available for 34 of 38 participants, and for 3 more participants, takeover data were available for 5 of 6 scenarios. Fig. 7 depicts the trajectories of participants throughout the six takeover scenarios. The hands-on-wheel time was relatively similar across all six types of takeover scenarios, as presented in Fig. 8. Nevertheless, it is observable that participants showed a faster hands-on-wheel time when the time budget was shorter.

For long time budgets, participants exhibited a broad range of responses. Some participants opted for a quick lane change following the takeover request, while others used the available time budget, waiting before executing a lane change. This pattern is illustrated in Fig. 9, which displays the minimum time to collision. Note that a low minimum TTC, indicating a hazardous situation, is caused by initiating the lane change late; participants can also choose to increase the minimum TTC themselves by decelerating their vehicle.

An inspection of the darkness of the lines in Fig. 7 allows for the inference that participants occasionally resorted to a stop. This was especially common in scenarios characterised by medium traffic density and short time budgets, wherein there was a car present in the participant's blind spot. The degree of deceleration was quantified by determining the minimum speed; the boxplots of this measure are presented in Fig. 10.

Finally, we calculated the lane change duration as a measure of driving style, similar to the process used in manual driving session 1. The corresponding boxplots are shown in Fig. 11. The results shown in Figs. 7–11 replicate the findings of an earlier experiment by Doubek et al. (2020) with a new cohort of participants.

3.3. Predicting takeover behaviour from manual driving style

The question we aimed to answer concerned whether individual behaviour in manual driving is predictive of takeover behaviour. For this purpose, the Spearman rank-order correlation coefficient was used. This measure is robust to outliers, and was used because some measures may be skewed (e.g., minimum speed, see Fig. 10).

The correlation coefficients between the measures described above are shown in Table 1. The main results are as follows: Many of the manual driving style measures correlated strongly with each other. For example, the distance headways in the two consecutive sessions (manual driving sessions 1 and 2) were strongly associated (Spearman's $\rho = 0.83$). We also found, for manual driving session 1, that the lane change was initiated later when participants had a longer headway ($\rho = 0.61$), presumably because the time budget to the truck was longer and therefore participants felt less urgency to make a lane change after the lead vehicle did so. Furthermore, we found that participants with a longer headway in manual driving sessions 1 and 2 drove at a lower speed in manual driving session 3 ($\rho = -0.41$ and -0.44, respectively).

Takeover behaviour was reasonably predictable from the manual measures. In particular, there were indications that a more cautious driving style, as characterised by a longer headway during manual driving in sessions 1 and 2, predicted more braking, i.e., a lower minimum speed after takeover ($\rho = -0.31$ and -0.45, respectively), and a higher minimum TTC ($\rho = 0.35$ and 0.43, respectively). Furthermore, we found that the lane change duration in manual driving (indicative of the speed with which participants executed their lane changes) strongly predicted the lane change duration after a takeover request ($\rho = 0.66$). This can be explained by the fact that the lane change was essentially the same, namely manually controlled. The difference was that in the automated driving session, the lane change was preceded by a period of not actively driving the vehicle.

3.4. Role of driving experience

Finally, we examined the Spearman correlation coefficients between the above behavioural measures and the experience score of the participants. This experience score was calculated based on responses in a pre-experiment questionnaire, the calculation of which is provided in the Appendix of this paper. The results in Table 1 show that more experienced drivers drove faster (manual driving session 3) and initiated a lane change earlier (manual driving session 1). Additionally, more experienced drivers made a slower, i.e., a more gradual lane change (manual driving session 1 and automated driving session). A likely

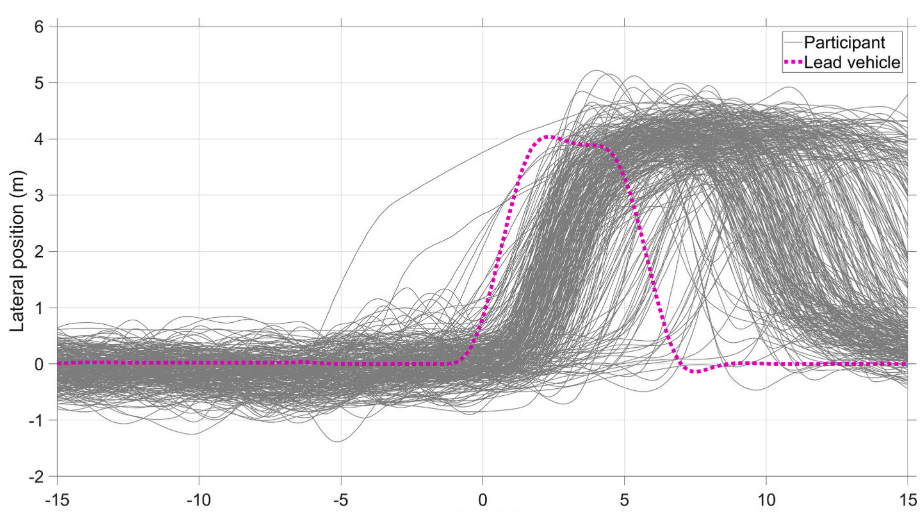

Fig. 5. Lateral position with respect to the centre of the right lane versus time relative to the lead vehicle overtake for all trials in manual driving session 1.

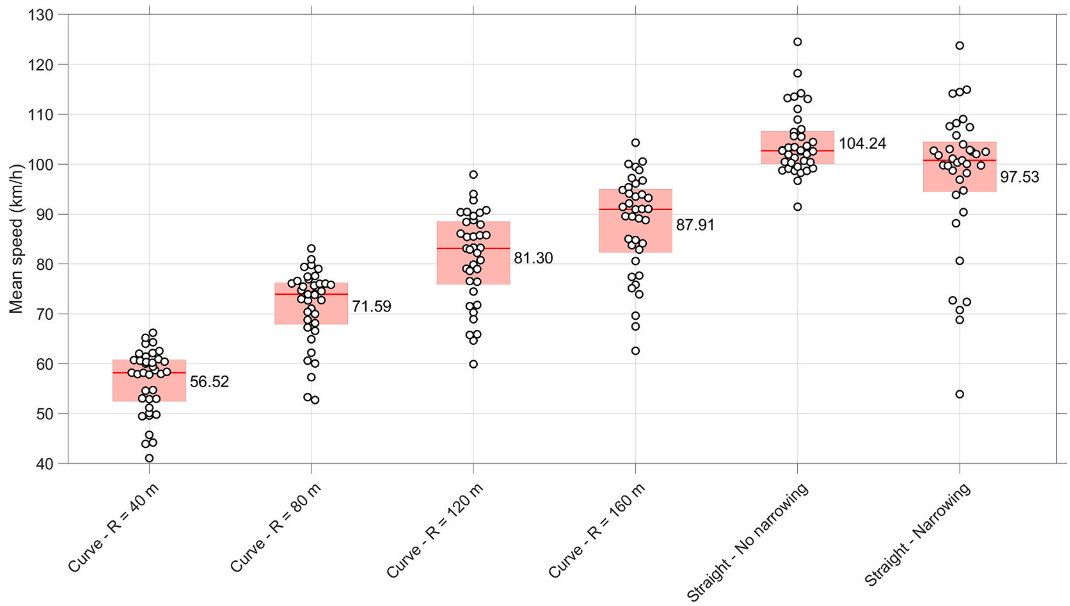

Fig. 6. Boxplots of the mean speed for curves with different radii (R = 40, 80, 120, 160 m), straights, and road narrowings, for manual driving session 3. The boxes capture the 25th and 75th percentiles, and the red lines mark the medians. The numbers next to each box represent the means of participants. The average number of road segments per participant for the six different road segment types was 7.03, 7.84, 6.92, 6.89, 14.97, and 12.76, respectively.

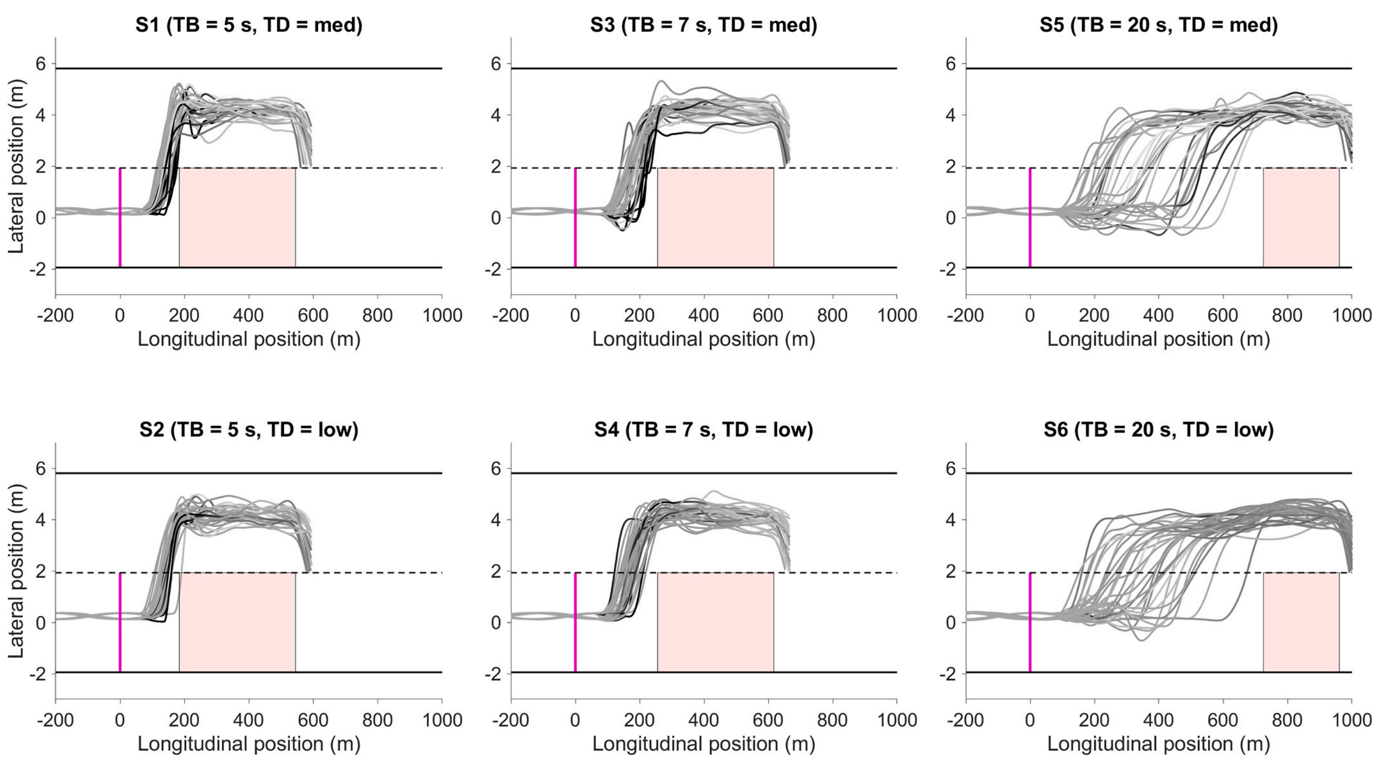

Fig. 7. Lateral position with respect to the centre of the right lane versus longitudinal position in the world (i.e., along the road) for all participants and the six takeover scenarios (S1–S6) of the automated driving session. The greyscale lines represent the ego-vehicle and are colour-coded from 90 km/h (black) to 151 km/h (white). The vertical magenta line represents the moment of the takeover request, and the light red rectangle represents the obstacle. TB: time budget (5 s, 7 s, or 20 s); TD: traffic density (medium or low).

explanation is that experienced drivers are better able to control a responsive vehicle such as a Porsche Taycan, without abrupt actions or overshooting. On a scale of 1 (very low) to 20 (very high), the average mental workload was 5.27, 6.77, and 8.00 for manual driving sessions 1, 2, and 3, respectively. These values correlated slightly negatively with the experience score (ρ = −0.26, −0.39, and −0.10).

Having established that the driver experience score exhibits substantial correlations with the driving measures, as depicted in Table 1, a subsequent question arises: is it necessary to measure manual driving behaviour for valid predictions, or is assessing experience alone through a brief questionnaire sufficient? To this end, we calculated a Spearman correlation matrix in which the experience variable was partialled out.

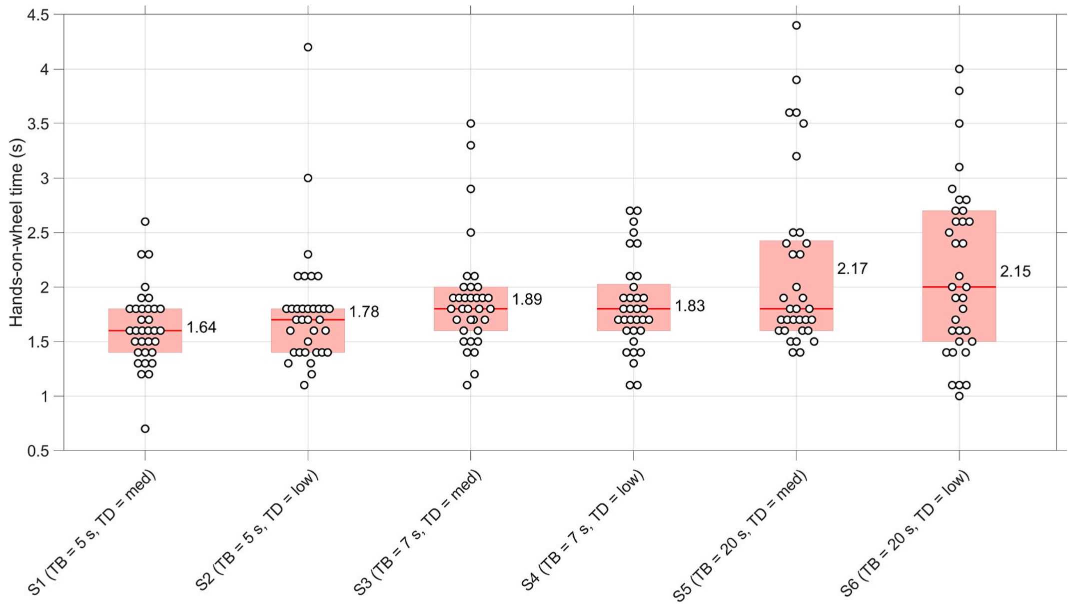

Fig. 8. Boxplots of the hands-on-wheel time for the six takeover scenarios (S1–S6) of the automated driving session. The boxes capture the 25th and 75th percentiles, and the red lines mark the medians. The numbers next to each box represent the means of participants. TB: time budget (5 s, 7 s, or 20 s); TD: traffic density (medium or low).

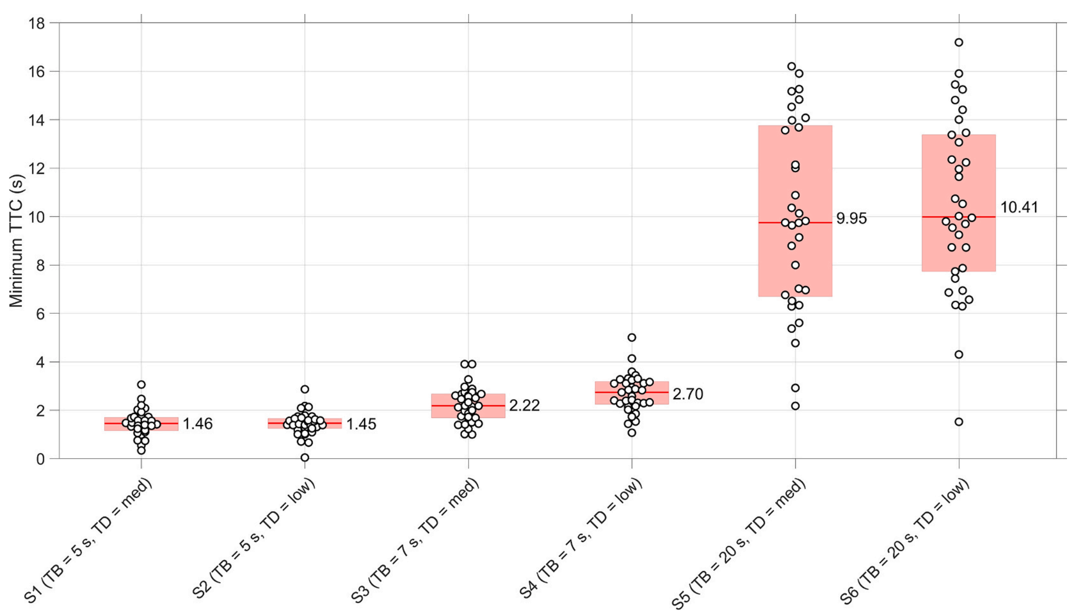

Fig. 9. Boxplots of the minimum time to collision (TTC) for the six takeover scenarios (S1–S6) of the automated driving session. The boxes capture the 25th to 75th percentiles, and the red lines mark the medians. The numbers next to each box represent the means of participants. TB: time budget (5 s, 7 s, or 20 s); TD: traffic density (medium or low).

More specifically, we were interested in understanding the relationship between behavioural measures, but wanted to control for experience level. The partial correlation allows for this by statistically removing the effect that participants' experience levels have on both behaviours. Thus, the resulting partial correlation coefficient represents the relationship between the behavioural measures, after the influence of experience has been removed.

The partial correlation coefficients presented in Table 2 indicate that most correlations remained largely similar. Specifically, headway during manual driving continued to predict minimum speed (indicative of the degree of braking) in the takeover scenario (manual driving session 1: $\rho = -0.31$ vs. $\rho_{partial} = -0.43$; manual driving session 2: $\rho = -0.45$ vs. $\rho_{partial} = -0.54$). Additionally, the predictive value of headway in manual driving for minimum TTC was robust (manual driving session 1: $\rho = 0.35$ vs. $\rho_{partial} = 0.38$; manual driving session 2: $\rho = 0.43$ vs. $\rho_{partial} = 0.44$). The association between lane change speed in manual driving and automated driving was moderately attenuated (from $\rho = 0.66$ to $\rho_{partial} = 0.48$) after controlling for the influence of experience. This finding lends further support to the above statement that more experienced drivers exhibited greater aptitude in operating the simulator vehicle. The results of Tables 1 and 2 suggest that self-reported driving experience predicts driving behaviour, but that driving behaviour itself confers unique predictive validity. The latter inference is consistent with our hypothesis mentioned in the Introduction that future behaviour is predictable based on past behaviour.

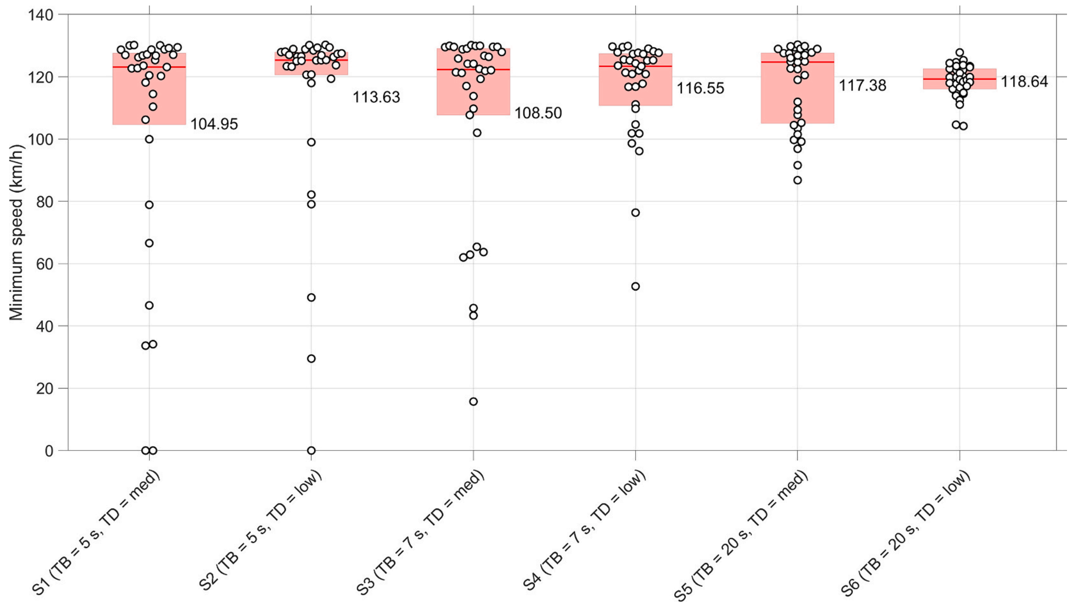

Fig. 10. Boxplots of the minimum speed for the six takeover scenarios (S1–S6) of the automated driving session. The boxes capture the 25th and 75th percentiles, and the red lines mark the medians. The numbers next to each box represent the means of participants. TB: time budget (5 s, 7 s, or 20 s); TD: traffic density (medium or low).

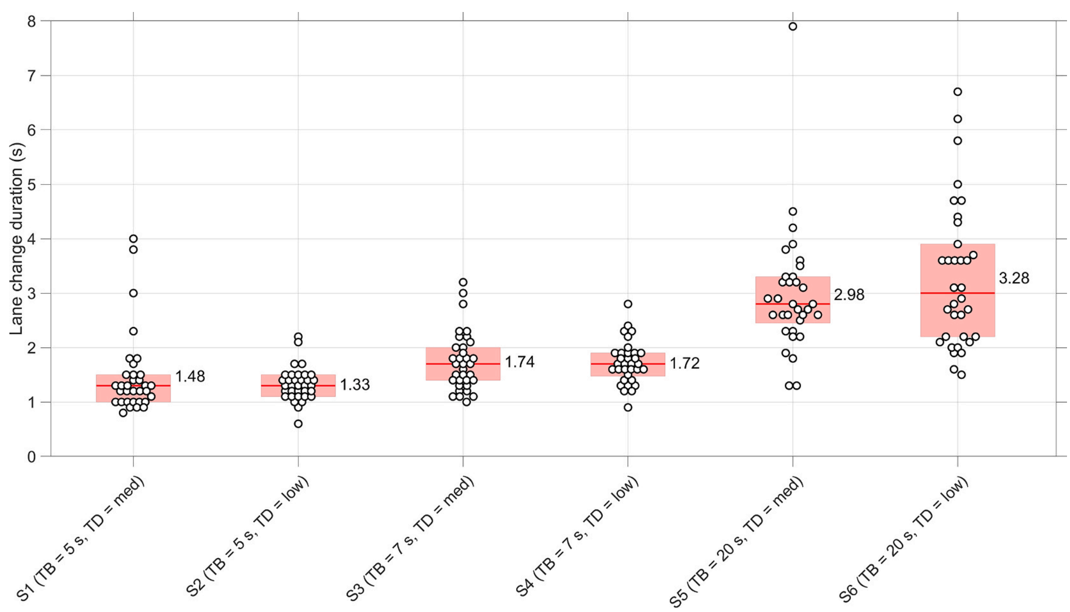

Fig. 11. Boxplots of the lane change duration for the six takeover scenarios (S1–S6) of the automated driving session. The boxes capture the 25th and 75th percentiles, and the red lines mark the medians. The numbers next to each box represent the means of participants. TB: time budget (5 s, 7 s, or 20 s); TD: traffic density (medium or low).

4. Discussion

This study has provided various insights into the predictability of behaviour in situations where drivers need to take control of an automated vehicle. Our work demonstrates the possibility to predict takeover behaviour based on manual driving style, a term which, in this context, refers to driving behaviours shaped by a driver's motivational process. One of the key findings was that drivers who adopted longer headways in manual driving showed more cautious behaviours (higher minimum TTC and lower minimum speed) during takeover scenarios.

Our findings are consistent with prior research demonstrating the predictive validity of driving style measures; for example, studies in driver training have shown driving style measures to be stable over time and predictive of subsequent driving behaviour (De Winter 2013; De Winter et al., 2009; Groeger, 2001), and naturalistic driving studies have shown that such measures are predictive of accident involvement and traffic fines (Chen and Chen, 2022; Engström et al., 2019; Stankevich et al., 2022; Summala et al., 2014). Our work also resonates with prior research suggesting that better driving skills often correspond with a faster driving style (De Winter et al., 2009; Fuller, 2005; Hatakka et al., 2002). That is, as drivers become more experienced, they tend to experience lower workload, allowing them to drive faster (or brake less) without sacrificing safety (e.g., Fuller, 2005; for similar findings in takeover scenarios, see Chen et al., 2020, 2021).

Table 1
Mean (M), standard deviation (SD), and pairwise Spearman rank-order correlation coefficients among dependent measures.

		M	SD	N	1	2	3	4	5	6	7	8	9
1	Experience score (z-score)	0.00	1.00	38									
2	M1. Headway (m)	67.60	27.90	36	−0.31								
3	M1. Lane change moment (s)	2.21	1.40	36	−0.55	0.61							
4	M1. Lane change duration (s)	2.05	0.59	36	0.54	0.14	−0.35						
5	M2. Headway (m)	48.30	23.00	34	−0.23	0.83	0.41	0.19					
6	M3. Mean speed (km/h)	83.20	7.50	37	0.52	−0.41	−0.38	0.11	−0.44				
7	A. Hands-on-wheel time (s)*	0.00	1.00	34	0.13	0.08	0.04	0.35	0.03	0.08			
8	A. Minimum TTC (s)*	0.00	1.00	34	−0.07	0.35	−0.09	0.15	0.43	−0.14	−0.43		
9	A. Lane change duration (s)*	0.00	1.00	34	0.58	−0.06	−0.43	0.66	−0.05	0.22	0.26	0.01	
10	A. Minimum speed (km/h)*	0.00	1.00	34	−0.20	−0.31	0.11	−0.36	−0.45	0.07	−0.16	−0.27	−0.16

Note. M1, M2, M3, and A stand for manual driving session 1, manual driving session 2, manual driving session 3, and the automated driving session, respectively. The colour coding is applied on a linear scale, where −1 is coloured red (RGB 255,0,0), 0 is coloured white, and 1 is coloured blue (RGB 0,176,240). Reported correlations of 0.35 and −0.35 and stronger are statistically significantly different from 0 ($p < 0.05$). Pairwise sample sizes range between 31 and 37.
*Scores have been z-transformed for each of the six takeover scenarios, subsequently averaged across the six takeover scenarios, and again z-transformed.

Table 2
Pairwise Spearman rank-order correlation coefficients among dependent measures, with the driver experience score partialled out.

		N	1	2	3	4	5	6	7	8	9
1	Experience score (z-score)	38									
2	M1. Headway (m)	36	–								
3	M1. Lane change moment (s)	36	–	0.55							
4	M1. Lane change duration (s)	36	–	0.39	−0.08						
5	M2. Headway (m)	34	–	0.82	0.35	0.39					
6	M3. Mean speed (km/h)	37	–	−0.31	−0.14	−0.24	−0.39				
7	A. Hands-on-wheel time (s)*	34	–	0.10	0.10	0.42	0.06	0.02			
8	A. Minimum TTC (s)*	34	–	0.38	−0.09	0.18	0.44	−0.12	−0.43		
9	A. Lane change duration (s)*	34	–	0.12	−0.14	0.48	0.06	−0.10	0.23	0.06	
10	A. Minimum speed (km/h)*	34	–	−0.43	−0.08	−0.25	−0.54	0.20	−0.13	−0.29	−0.06

Note. M1, M2, M3, and A stand for manual driving session 1, manual driving session 2, manual driving session 3, and the automated driving session, respectively. The colour coding is applied on a linear scale, where −1 is coloured red (RGB 255,0,0), 0 is coloured white, and 1 is coloured blue (RGB 0,176,240). Reported correlations of 0.35 and −0.35 and stronger are statistically significantly different from 0 ($p < 0.05$). Pairwise sample sizes range between 31 and 37.
*Scores have been z-transformed for each of the six takeover scenarios, subsequently averaged across the six takeover scenarios, and again z-transformed.

In our study, more experienced drivers adopted higher speeds in manual driving. Furthermore, the duration of lane changes, both after the takeover request and during manual driving, was longer among more experienced drivers, suggesting superior driving skills. The sensitivity of the car to steering inputs might have led more experienced drivers to opt for a slower lane change to ensure vehicle stability when transitioning into the second lane. Additionally, more experienced drivers might possess greater spare mental capacity, allowing them to recognise that they have enough time to change lanes cautiously.

Existing studies in takeover situations have predominantly focused on driving skill measures. In particular, much research has been dedicated to determining how rapidly people react to a takeover request (for a meta-analysis, see Zhang et al., 2019a). It is worth mentioning here that predicting the hands-on-wheel time (takeover time) in driving behaviour presents a challenge: reaction times of individual trials have low test-retest reliability, making it necessary to take the average from multiple trials to arrive at a reasonable prediction at an individual level (Jensen, 2006). Although takeover times have been widely studied, considerably less focus has been placed on the choices made by the drivers in these situations. The current study illustrated that, to a certain degree, driver actions after the takeover request can be predicted from their manual driving style recorded in earlier sessions.

Several limitations of this study have to be acknowledged. First, although a realistic driving simulator was used, the data were not collected in a real vehicle. Therefore, there remains a question regarding the extent to which the takeover scenarios studied herein are a realistic representation of how automated driving might be implemented in the future. In reality, takeover scenarios may be more varied, and the automated vehicle may not be capable of issuing a takeover request at all times. Current developments in automated driving demonstrate major potential for the further advancement of Level 2 automation, where the driver must remain attentive. This contrasts with the Level 3 automation that has been examined in the current study, a concept not available for driving at high speeds on public roads as of today. Another limitation lies in our use of measures describing the state of the vehicle relative to the road (e.g., speed, lateral movement) for predicting takeover behaviour. As indicated in the Introduction, there is also potential value in monitoring the state of the driver; for example, examining whether visual distraction or attention allocation is predictive of takeover behaviour. Figure A1 in the Appendix provides insights into how quickly participants were able to focus their attention on the road during our study. However, we found that the hands-on-wheel time did not strongly correlate with the other measures (see Tables 1 and 2), and the same was true for the eyes-on-road time. The underlying explanation for this is that these response times are largely reflexive, may not be statistically reliable (as pointed out above), and do not evidently relate to the more voluntary driving style that we aimed to investigate in this paper.

There are multiple strategies by which the present results could be used to improve safety and comfort. The driving-style measures could potentially aid the driver during takeover scenarios. For example, introducing pre-emptive deceleration (e.g., Ibrahim et al., 2019) could accommodate those drivers who are likely to slow down after assuming control, in order to reduce driver stress and improve comfort. Likewise, the automated vehicle could be programmed to mimic the driver's preferred speed or time-to-collision values, to match their driving style. Another strategy could involve identifying drivers with atypical or risky driving styles. Training may be a viable approach to address deviant driving behaviours. For example, scenario-based training can equip drivers with an understanding of the risks associated with abrupt deceleration post-takeover and promote safer driving practices. In addition to training, ensuring system familiarisation and providing detailed instructions on takeover procedures are vital for safe driving (Hergeth et al., 2017; Sahaï et al., 2021).

Besides practical implications, the current study also offers scientific insights. Previously, De Winter et al. (2021) estimated that there are already more than 200 studies published on the topic of how drivers reclaim control from an automated vehicle. They also critically noted that much of the research on takeovers might be redundant with existing knowledge, because the same findings have also been obtained, or are directly derivable, from studies on brake reaction times in manual driving, as well as studies on reaction times in more elementary research settings. The current study adds a dimension to this by showing that the takeover behaviour itself, such as changing lanes, is essentially manual behaviour and strongly correlates with the same manoeuvre in a fully manual driving session. Additionally, other driving measures, such as the minimum speed and the minimum TTC, are partly predictable from cautious driving behaviour in manual driving. Based on these findings, we recommend considering takeover behaviour not as a separate phenomenon, but rather to view it within the broader context of manual driving skill and driving style, as well as driver experience.

In conclusion, our study used specially designed manual driving scenarios to gauge driving style. These scenarios effectively enabled the prediction of driver behaviour in takeover situations. Using these insights may benefit safety and comfort during automated vehicle takeovers.

CRediT authorship contribution statement

Joost C.F. de Winter: Writing – review & editing, Writing – original draft, Visualization, Supervision, Formal analysis, Conceptualization. **Koen Verschoor:** Writing – review & editing, Investigation, Formal analysis, Conceptualization. **Fabian Doubek:** Writing – review & editing, Supervision, Conceptualization. **Riender Happee:** Writing – review & editing, Conceptualization.

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.

Appendix A

Supplementary analyses for this article can be found online at https://doi.org/10.1016/j.apergo.2024.104366.

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