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Predicting drivers' takeover time for safe and comfortable vehicle control transitions: The role of spare capacity and driver characteristics

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ABSTRACT

Conditionally automated driving requires drivers to resume vehicle control within constrained time budgets upon receiving takeover requests. Accurately predicting drivers' takeover time (ToT) is essential for dynamically adjusting time budgets to individual needs across scenarios. This study addresses enduring challenges in reliability and interpretability of ToT prediction models by optimizing predictor selection. Using a driving simulator experiment, we examine the relationship between ToT, driver characteristics, and perceived Spare Capacity (pSC, a cognitive construct from Task-Capability Interface theory) using Category Boosting models. Results show that (i) incorporating 13 additional driver characteristics does not significantly improve prediction accuracy when pSC is already considered; and (ii) individual characteristics influence how drivers cognitively process takeover scenarios, and their predictive contribution likely overlaps with pSC. These findings suggest that monitoring cognitive states may be more effective for ToT prediction than extensive profiling of driver characteristics. This study provides a critical first step toward predictive frameworks for adaptive takeover strategies and offers guidance for designing personalized human–vehicle interactions.

1. Introduction

In conditionally automated driving, one primary concern pertains to the transition of vehicle control (ToC) between human drivers and automation. This transition contains complex human-automation interactions (Lu et al., 2016), especially during takeovers when drivers must promptly detach from non-driving-related activities and resume active driving within constrained time budgets. Ensuring safety and comfort during ToC requires providing sufficient time budgets (Weaver and DeLucia, 2022) to accommodate drivers' takeover time (ToT, the interval between the initiation of a takeover request and drivers' resumption of manual vehicle control ISO 21959:2020, 2020). Tight time budgets that fail to allow drivers' required ToT can elevate accident risks and compromise driver comfort (Gold et al., 2013), while time budgets that excessively exceed the necessary ToT may be perceived as false alarms, resulting in decreased vigilance and increased danger (Huang and Pitts, 2022). Thus, determining sufficient time budgets necessitates a deep understanding and precise prediction of drivers' ToT.

Predicting drivers' ToT can facilitate the development of adaptive takeover strategies (Du et al., 2020), particularly by tailoring time budgets to accommodate drivers' varied needs across diverse scenarios. To our knowledge, research on predicting drivers' ToT is limited in both reliability (consistency and accuracy across scenarios and drivers) and interoperability (clarity in how input features influence predictions). Specifically, (i) concerning model inputs, existing literature have identified diverse predictors for ToT. For example, Huang et al. (2023) broadly classified influencing factors into system-, scenario-, and human-related categories, emphasizing the complexity of thoroughly examining human-related factors. Chen et al. (2024) developed a comprehensive ToT prediction model using 18 predictive features, including individual traits, environment, and situation awareness. Despite these contributions, the dynamic and complex nature of real-world driving suggests further refinement of feature selection is needed to enhance model reliability and generalizability; (ii) regarding model outputs, existing studies have made notable contributions to ToT, particularly through classification and average-based approaches. For instance, Pakdamanian et al. (2021) proposed a Deep Neural Network (DNN)-based model that achieved high accuracy (93%) in classifying ToTs into three intervals: short (< 3 s), medium (3–7 s), and long (> 7 s). Similarly, Ayoub et al. (2022) applied an eXtreme Gradient Boosting (XGBoost) model to predict average ToT using literature data, reporting an RMSE of 0.806 and an MAE of 0.505. These models offer useful insights and represent meaningful steps forward in the field.

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Fig. 1. The driving simulator at Delft University of Technology.

However, ToT is known to vary widely across drivers and scenarios. For example, Zhang et al. (2019) observed a range from 0.69 s to 19.79 s across 520 takeovers. The classification and average-based predictions therefore oversimplify this variability and risk overlooking individual differences. In sum, improving drivers' actual ToT prediction models with reliable and interpretable feature selection is critical for aligning adaptive strategies with drivers' cognitive capacities and situational demands, ultimately enhancing the safety and comfort of Conditionally Automated Driving Systems (CADS).

This study takes a fundamental step toward improving the reliability and interpretability of ToT prediction models by optimizing input feature selection. We examine the influence of both latent cognitive constructs and observable driver characteristics. Guided by Fuller's Task-Capacity Interface (TCI) model, our findings in Liang et al. (2024) suggest that ToT is negatively correlated with perceived spare task capacity (pSC), that is, the difference between the total cognitive and perceptual-motor resources drivers believe they have available for a specific task (pTC) and the amount of those resources they perceive the task to demand (pTD). In the current study, we therefore consider pSC (=pTC-pTD) as an explanatory variable to predict ToT, which can help to reveal the underlying influencing mechanisms behind drivers' ToT and improve the interpretability of the prediction models. Besides, we conduct a comprehensive investigation of inter-driver heterogeneity in ToT by examining 13 driver characteristics (covering demographic, skill-related, and style-related factors) using tailored questionnaires. Based on data from a driving simulator experiment, we propose CatToT, a CatBoost-based ToT prediction model, to analyze the relationship among drivers' ToT, pSC, and driver characteristics using feature importance and SHapley Additive exPlanations (SHAP).

This study has three main contributions:

- provides more contextually relevant and valid tools for assessing driver profiles in takeover scenarios;
- reveals the cognitive mechanism underlying takeover behaviors and supports the development of dynamic time budget strategies that accommodate individual driver needs across various scenarios; and
- contributes to understanding inter-driver heterogeneity in cognitive responses, informing the design of more personalized and adaptive conditionally automated driving systems.

The findings provide valuable insights to readers who are interested in drivers' heterogeneous takeover behaviors and their implications for designing personalized interventions and training strategies tailored to diverse driver needs.

2. Related work

Predicting drivers' actual takeover time (ToT) necessitates a thorough understanding of driver heterogeneity, as it accounts for the diverse range of behaviors exhibited by drivers (Ansar et al., 2024; Sharma et al., 2018). From this point of view, we examine previous studies on ToT predictions from two dimensions: inter-driver heterogeneity and intra-driver heterogeneity.

In terms of inter-driver heterogeneity, driver characteristics have been shown to affect drivers' behaviors and performance in various driving contexts (Eboli et al., 2017; Zhao et al., 2019). Differences in driver characteristics will thus likely affect drivers' responses to takeover requests. Zhang et al. (2024) observed that different driving styles lead to varied ToT, where defensive drivers exhibited shorter ToT compared to aggressive drivers. However, such characteristics have not been sufficiently considered in ToT prediction models. Gold et al. (2018) integrated age in a generalized non-linear model and argued that drivers' age is correlated to their reaction time, physical skills and driving experience. Results show that drivers' age has a positive correlation with their ToT. Ayoub et al. (2022) considered gender as an important input in a deep neural network-based ToT prediction model which achieved accurate (93%) prediction of ToT intervals. Investigations of integrating other driver characteristics (such as drivers' driving skills and trust in conditionally automated driving) in ToT prediction models are required to capture drivers' attributes from diverse aspects. Therefore, this study constructs a prediction model for drivers' actual ToT with 13 driver characteristics, which is critical for the reliability of the prediction model across diverse drivers.

As for intra-driver heterogeneity, previous studies on ToT predictions have primarily focused on situational factors which can be divided into objective situational factors and subjective situational factors. On one hand, objective situational factors are derived from vehicle and environment settings. Yoon et al. (2021) modeled drivers' ToT with physical, visual, and cognitive attributes of non-driving related tasks using multiple linear regression analysis. The prediction results are generally shorter than the drivers' actual ToT. Ayoub et al. (2022) considered 17 scenario settings in predicting drivers' average ToT, including automation level, situation complexity, etc. While many factors are already considered, drivers' ToT can be affected by other objective situational factors, such as takeover information support (Weaver and DeLucia, 2022). Given the multitude of these objective situational factors, selecting appropriate objective situational features for ToT prediction models is crucial for ensuring the models' reliability and practical feasibility. On the other hand, subjective situational factors are derived from human drivers, typically including drivers' psychophysiological and/or behavioral data. Rangesh et al. (2021) trained a Long Short Term Memory (LSTM) model using drivers' eyes-on-road time, foot-on-pedal time, and hands-on-wheel time before takeover requests. Results show that the proposed model can achieve continuous predictions of ToT under various secondary activity conditions. Du et al. (2020) employed drivers' gaze behaviors, heart rates, and galvanic skin responses to predict ToT and identified average heart rate as well as maximum and average phasic GSRs are important physiological factors for drivers' ToT. Such subjective situational factors-based models generally possess two limitations: (i) potential lurking factors behind the changes in physiological signals and behaviors may reduce the reliability of prediction results (McDonald et al., 2019), and (ii) the opacity of these models diminishes both algorithm interpretability and result reliability. These limitations can introduce uncertainties and potential safety risks to control transitions. This study emphasizes the importance of integrating cognitive constructs into the ToT prediction model, as cognitive constructs: (i) represent drivers' comprehensive understanding of the entire objective scenarios, which synthetically reflect the effects of all related objective situational factors. (ii) play a decisive role in drivers' decision-making process (Endsley, 2021), which are responsible for the changes in drivers' physiological signals and behaviors. We argue that cognitive constructs hold the potential to be reliable predictors for drivers' actual ToT, thus improving the reliability and interpretability of the prediction models.

3. Method

This study recruited participants through the method described in Section 3.1. They were instructed to detach from non-driving related tasks and take over vehicle control from a simulated Conditionally Automated Driving System (CADS) nine times (Section 3.2). Participants were required to complete a spare capacity survey after each takeover and another post-questionnaire detailing their takeover-related characteristics. The relationship between participants' ToT, perceived spare capacity, and driver characteristics was analyzed by the method in Section 3.3. This study was approved by the Human Research Ethics Committee (HREC) of Delft University of Technology (ID: 3499).

3.1. Recruitment

Participants were recruited through both online (emails and LinkedIn) and offline (flyers) channels. Eligibility criteria require individuals to possess a valid driver's license and the ability to drive without glasses. Details about the study, encompassing research objectives, experimental procedures, anticipated duration, and data anonymization principles, were conveyed to participants through Informed Consent Forms. Additionally, participants were informed of the financial compensation, with each participant receiving a 20-euro voucher for their participation.

The target sample size for this study was 40 participants, based on practical considerations (e.g., participant availability and experimental resources) and reference to comparable driving simulator studies in takeover time prediction. For example, Yoon et al. (2021) modeled takeover time using multiple linear regression with 30 participants; Liu et al. (2024) adopted a Latin square design with 37 participants to explore takeover time using Convolutional Neural Networks (CNN); and Liu et al. (2025) predicted takeover time using a Deep Learning framework distilled by Gradient Boosting Decision Tree (DeepGBM), with an average of 27 data points per variable across 15 features. To enhance statistical robustness and account for participant variability, we actively recruited beyond the initial target and ultimately included 57 valid participants in the final analysis. We believe our sample provides a strong basis for exploratory modeling and interpretation, though we also acknowledge its limitations and highlight the value of larger samples in future research (see Section 5.3).

3.2. Driving simulator experiment

3.2.1. Instrumentation

The experiment was conducted in a fixed-base, medium-fidelity driving simulator on the campus of Delft University of Technology. A demonstration of the simulator can be seen in Fig. 1. The views from the windshield and two side windows are provided by three 4k-resolution screens. To imitate the interior of a vehicle, this driving simulator comprises a driver's seat, a steering wheel, three pedals, a turn signal lever, and a mock dashboard on the bottom of the middle screen. Experiment scenarios are programmed in a desktop computer running Windows 10.

3.2.2. Experiment setup

The experiment takes place on a two-lane motorway with a speed limit of 100 km/h (following daytime regulations on Dutch motorways). The CADS enables participants to engage in non-driving related activities in the automated mode, while the boundary of the Operational Design Domain (ODD) is programmed to be the point at which the CADS encounters two vehicles that have collided in the path of the ego vehicle. A takeover request is initiated when the time gap between the collision location and the ego vehicle reaches seven seconds, a widely used time budget in takeover-related research (Deniel et al., 2024; Gold et al., 2013). The request is signaled by three beeps and three text messages "Please Take Over!" in the top-left corner of the windshield. To mitigate potential simulator sickness, takeover requests only occur on straight road sections (Hock et al., 2018).

The experiment comprises nine takeover scenarios (3 traffic densities × 3 non-driving related tasks) to vary drivers' ToT. Three traffic density levels (low/medium/high) are manipulated by generating 0/10/20 vehicles per kilometre. Three non-driving related task levels (low/medium/high) are controlled by assigning participants to n-back tasks ($n = 0, 1, 2$) of varying cognitive workloads. In n-back tasks, participants view a sequence of positions of a blue box and are instructed to press a button when the current position is the same as the one that occurred n steps back in the sequence. A demonstration of the 1-back and 2-back tasks is shown in Fig. 2, while the 0-back task is a reference and requires no sequence recall.

These nine takeover scenarios are arranged using a Latin Square design (Calvert et al., 2014) to minimize potential order effects. Each scenario appears equally across all ordinal positions (1st to 9th) to ensure balanced representation. Because we have an odd number of scenarios (nine), achieving full pairwise balance requires 18 order groups, so that each scenario precedes and follows every other scenario equally often. The full set of Latin Square orderings used in the study is provided in Appendix A.

3.2.3. Procedures

This experiment included three main procedures, i.e., preparation procedure, takeover procedure, and post-questionnaire procedure. Specifically,

(1) Preparation procedure: Participants were briefed on the abilities and boundaries of the CADS, as well as on the n-back task. A ten-minute practice drive was provided for participants to get familiar with the simulator and the takeover process, which helped to reduce the learning effects during the experiment. Participants could ask for more time to practice until they were confident in controlling the ego vehicle. They were queried if they felt uncomfortable while driving in the simulator and were instructed to inform the experimenter if the discomfort increased.

(2) Takeover procedure: Each participant experienced nine takeover events, with each event including five phases:

(i) *Automated mode:* The takeover event started from automated mode while participants were engaged in the n-back task.

(ii) *Takeover request:* The takeover request was randomly initiated between 30 and 60 s after entering the automated mode. This time window ensures participants have sufficient time to engage with the n-back task before the request, as well as to take over and stabilize the ego vehicle after the request. Randomizing the timing of takeover requests aims to eliminate predictability associated with fixed duration in automated mode.

(iii) *Takeover:* Participants were instructed to promptly detach from the n-back task and begin resuming control of the ego vehicle upon receiving the request. Drivers' takeover time was measured as the interval between the takeover request and the first conscious manual input, i.e., when the steering wheel angle exceeded 2 degrees or the braking/accelerator pedal position surpassed 10% (Liang et al., 2024; Gold et al., 2013).

(iv) *Manual mode:* After regaining conscious control of the ego vehicle, participants were tasked with an evasive manoeuvre, which involved pulling out to the left lane, overtaking the detected collision ahead, and pulling over to the right lane after bypassing the collision.

(v) *Handover:* Participants were instructed to hand over vehicle control back to the CADS once they believed it was safe to do so after stabilizing the vehicle on the right hand lane.

A flow chart of a takeover event is shown in Fig. 3. The duration of each takeover event is flexible: it consists of a randomized automated driving period (30–60 s), followed by the driver's takeover time, a variable period of manual driving, and then

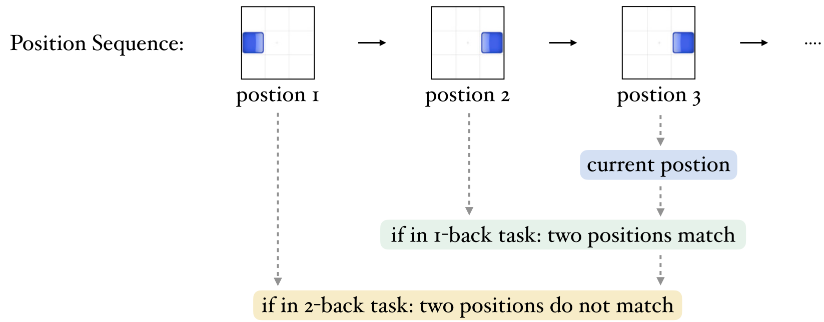

Fig. 2. Demonstration of the n-back task: example of 1-back and 2-back tasks.

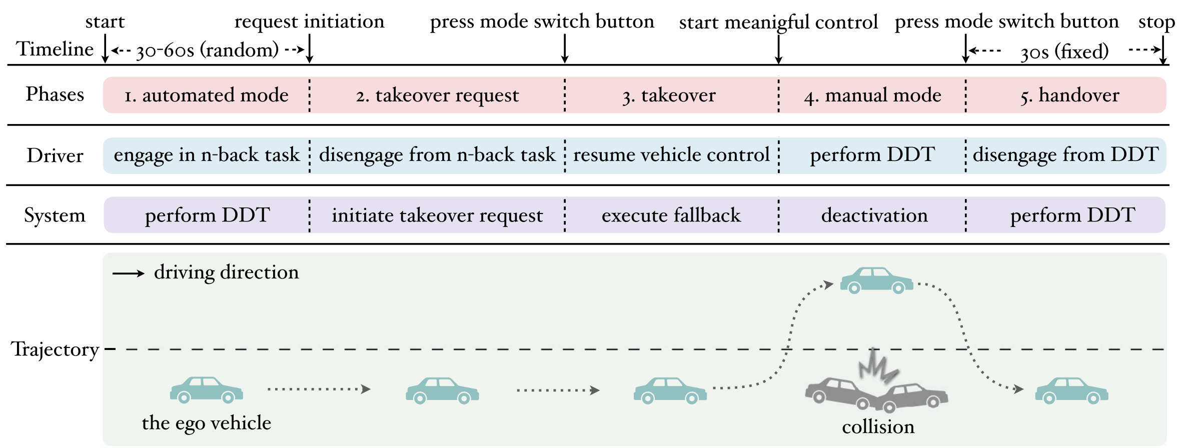

Fig. 3. The flowchart of a takeover event (DDT: Dynamic Driving Task).

another fixed 30-second automated driving. After each takeover event, participants took a short break and completed a survey assessing their perceived Task Demand (pTD) and perceived Task Capability (pTC) during the preceding takeover. The survey was adapted for takeover contexts using items from the NASA Task Load Index (NASA-TLX) (Hart and Staveland, 1988), the Driving Activity Load Index (DALI) (Pauzié, 2008), and the Driver Skill Inventory (DSI) (Lajunen and Summala, 1995; Martinussen et al., 2014). The complete survey is provided in Appendix B.

(3) Post-questionnaire procedure: After completing nine takeover events, participants were requested to fill in a questionnaire which collected their background information (e.g., age, gender, etc.) and measured their perceived risk-taking attitude, takeover skill, takeover style, and trust in the CADS. Details of the questionnaire are provided in Appendix C.

An overview of all three procedures of the experiment is provided in Fig. 4 to ensure methodological clarity and enhance the reproducibility of the study.

3.3. CatBoost-based takeover time prediction model

To better understand the mechanisms shaping drivers' takeover time (ToT), we developed CatBoost models to predict ToT based on perceived spare capacity (pSC) and driver characteristics (Section 3.3.1). Model performance is evaluated using four metrics (Section 3.3.2), and interpretability is enhanced through feature importance and SHAP analysis (Section 3.3.3).

3.3.1. Model development

CatBoost is a high-performance gradient boosting algorithm that reduces overfitting and delivers strong predictive accuracy with minimal tuning (Prokhorenkova et al., 2018; Kulkarni, 2022). It has been applied successfully in ranking, classification, and regression tasks (Ma et al., 2021; Liu et al., 2020; Li et al., 2023). While ToT prediction has typically used XGBoost (Wang et al., 2024; Chen et al., 2024; Ayoub et al., 2022), CatBoost offers key advantages: (i) efficient handling of categorical features common in driver data, (ii) reduced gradient bias and prediction shift, and (iii) faster training suited for large-scale and real-time applications (Dorogush et al., 2018). These strengths make CatBoost well-suited for predicting drivers' ToT.

Assume that a dataset is given as $D = \{X_i, y_i\}_{i=1,2,\ldots,n}$ where $X_i = \{x_i^k\}_{k=1,2,\ldots,m}$ is a vector of m input variables that include both numerical and categorical features; $y_i \in \mathbb{R}$ is a target variable; and n is the total number of the observations. In this study, the dataset is randomly split into a training set D_{train} (80%) and a test set D_{test} (20%). To process features containing both categorical and numerical data, CatBoost (i) performs a random permutation of the dataset as $\sigma = (\sigma_1, \ldots, \sigma_n)$; and (ii) substitutes the categorical feature x_i^k with a new numerical feature calculated by the corresponding Ordered Target Statistics (TS) on a subset of examples $\mathcal{D}_i = \{X_j : \sigma_j < \sigma_i\}$:

$$\hat{x}_i^k = \frac{\sum_{X_j \in D_i} \left[x_j^k = x_i^k\right] * y_j + \alpha \cdot P}{\sum_{X_j \in D_i} \left[x_j^k = x_i^k\right] + \alpha} \tag{1}$$

where P represents the prior value, which is typically set to the average target value (Micci-Barreca, 2001); parameter α (> 0) signifies the weight of the prior; and $[\cdot]$ denotes Iverson brackets, i.e., $\left[x_j^k = x_i^k\right] = 1$ if $x_j^k = x_i^k$ and 0 otherwise.

Catboost uses oblivious decision trees as base predictors, where all decision nodes employ the same splitting criteria at every depth level. This symmetrical approach helps mitigate over-fitting and enhances execution speed. On this basis, CatBoost iteratively builds a sequence of approximations to minimize the expected loss, which is Root Mean

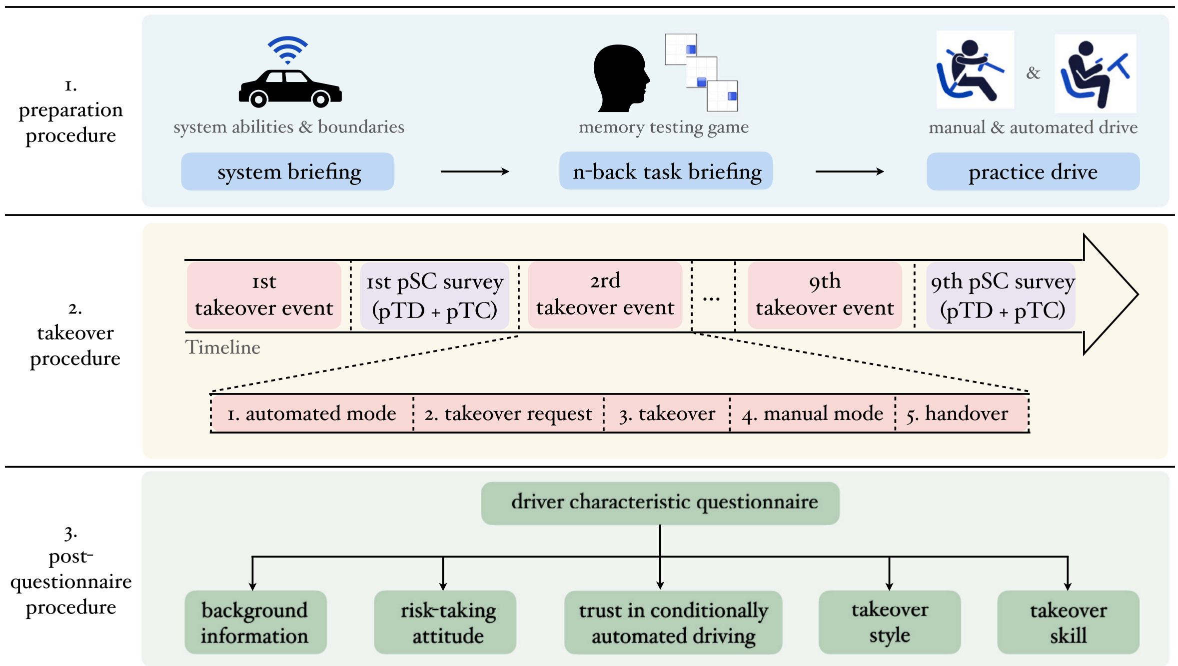

Fig. 4. Overview of the experiment procedures (pSC: perceived Spare Capacity; pTD: perceived Task Demand; pTC: perceived Task Capacity).

Squared Error (RMSE) in this study:

$$Loss^{(t)} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y_i - \hat{y}_i^{(t)}\right)^2} + \Omega(f_t)$$
$$= \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left[y_i - (\hat{y}_i^{(t-1)} + f_t(x_i^k))\right]^2} + \Omega(f_t) \tag{2}$$

where N is the number of samples; y_i is the true target value; $\hat{y}_i^{(t)}$ and $\hat{y}_i^{(t-1)}$ are the predicted target values for sample i at the tth and (t-1)th iterations respectively; $f_t(x_i^k)$ is the tth tree to be added; and $\Omega(f_t)$ is the regularization term to avoid over-fitting.

This study develops three CatBoost-based models for predicting ToT: CatToT$_{dc}$, incorporating 13 driver characteristics as inputs, CatToT$_{sc}$, utilizing drivers' pSC as the only input, and CatToT$_{dc+sc}$, incorporating both driver characteristics and pSC. Similarly, we construct another three CatBoost-based models for predicting drivers' pSC: CatSC$_{dc}$, which leverages 13 driver characteristics as inputs, CatSC$_{dn}$, which incorporates only $density$ and $ndrt$ as inputs, and CatSC$_{dc+dn}$, which integrates 13 driver characteristics, $density$, and $ndrt$. To achieve stable model performance, this study runs the 10-fold cross-validation 100 times during training.

3.3.2. Model evaluation

The performance of the CatBoost-based models is studied using multiple metrics to provide a comprehensive assessment of their predictive capabilities. Following previous research (Antypas et al., 2024; Ayoub et al., 2022; Yang et al., 2021), four metrics are selected: Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Coefficient of Determination (R^2), and Pearson Correlation Coefficient (r). By using a combination of these metrics, this study assesses the models' predictive capabilities across different aspects of their performance. A better prediction performance is indicated by lower RMSE, lower MAE, higher R^2, and higher absolute value of r.

3.3.3. Model explanation

Explainability is crucial for enhancing users' trust and acceptance of a machine-learning-based prediction model (Ayoub et al., 2022). Therefore, two tools are employed to interpret the model prediction processes: feature importance from the CatBoost model (Hastie et al., 2009) and SHapley Additive exPlanation (SHAP) values from game theory (Lundberg and Lee, 2017).

On one hand, feature importance provides a high-level overview of the relative contributions of input features in changing the model's output. A larger importance value indicates a greater potential for changing the prediction output when that feature is altered. The feature importance values sum to 100, enabling direct comparison of the relative contribution of each feature on the model's predictions. Specifically, for a given feature x^k, its importance is calculated as the sum of the gains (i.e., the reduction of loss) of all splits across the entire dataset (Hastie et al., 2009):

$$Feature\_Importance_{x^k} = \sum_{trees,leafs_{x^k}}\left(v_1 - \frac{v_1 \cdot c_1 + v_2 \cdot c_2}{c_1 + c_2}\right)^2 \cdot c_1 + \left(v_2 - \frac{v_1 \cdot c_1 + v_2 \cdot c_2}{c_1 + c_2}\right)^2 \cdot c_2 \tag{3}$$

where c_1 and c_2 denote the total weight of objects in the left and right leaves respectively; v_1 and v_2 represent the formula value in the left and right leaves respectively.

On the other hand, SHAP values dive deeper by capturing both the direction and magnitude of each feature's impact on predictions, which offer a more detailed explanation of model behaviors. SHAP values assign an importance value to each feature, indicating its contribution to the prediction. Positive SHAP values denote features that increase the prediction, whereas negative values denote features that decrease the prediction. For a given feature x^k, its SHAP values are calculated as (Shapley et al., 1953):

$$SHAP\_Values_{x^k} = \sum_{S\subseteq X\backslash\{x^k\}} \frac{|S|!\,(m-|S|-1)!}{m!}\left[f\left(S\cup\{x^k\}\right) - f(S)\right] \tag{4}$$

where m is the total number of input features; X denotes the set of all input features; $X\backslash\{x^k\}$ refers to removing feature x^k from the set X; S is the set of non-zero feature indices, with the summation covering all subsets of X that do not include feature x^k; and $f\left(S\cup\{x^k\}\right) - f(S)$ signifies the contribution margin of feature x^k.

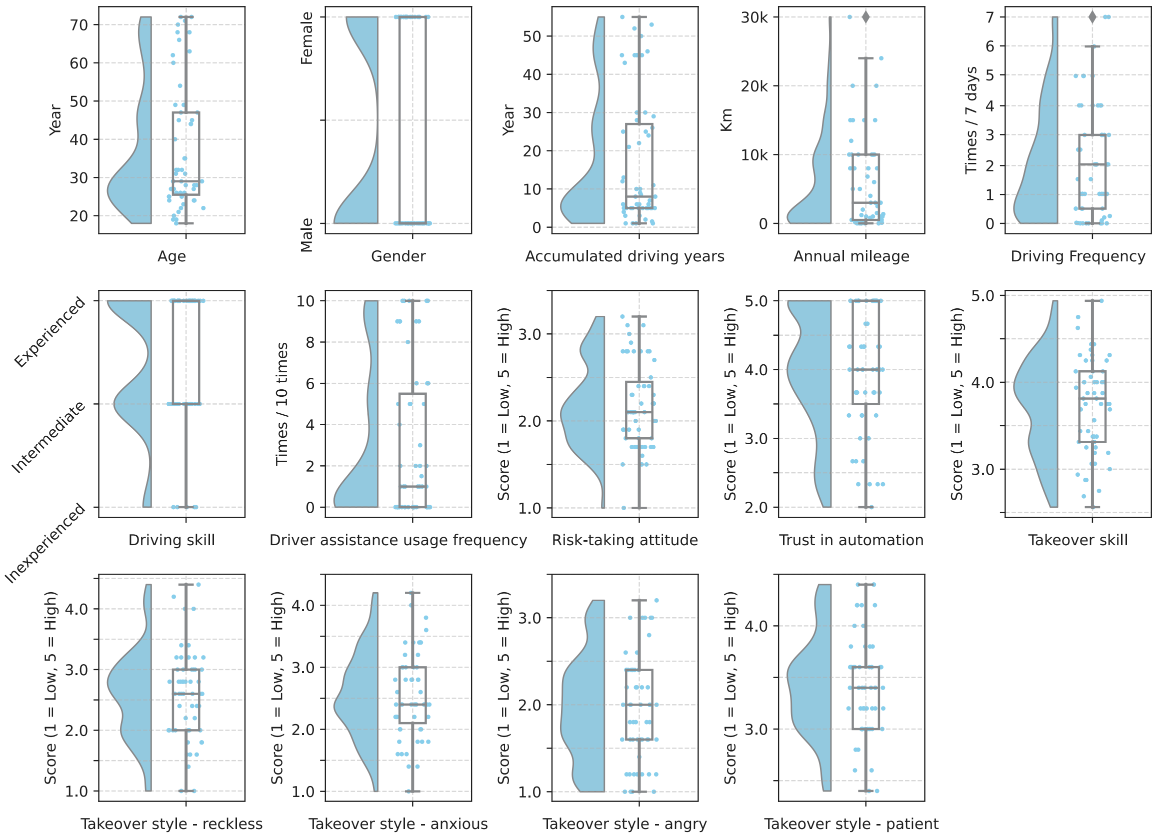

Fig. 5. The distribution of driver characteristics among participants.

4. Results

4.1. Participants

A total of 57 drivers participated in this study, including 33 males and 24 females. Their average age is 38.51 years (SD = 17.23). The relatively balanced gender distribution and broad age variability support the representativeness of the sample by capturing a diverse spectrum of life stages and driving backgrounds. The distribution of individual driver characteristics is illustrated in Fig. 5, which further demonstrates diversity across a wide range of relevant attributes. While only a small number of participants self-identified their driving skill as "inexperienced" in the subjective questionnaire, the sample reflects broader diversity in objective indicators such as driving frequency, years of driving experience, and accumulated driving distance. This discrepancy highlights the distinction between perceived and actual driving experience. By including participants with a broad spectrum of characteristics, this study ensures a robust and representative analysis of the factors shaping takeover time (ToT). Additionally, drivers' perceived task demands (pTD) and perceived driver task capabilities (pTC) across nine takeovers are shown in Fig. 6. The wide variability in these cognitive constructs highlights the diversity in drivers' cognitive styles, even when faced with identical takeover scenarios. This emphasizes the significance of considering driver heterogeneity in drivers' ToT and takeover behaviors.

The experiment initially generated a dataset of 513 takeovers. 16 takeovers were excluded, because participants (i) resumed vehicle control before takeover requests, or (ii) neglected to press the button for activating manual inputs. These exclusions are necessary as they can lead to considerable deviations between the measured ToT and the actual ToT. Moreover, 18 takeovers from two participants were removed due to incomplete questionnaire responses. Consequently, the refined dataset, comprising 479 takeovers, is further analyzed.

Table 1
Feature Importance from the CatToT$_{dc+sc}$ model.

Feature	Importance	Feature	Importance
pSC	64.82	age	1.54
$accu\_dis$	11.39	$takeover\_style\_anxious$	1.53
$takeover\_style\_angry$	4.64	$takeover\_skill$	1.16
RTA	3.85	$driving\_skill$	0.94
$driving\_fre$	3.23	$takeover\_style\_reckless$	0.88
$trust$	2.62	$assist\_fre$	0.78
$takeover\_style\_patient$	2.09	$gender$	0.53

4.2. Takeover time prediction

According to Task-Capability Interface (TCI) theory, drivers adjust their driving behaviors based on the dynamic interactions between their perceived task demand (pTD) and perceived driver task capability (pTC) (Fuller, 2011). Liang et al. (2024) found that drivers generally experience longer takeover time (ToT) as their perceived Spare Capacity (pSC, i.e., pTC - pTD) diminishes. On this basis, this study explores the relationship among drivers' ToT, pSC, and multiple driver characteristics.

In this research, we collected 14 characteristics of participants using the questionnaire described in Appendix C. Variance Inflation Factors (VIF) are computed for these characteristics to identify the potential multicollinearity. The analysis reveals a high correlation between age (VIF: 22.67) and $accu_{y}ears$ (VIF: 24.60). Hence, the effect of $accu\_years$ on drivers' ToT is not further examined in this study. The remaining 13 characteristics, along with drivers' pSC, were incorporated into the CatToT$_{dc+sc}$ model for predicting drivers' ToT. The mean importance of each input feature, obtained after 10-fold cross-validation repeated 100 times, is given in Table 1.

The experimental results indicate that pSC stands out as the most influential feature concerning drivers' ToT, whereas the impact of other

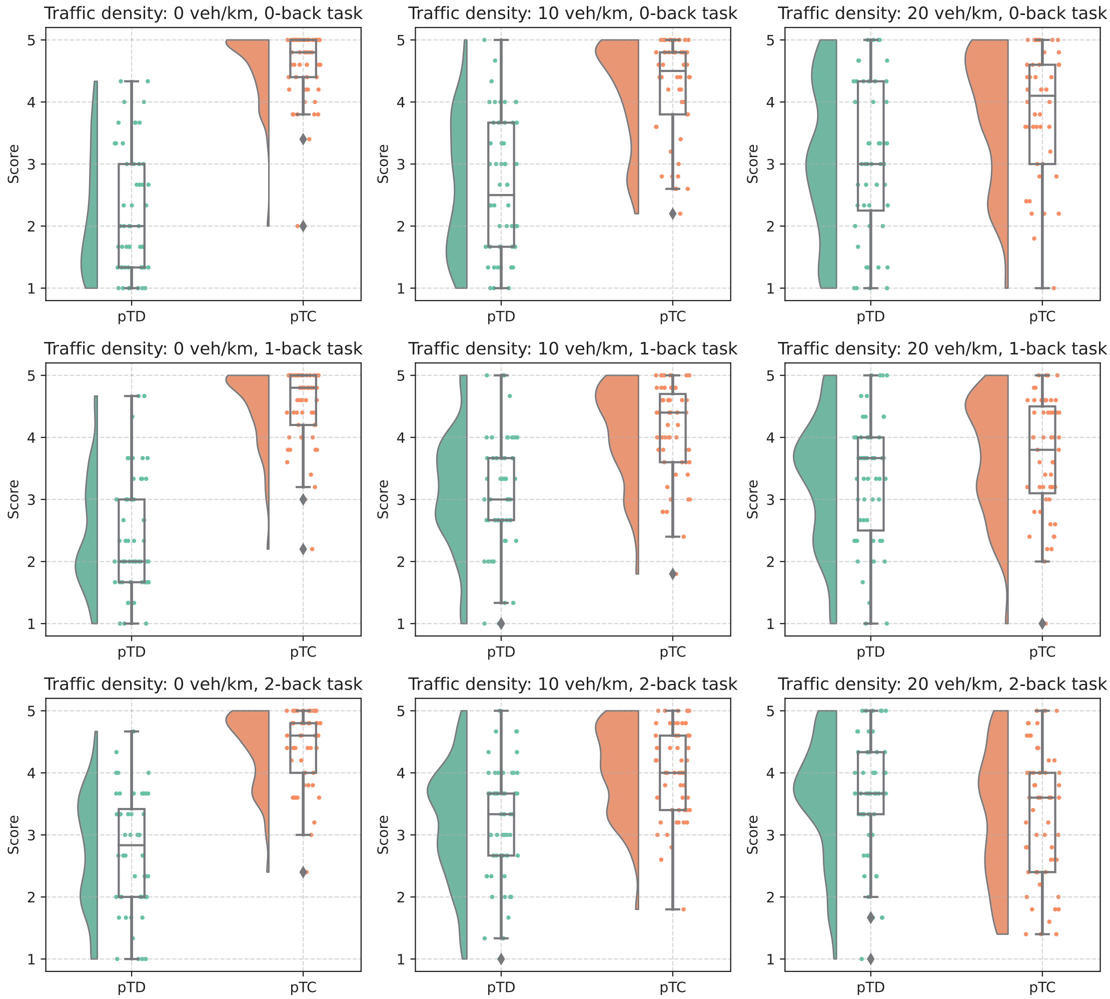

Fig. 6. Drivers' perceived task demand (pTD) and perceived driver task capability (pTC) across nine takeover scenarios (Score: 1 = low, 5 = high).

Table 2
Performance of CatToT$_{dc}$ model, CatToT$_{sc}$ model, and CatToT$_{dc+sc}$ model.

Model	Inputs	RMSE (↓)	MAE (↓)	R^2 (↑)	r (↑)
CatToT$_{dc}$	13 driver characteristics	1.3030	1.0042	0.0116	0.2000
CatToT$_{sc}$	pSC	1.2163	0.9418	0.1315	0.4029
CatToT$_{dc+sc}$	13 driver characteristics + pSC	1.2146	0.9376	0.1371	0.4135

features appears limited. This underscores the potential significant influence of drivers' pSC on the model learning process. Consequently, an ablation study is conducted to delve deeper into the contributions of pSC and driver characteristics to drivers' ToT. To this end, three additional CatBoost-based models are trained: (i) the CatToT$_{dc}$ model, incorporating 13 driver characteristics as inputs; (ii) the CatToT$_{sc}$ model, incorporating only pSC; and (iii) the CatToT$_{dc+sc}$ model, incorporating both 13 driver characteristics and pSC. To assess model performance, four metrics (namely, RMSE, MAE, R^2, and r) are employed, as detailed in Section 3.3.2. Lower values of RMSE and MAE indicate better predictive accuracy, while higher values of R^2 and r reflect stronger explanatory power and correlation, respectively. The stabilized results following 10-fold cross-validation repeated 100 times are presented in Table 2.

These results indicate that the CatToT$_{sc}$ model significantly outperforms the CatToT$_{dc}$ model ($p < 0.01$), reducing RMSE by 6.65% and MAE by 6.21% while increasing R^2 by 1033.62% and r by 101.45%. This demonstrates that pSC is a more effective predictor of ToT than driver characteristics alone. Particularly, the significant increases in R^2 and r highlight that pSC not only captures a greater proportion of the variance in ToT but also aligns more closely with actual takeover behaviors, making it a more reliable and interpretable predictor for ToT predictions. Notably, there is no significant difference between the CatToT$_{sc}$ model and the CatToT$_{dc+sc}$ model ($p > 0.05$). This suggests that the addition of 13 driver characteristics does not meaningfully enhance prediction accuracy when pSC is already included.

The above findings give grounds to further explore the relationship between drivers' pSC and their ToT. As shown in Fig. 7, a statistically significant negative linear correlation is observed between drivers' average takeover time ($\overline{ToT}$) and perceived spare capacity (pSC) ($r = -0.98, p < 0.01$), except for a slight upward fluctuation when drivers' pSC reaches its highest level. This linear relationship can be effectively represented by the equation (R^2=0.96, RMSE = 0.16):

$$\overline{ToT} = -0.33 * pSC + 3.01 \tag{5}$$

This strong linear relationship between $\overline{ToT}$ and pSC indicates that predicting drivers' ToT using pSC without incorporating driver characteristics is feasible and yields reliable predictions. However, previous research has established correlations between drivers' ToT and various characteristics (Chen et al., 2023; Gasne et al., 2022), such

Table 3
Performance of CatSC$_{dc}$ model, CatSC$_{dn}$ model, and CatSC$_{dc+dn}$ model.

Model	Inputs	RMSE (↓)	MAE (↓)	R^2 (↑)	r (↑)
CatSC$_{dc}$	13 driver characteristics	1.5291	1.2280	0.2013	0.4786
CatSC$_{dn}$	$density + ndrt$	1.5481	1.2654	0.1797	0.4525
CatSC$_{dc+dn}$	13 driver characteristics + $density + ndrt$	1.3321	1.0645	0.3924	0.6647

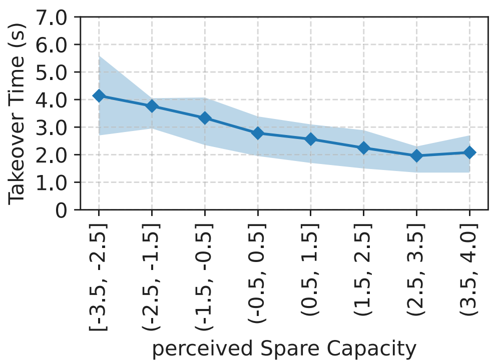

Fig. 7. Drivers' takeover time across perceived spare capacity (confidence bounds: 25th and 75th percentiles).

differences with our finding may stem from the influence mechanism of driver characteristics. It is plausible that these characteristics affect how drivers cognitively process the objective takeover scenarios, consequently shaping their pSC, and ultimately impacting ToT. Therefore, it appears that driver characteristics do not directly influence the relationship between pSC and ToT. To delve deeper into this hypothesis, this study investigated the effects of driver characteristics on drivers' pSC across different takeover scenarios in Section 4.3.

4.3. Effects of driver characteristics

To examine the influence of diverse driver characteristics on drivers' perceived spare capacity (pSC) under varying traffic densities ($density$) and non-driving-related tasks ($ndrt$), an ablation study is conducted. This approach allows us to isolate the impact of different sets of variables on pSC and understand their relative importance. Specifically, three CatBoost-based models are developed for predicting drivers' pSC: (i) the CatSC$_{dc}$ model, incorporating the full set of 13 driver characteristics as inputs; (ii) the CatSC$_{dn}$ model, incorporating only $density$ and $ndrt$; (iii) the CatSC$_{dc+dn}$ model, incorporating 13 driver characteristics, $density$, and $ndrt$. The use of these specific models allows for a comprehensive analysis of how both situational and personal attributes influence pSC. Model performance is evaluated using four metrics: RMSE, MAE, R^2, and r. Lower values of RMSE and MAE indicate better predictive accuracy, while higher values of R^2 and r reflect stronger explanatory power and correlation, respectively. The results from 100 iterations of 10-fold cross-validation are presented in Table 3.

The comparison of model performance demonstrates that among the three models, the CatSC$_{dc+dn}$ model provides the most accurate predictions of drivers' perceived pSC. Specifically, when comparing with the CatSC$_{dc}$ model, incorporating objective situational factors ($density$ and $ndrt$) results in enhanced performance ($p < 0.01$), reflected in lower RMSE (−13%), lower MAE values (−13%), higher R^2 (+95%), and stronger r (+39%). Similarly, compared to the CatSC$_{dn}$ model, integrating 13 driver characteristics yields improved performance ($p <$ 0.01), indicated by lower RMSE (−14%) and MAE values (−16%), higher R^2 (+118%), and stronger r (+47%). This finding emphasizes the impact of both driver characteristics and objective takeover scenarios on drivers' pSC.

From the results in Table 3 we can derive that the CatSC$_{dc}$ model slightly outperforms the CatSC$_{dn}$ model ($p < 0.05$), evident in lower RMSE (−1%) and MAE values (−3%), higher R^2 (+12%), and stronger r (+6%). While objective scenario factors contribute to predictive accuracy, the inclusion of driver characteristics alone can yield more precise predictions of drivers' pSC. This finding reveals the importance of considering individual differences in understanding drivers' cognitive constructs, highlighting the potential for more accurate takeover time prediction models. To dive deeper into the influence of these characteristics on drivers' pSC, the average importance of each input feature derived from the CatSC$_{dc+dn}$ model is shown in Table 4.

Table 4 indicates that the objective situational factor $density$ holds the highest importance in determining drivers' pSC. Following closely are $takeover\_style\_anxious$, $trust$, and the other objective situational factor $ndrt$. Conversely, characteristics such as $gender$, $driving\_skill$, $takeover\_style\_patient$, and $assist\_fre$ exhibit minimal impact on drivers' pSC. It is intuitive that $density$ and $ndrt$ significantly impact drivers' pSC, as these situational factors directly influence the demands placed on drivers during takeover tasks and their capability to effectively resume vehicle control. It is noteworthy that two driver characteristics, namely $takeover\_style\_anxious$ and $trust$, demonstrate greater importance in shaping drivers' pSC compared to $ndrt$. This is a clear indication of the significance of integrating driver characteristics into pSC prediction models, as it suggests that certain driver traits have a more substantial influence on drivers' cognitive processes during takeovers than objective situational factors.

To further interpret the determination processes of drivers' pSC, the SHAP summary plot of the CatSC$_{dc+dn}$ model is illustrated in Fig. 8. Each point in the plot represents a SHAP value corresponding to its respective variable instance. As depicted in Fig. 8, there exists a negative correlation between $density$ and drivers' pSC. This correlation may stem from the fact that higher traffic density often entails more complex driving environments, necessitating drivers to allocate additional effort to execute a safe takeover of vehicle control, consequently diminishing their pSC. Notably, the influence of medium traffic density on pSC appears concentrated around zero, indicating a more consistent impact on drivers' perceptions. However, for the highest and lowest traffic densities, the distributions of their influence exhibit right-tailed and left-tailed patterns respectively. This observation suggests that drivers demonstrate more consistent takeover behaviors and responses in moderately busy traffic conditions. However, in extreme traffic density scenarios, other factors (such as takeover styles) could have a more significant impact on drivers' ToT compared to situations with medium traffic density. Another objective situational factor $ndrt$ also exhibits a negative correlation with drivers' pSC. Specifically, the highest level of $ndrtT$ decreases pSC by approximately 0.2, while the lowest level increases it by the same amount. Unlike the traffic density, the impact of extreme $ndrt$ levels on ToT is more focused, with short tails in the distribution. This suggests that the relatively lower feature importance of $ndrt$ (compared with $takeover\_style\_anxious$ and $trust$) does not stem from drivers employing coping strategies to mitigate the impact of $ndrt$ based on their individual characteristics. Rather, it implies that drivers may exhibit heightened vigilance and preparedness to resume vehicle control promptly, even in distracting environments.

While the impacts of $density$ and $ndrt$ on drivers' pSC exhibit nearly symmetric distributions, those of $takeover\_style\_anxious$ and $trust$ display short-head-long-tail patterns. For example, the impacts of low and medium levels of $takeover\_style\_anxious$ on pSC are concentrated, with minimal differences between the two levels. This results in shorter heads in the distributions of the impact of $takeover\_style\_anxious$, indicating drivers' similar cognitive processing of takeovers. However,

Table 4
Feature importance from the $CatSC_{dc+dn}$ model.

Feature	Importance	Feature	Importance	Feature	Importance
density	37.33	*takeover_style_reckless*	5.37	*accu_dis*	0.96
takeover_style_anxious	18.77	*takeover_style_angry*	2.89	*gender*	0.31
trust	14.81	*age*	2.87	*driving_skill*	0.22
ndrt	6.63	*driving_fre*	2.54	*assist_fre*	0.22
takeover_skill	5.88	*RTA*	0.99	*takeover_style_patient*	0.20

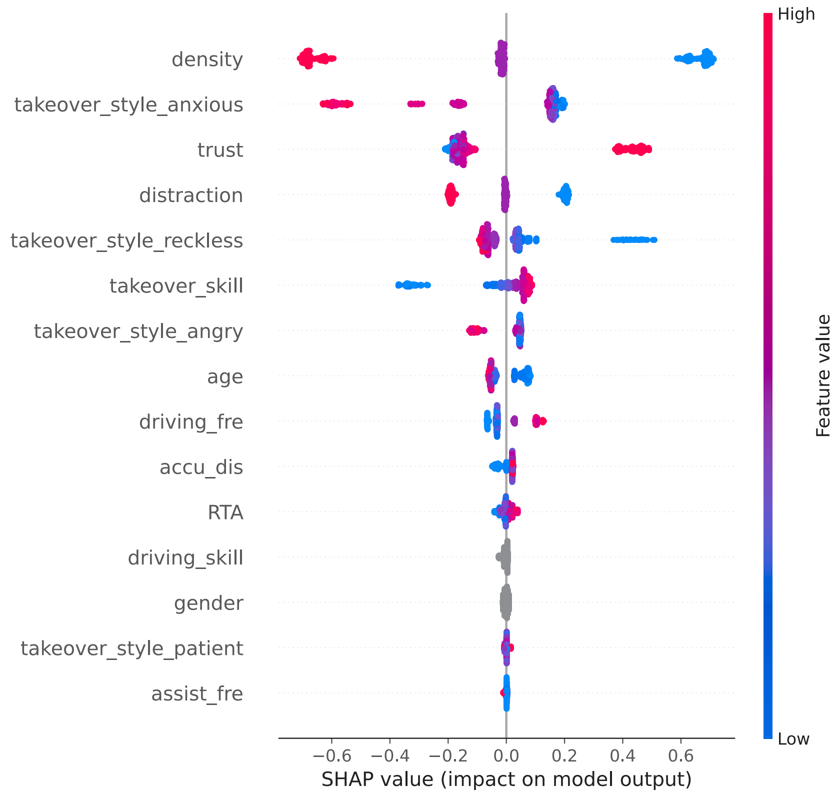

Fig. 8. Feature contributions in the $CatSC_{dc+dn}$ model.

the high value of *takeover_style_anxious* exhibits a spreading impact on drivers' pSC, leading to long tails. This phenomenon may be due to anxious drivers experiencing heightened stress, leading them to potentially overestimate task demands and/or underestimate their capability to different extents, resulting in lower and more varied pSC. Conversely, heightened levels of *trust* may promote a more relaxed attitude toward takeover scenarios. This relaxed attitude could lead drivers to underestimate task demands and/or overestimate their capability to different extents, resulting in larger and more varied pSC.

5. Discussion

To develop a reliable and interpretable prediction model for drivers' actual takeover time (ToT), this research focuses on predictive feature selection. For this purpose, we analyze the effects of drivers' perceived Spare Capacity (pSC) and 13 driver characteristics. In this section, we further discuss the input features in ToT predictions (Section 5.1), the effects of driver characteristics (Section 5.2), and the limitations of the study (Section 5.3).

5.1. Features in takeover time predictions

Previous studies have made important progress in developing ToT prediction models by incorporating a broad range of takeover-related factors. Building on that foundation, this study emphasizes the importance of feature selection, particularly the role of cognitive constructs. Specifically, we concentrate on drivers' perceived spare capacity (pSC, pTC - pTD), an important cognitive construct that potentially affects drivers' takeover decisions according to TCI theory. Three CatBoost-based ToT prediction models are constructed with different inputs: $CatToT_{dc}$, $CatToT_{sc}$, and $CatToT_{dc+sc}$. We find that predicting drivers' ToT solely through pSC, without considering driver characteristics, proves feasible and yields reliable predictions. This suggests that monitoring cognitive states such as pSC may be more effective for predicting ToT than collecting extensive driver-specific data. This offers a more efficient and generalizable modeling approach across diverse driver populations and takeover contexts. Building on this, we develop three additional CatBoost-based spare capacity prediction models: $CatSC_{dc}$, $CatSC_{dn}$, and $CatSC_{dc+dn}$. Our findings indicate that, apart from objective takeover situations (e.g., traffic density), multiple driver characteristics significantly influence drivers' pSC. It underscores that drivers' cognitive constructs stem from both the influence of objective takeover situations and diverse driver characteristics, making them comprehensive and reliable predictors of ToT.

We infer that the mechanism underlying drivers' ToT is as follows: drivers perceive and interpret objective takeover situations (e.g., traffic density, non-driving related task) differently depending on their individual characteristics (e.g., driving skill, risk-taking attitude). These variations lead to diverse driver cognition, typically indicated by psychophysiological signals (e.g., eye movements, heart rate) and self-reported perceptions (e.g., perceived spare capacity). These cognitive states shape observable driver behavior (e.g., speed adjustments, lane

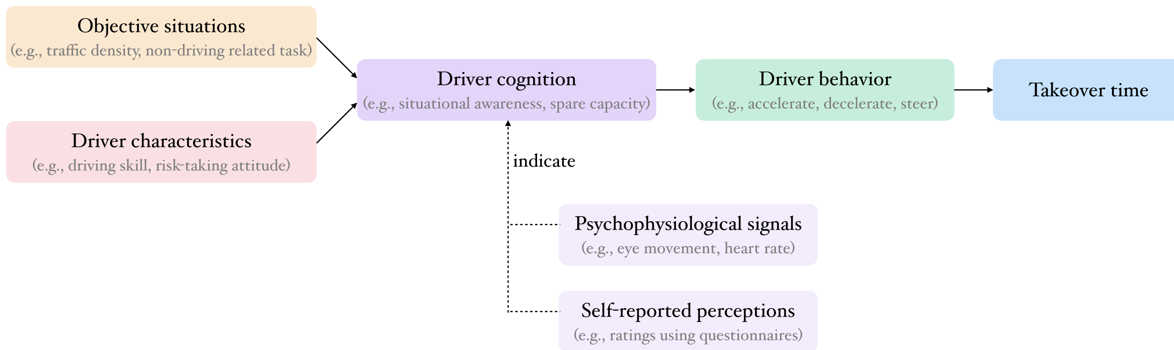

Fig. 9. Conceptual framework of how driver characteristics and cognition influence takeover time.

changes), which ultimately contributes to variations in drivers' ToT. Based on this hypothesis, we present the structure of factors influencing ToT in Fig. 9.

This overview of input features offers valuable insights into feature selection for ToT prediction models. It can also aid in selecting psychophysiological, perceptive, and behavioral data for predicting ToT, as these data should align closely with specific takeover-related cognition, such as perceived spare capacity in this study. By substituting drivers' cognition with psychophysiological, perceptive, and/or behavioral data, the practical validity of the proposed ToT prediction model can be enhanced while maintaining model interpretability. However, further investigation is needed in this regard.

Note that while adding 13 driver characteristics did not significantly improve ToT prediction beyond pSC, these characteristics still hold value. In cases where pSC is difficult to assess or unavailable, static characteristics can provide a baseline for initializing driver models, setting defaults, or serving as fallback inputs. They also offer useful context for interpreting dynamic cognitive data. Rather than being excluded, static driver characteristics and dynamic cognitive indicators can play complementary roles. A hybrid approach may enhance the robustness and personalization of adaptive takeover strategies, particularly in complex or uncertain scenarios.

5.2. Effects of driver characteristics

According to the feature importance (Table 4) and SHAP values (Fig. 8) from the CatSC$_{dd+dc}$ model, we find that in predicting drivers' perceived spare capacity (pSC): (i) $density$, $takeover\_style\_anxious$, and $trust$ are the most relevant features, (ii) $ndrt$, $takeover\_skill$, and $takeover\_style\_reckless$ are moderately relevant features, (iii) $takeover\_style\_angry$, age, $driving\_fre$, RTA, and $accu\_dis$ are less relevant features, and (iv) $gender$, $driving\_skill$, $assist\_fre$, and $takeover\_style\_patient$ have minimal relevance. The above findings can help designers prioritize the most important factors in the development of CADS, highlight the focus of driver training and education, and inform customized interventions to promote safer and more efficient human–vehicle interactions. Additionally, two observations from the study initially seem counterintuitive, but upon closer inspection, they reflect nuanced insights rather than genuine contradictions:

(i) Although the direct relationship between drivers' general $driving\_skill$ ratings and their pSC is not significant, specific skill-related metrics such as $accu\_dic$ and $driving\_fre$ do correlate with pSC. This discrepancy may be attributed to two factors. First, there were few participants who identified themselves as "inexperienced". While the remaining participants were fairly evenly distributed between the "intermediate" and "experienced" groups-suggesting some variation still exists-the limited presence of low-skill self-ratings may have reduced the sensitivity of the general $driving\_skill$ measure. Second, $accu\_dic$ and $driving\_fre$ represent objective, precise indicators of driving ability. This suggests that the observed discrepancy may not be inherently contradictory but rather underscores the potential inaccuracy of self-assessed general driving skills. It highlights the importance of incorporating objective metrics when evaluating driver skills, aligning with suggestions from prior research (Sundström, 2008; Kosuge et al., 2021). (ii) Similarly, while the direct relationship between drivers' RTA and their pSC lacks statistical significance, specific characteristics associated with RTA—such as $takeover\_style\_anxious$ and $trust$—show strong correlations with pSC. This apparent discrepancy may result from the context-dependent measurement of RTA within automated driving scenarios, where drivers may adjust their usual risk preferences when interacting with CADS. Rather than being contradictory, this finding underscores the phenomenon of behavioral adaptation, where drivers modify their behavior to suit CADS. Such adaptations have been well-documented in existing studies (Varotto et al., 2020; Soni et al., 2022), emphasizing the importance of understanding how automation influences driver behavior to design effective human-automation interactions that promote both safety and user comfort.

In summary, driver characteristics influence the development of drivers' cognition (such as spare capacity) to varying extents during the transition of control. When measuring these characteristics, it is essential to use specific questions adjusted appropriately for takeover contexts to ensure the validity and reliability of research findings.

5.3. Limitations

This study is subject to the following limitations: (i) although the final sample size of 57 participants is comparable to those used in similar studies (Liu et al., 2025, 2024; Yoon et al., 2021), we acknowledge that a larger sample could further enhance the robustness and generalizability of our findings. A limited sample size may reduce statistical power, particularly in detecting subtle interaction effects or non-linear relationships among multiple influencing factors. Moreover, while the sample includes a range of drivers in terms of years of driving experience, accumulated mileage, and driving frequency, relatively few participants subjectively identified as inexperienced. This discrepancy between objective and perceived experience may influence how self-reported driving competence interacts with perceived spare capacity and takeover time. Future research would benefit from recruiting larger and more diverse participant pools, and from further examining how discrepancies between perceived and actual driving ability shape takeover behavior and cognitive self-assessments. (ii) the experiment was conducted in a simulated environment rather than in real-world driving conditions. While simulators provide controlled environments for experimentation, driver behavior may differ in real-world settings, limiting the generalizability of our findings. Given that this study serves as a foundational step toward optimizing feature selection in takeover time prediction models, future research should evaluate the model's effectiveness under more varied and dynamic conditions. Specifically, our scenarios were structured and non-time-critical, whereas urgent takeovers—such as reacting to sudden hazards or system failures—may involve different cognitive and behavioral dynamics, potentially altering the relationship between perceived spare capacity and actual takeover time. As a result, the current findings may be more applicable to routine or moderately urgent transitions. Future work should test the model in more diverse scenarios, especially those involving real traffic and time-critical demands, to evaluate its robustness and adaptability. (iii) repeated exposure to similar takeover scenarios may lead to faster or more confident responses, potentially inflating performance measures and altering perceived spare capacity. This trial order effect could confound results and limit generalizability to real-world conditions, where takeovers are less predictable and not repeated systematically. To mitigate learning effects in this study, participants completed a 10 min practice drive (Radhakrishnan et al., 2023), and the nine takeover scenarios were arranged using a Latin Square design to balance order effects across participants (Calvert et al., 2014). Additionally, takeover requests were randomized between 30 and 60 s after automated driving began to reduce predictability within trials (Eriksson and Stanton, 2017). Despite these design features, some residual learning or anticipation effects may still remain and should be considered in future research and experimental designs, particularly in studies involving repeated within-subject measurements. (iv) this study used self-report questionnaires to assess driver cognition, aligning with our aim to capture subjective comfort and cognitive experience during takeovers. We adopted well-established instruments (such as NASA-Task Load Index, Driving Activity Load Index, and Driver Skill Inventory) and carefully adapted them to suit the context of takeover scenarios. While these instruments are widely used and validated in driving research, the reliance on self-report still introduces limitations related to response subjectivity and the lack of continuous data, potentially affecting the reliability of real-time predictions. Future studies could benefit from exploring the integration of psychophysiological data (such as eye movements, heart rates, and EEG), which can serve as real-time, non-intrusive proxies for cognitive load and capacity. Such data has the potential to enhance the practical validity of the proposed takeover time prediction model while maintaining model interpretability, provided that the correlation between these psychophysiological data and drivers' cognitive constructs is validated. In our future work, we will further explore this relationship to improve model robustness and applicability. Addressing these limitations could further enhance the validity and applicability of the findings to additional driving contexts.

6. Conclusions

This study contributes to improving the reliability and interpretability of takeover time (ToT) prediction models by optimizing predictor selection, enabling the exclusion of redundant predictors—such as extensive driver characteristics—without compromising accuracy. We examine the complex relationship between drivers' ToT, cognitive constructs, and diverse driver characteristics within a driving simulator experiment encompassing nine takeover scenarios. Using CatBoost-based prediction models and a linear regression model, our findings demonstrate that perceived spare capacity (i.e., perceived driver task capability minus perceived task demand) alone serves as a strong predictor of drivers' actual ToT. Notably, incorporating 13 additional driver characteristics does not significantly improve prediction accuracy when perceived spare capacity is already considered. Furthermore, our results reveal that driver characteristics influence ToT indirectly by shaping how drivers cognitively process objective takeover situations. These findings deepen our understanding of drivers' cognitive mechanisms during takeovers and highlight the importance of prioritizing cognition-based predictors over extensive driver characteristics when designing ToT prediction models. We argue that real-time cognitive monitoring, rather than static driver characteristics, may be more effective in predicting ToT and designing adaptive automation strategies. Implementing systems that assess perceived spare capacity dynamically could enable personalized takeover interventions, ensuring drivers receive appropriate support based on their actual cognitive state.

By refining the selection of predictive features, this study provides a framework for more interpretable and reliable ToT predictions, which can support the development of adaptive takeover assistance systems. Future studies should explore the integration of psycho-physiological and behavioral data—such as eye-tracking or heart rate variability—as additional indicators of cognitive states related to ToT. Besides, the generalizability of these models should be tested across different driving conditions to validate their applicability.

CRediT authorship contribution statement

Kexin Liang: Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Simeon C. Calvert:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Sina Nordhoff:** Writing – review & editing, Methodology, Conceptualization. **Ming Li:** Writing – review & editing, Methodology, Conceptualization. **J.W.C. van Lint:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT in order to improve language and readability. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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.

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Appendix A. Latin square orderings

To minimize potential order effects, the nine takeover scenarios were arranged using a Latin Square design. Table 5 lists the 18 counterbalanced order groups used in the study, ensuring that each scenario appears in every ordinal position and maintains full pairwise balance across participants.

Appendix B. Spare capacity survey

This study assesses drivers' perceived spare capacity (pSC) using a survey composed of items measuring perceived takeover task demand (pTD) and perceived task capability (pTC). These questions were presented randomly to reduce order effects. Participants were asked to indicate their agreement with the scale statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree).

B.0.1. Perceived task demand for takeovers

Drivers' pTD for takeovers is deconstructed into their perceived mental demand ($\mathrm{pTD}_{\mathrm{mental}}$), visual demand ($\mathrm{pTD}_{\mathrm{visual}}$), and temporal demand ($\mathrm{pTD}_{\mathrm{temporal}}$) for takeover contexts. Accordingly, three scales for measuring drivers' pTD are developed based on NASA Task Load Index (NASA-TLX) (Hart and Staveland, 1988) and Driving Activity Load Index (DALI) (Pauzié, 2008), as listed in Table 6.

Table 5
Latin square order groups for the nine takeover scenarios.

Group/Order	1	2	3	4	5	6	7	8	9
1	A	B	I	C	H	D	G	E	F
2	G	F	H	E	I	D	A	C	B
3	C	D	B	E	A	F	I	G	H
4	I	H	A	G	B	F	C	E	D
5	E	F	D	G	C	H	B	I	A
6	B	A	C	I	D	H	E	G	F
7	G	H	F	I	E	A	D	B	C
8	D	C	E	B	F	A	G	I	H
9	I	A	H	B	G	C	F	D	E
10	F	E	G	D	H	C	I	B	A
11	B	C	A	D	I	E	H	F	G
12	H	G	I	F	A	E	B	D	C
13	D	E	C	F	B	G	A	H	I
14	A	I	B	H	C	G	D	F	E
15	F	G	E	H	D	I	C	A	B
16	C	B	D	A	E	I	F	H	G
17	H	I	G	A	F	B	E	C	D
18	E	D	F	C	G	B	H	A	I

Note: Letters A–I represent the nine experimental conditions:
A = (0 veh/km, 0-back), B = (0 veh/km, 1-back), C = (0 veh/km, 2-back),
D = (10 veh/km, 0-back), E = (10 veh/km, 1-back), F = (10 veh/km, 2-back),
G = (20 veh/km, 0-back), H = (20 veh/km, 1-back), I = (20 veh/km, 2-back).

Table 6
Scales measuring perceived task demand for takeovers.

Latent variable	No.	Observed variable	Reference
Mental demand	pTD_{mental}	Taking over car control in this situation was mentally demanding.	Hart and Staveland (1988), Pauzié (2008)
Visual demand	pTD_{visual}	Taking over car control in this situation was visually demanding.	
Temporal demand	$pTD_{temporal}$	The time left for me to take over car control was short.	

Table 7
Scales measuring perceived driver capability for takeovers.

Latent variable	No.	Observed variable		Reference
Anticipation capability	$pDC_{anticipation}$	When I started to take over car control, I believed ...	I anticipated what would happen next in this situation.	Zhang et al. (2019), Rosenbloom et al. (2010), Lajunen and Summala (1995)
Reaction capability	$pDC_{reaction}$		I responded to the takeover request promptly.	
Speed adjustment capability	pDC_{speed_adjust}		I could adjust speed effectively in this situation.	
Lane change capability	pDC_{lane_change}		I could change lanes fluently in this situation.	
Safety capability	pDC_{safety}		I could maintain sufficient distance from the cars around me in this situation.	

B.0.2. Perceived driver capability for takeovers

This study extends the scales in Rosenbloom et al. (2010) and deconstructs drivers' pDC for takeovers into five distinct dimensions based on the Driver Skill Inventory (DSI) (Lajunen and Summala, 1995; Martinussen et al., 2014). As shown in Table 7, drivers' pDC is measured from their perceived anticipation capability ($pDC_{anticipation}$), reaction capability ($pDC_{reaction}$), speed adjustment capability (pDC_{speed_adjust}), lane change capability (pDC_{lane_change}), and safety capability (pDC_{safety}). This is because the takeover manoeuvres in this study encompass anticipating the takeover situation, resuming motor readiness in response to takeover requests, adjusting driving speed to suit the takeover situation, changing lanes to bypass the detected collision ahead, and keeping sufficient distances from surrounding vehicles (Zhang et al., 2019). The developed scales are employed to measure drivers' pDC when they have made decisions for takeover manoeuvres, i.e., when they start to take over vehicle control.

Appendix C. Driver characteristic questionnaire

This study employs the following questionnaire to assess driver characteristics, drawing from established instruments. The questionnaire collects drivers' background information (Table 8), risk-taking attitudes (Table 9), trust in the conditionally automated driving systems (Table 10), takeover skills (Table 11), and takeover styles (Table 12).

Background information

This study employs seven questions to capture drivers' backgrounds as outlined in Table 8. The first two questions collect drivers' demographic information, including age and $gender$. The rest five questions measure general driving-related characteristics, namely accumulated driving years ($accu\_years$), accumulated driving distance ($accu\_dis$), driving frequency ($driving\_fre$), driving skill ($driving\_skill$), and driver assistance usage frequency ($assist\_fre$).

C.1. Risk-taking attitude

A driver' high risk-taking attitude has previously been observed to strongly correlate with risky driving behaviors (Iversen, 2004). Such risk-prone tendencies may become evident in takeover situations, potentially leading to risky takeover behaviors and shorter ToT than those necessary for safe ToC. This study measures drivers' risk-taking attitudes in driving situations using the scale in Table 9. This scale is derived from (Ma et al., 2010), Taubman-Ben-Ari et al. (2004), and Lajunen and Summala (1995). Participants were instructed to indicate their agreement with the following statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). The general risk-taking attitude (RTA) is calculated as:

$$RTA = \frac{\sum_{i=1}^{5}(6 - RTA_i) + \sum_{i=6}^{10} RTA_i}{N} \tag{6}$$

where RTA_1 to RTA_5 represent answers that are negatively related to drivers' RTA, RTA_6 to RTA_{10} represent answers that are positively

Table 8
Background questions, based on Nordhoff et al. (2023) and Lu et al. (2017).

Latent variables	Observed variables
age	What is your age?
gender	What is your gender? [Male; Female; Others]
accu_years	How many years of driving experience do you have?
accu_dis	How many kilometres (approximately) have you driven in the past 12 months?
driving_fre	How many days (on average) have you driven per week in the past 12 months?
driving_skill	How is your general driving skill? Please select the option that best matches your situation. [Inexperienced; Intermediate; Experienced]
assist_fre	How often (out of 10 times) do you use driver assistance functions while driving in the past 12 months?

Table 9
Scale measuring drivers' risk-taking attitude (RTA), based on Ma et al. (2010), Taubman-Ben-Ari et al. (2004), and Lajunen and Summala (1995).

Latent variables	Abbr.	Observed variables
RTA	RTA_1	I follow the traffic rules most of the time [−].
	RTA_2	I drive cautiously most of the time [−].
	RTA_3	I am not willing to compete with other drivers in traffic [−].
	RTA_4	I try to keep sufficient distances to the cars in front most of the time [−].
	RTA_5	I am willing to give up my right of way to other drivers to ensure safety [−].
	RTA_6	I enjoy the feeling of pushing a car to its maximum capability limits.
	RTA_7	It makes sense to exceed speed limits to get ahead of drivers who drive erratically, slowly, or extremely cautiously.
	RTA_8	Engaging in risky driving behaviours does not necessarily mean someone is a bad driver.
	RTA_9	It's acceptable to break some traffic rules if they are restrictive.
	RTA_{10}	It's acceptable to drive at the moment when traffic lights change from yellow to red.

[−] indicates reversed questions.

Table 10
Scale measuring drivers' trust in conditionally automated driving, based on Nordhoff et al. (2021).

Latent variables	Abbr.	Observed variables
trust	T_1	I trust the automated car to maintain sufficient distances from the cars around me.
	T_2	I trust the automated car to effectively detect the collisions ahead that it can not handle.
	T_3	I trust the automated car to alert me to take over car control in time.

related to drivers' RTA, and N represents the total number of the questions.

C.2. Trust in conditionally automated driving

Drivers' trust in CADS influences their readiness to resume vehicle control when required (Ayoub et al., 2021), which can, in turn, affect their ToT. To evaluate trust in the context of takeover situations, we selected and adapted three items (Cronbach's alpha = 0.75) from the broader trust scale developed by Nordhoff et al. (2021), which was originally designed to capture drivers' trust in partially automated vehicles. The employed three items specifically assessed trust in the system's ability to: (i) maintain safe following distances, (ii) detect hazards it cannot manage, and (iii) issue timely takeover alerts—core functions critical to safe control transitions. Items from the original scale that were unrelated to our setup, such as manual activation, mode awareness, or general engagement, were excluded, as all takeovers were system-initiated, mode status was clearly displayed, and participants were engaged in cognitively demanding n-back tasks. This focused selection helped reduce participant burden while maintaining contextual relevance. Table 10 lists the measurements of drivers' trust in three CADS functions. Participants were instructed to indicate their agreement with the following statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). Drivers' general trust in CADS (*trust*) is computed as the average of T_1, T_2, and T_3.

C.3. Takeover skill

Drivers' takeover skill in various aspects reflects their abilities to assume vehicle control effectively, which can be improved through practice and training. This study develops an inventory to assess drivers' takeover skill (*takeover_skill*) based on the Driver Skill Inventory (DSI) (Lajunen and Summala, 1995). Aligned with the DSI, this takeover skill inventory assesses drivers' perceptual-motor skills (PMS) and safety skills (SS) (Martinussen et al., 2014), with a specific focus on takeover contexts. Details of the takeover skill inventory are presented in Table 11. Participants were instructed to indicate their agreement with the statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). Drivers' *takeover_skill* is computed as the average of all variables, including PMS_1 to PMS_8 and SS_1 to SS_8.

C.4. Takeover style

To evaluate drivers' takeover styles, this study adapts the Multidimensional Driving Style Inventory (MDSI) (Taubman-Ben-Ari et al., 2004) for takeover contexts. A takeover style inventory is formulated based on the four-factor structure of the MDSI, categorizing drivers' characteristic takeover behaviors into: (i) reckless and careless (*takeover_style_reckless*); (ii) anxious (*takeover_style_anxious*); (iii) angry and hostile (*takeover_style_angry*); and (iv) patient and careful (*takeover_style_patient*). The specifics of the takeover style inventory are presented in Table 12. Participants were instructed to indicate their agreement with the statements on a five-point scale (1 = Strongly Disagree, 5 = Strongly Agree). For *takeover_style_reckless*, *takeover_style_anxious*, and *takeover_style_angry*, each is computed as the average of five observed variables in the same subcategory. For *takeover_style_patient*, it is calculated as the average of $\sum_{i=1}^{4} PC_i + (6 - PC_5)$, as PC_5 is measured via a reversed question.

Table 11
Takeover skill inventory, modified from Driver Skill Inventory (Lajunen and Summala, 1995).

Latent variables	Abbr.	Observed variables
Perceptual-Motor Skills (*PMS*)	PMS_1	Taking over car control from automation fluently was easy for me.
	PMS_2	Adjusting driving speed was easy for me.
	PMS_3	Controlling the car was easy for me.
	PMS_4	Bypassing the detected collisions ahead was easy for me.
	PMS_5	I realized that I needed to take over car control from automation before the takeover requests.
	PMS_6	I reacted to takeover requests fast.
	PMS_7	I knew the right actions to take in response to the takeover requests.
	PMS_8	I made firm decisions to take over car control from automation.
Safety Skills (*SS*)	SS_1	I followed the traffic rules while taking over car control from automation.
	SS_2	I was cautious while taking over car control from automation.
	SS_3	I paid attention to the cars around me in automated mode.
	SS_4	I paid attention to the cars around me while taking over car control.
	SS_5	Keeping sufficient distances from the cars ahead was easy for me.
	SS_6	Merging into the adjacent lane was easy for me.
	SS_7	Braking effectively (i.e., not too hard nor too soft) was easy for me.
	SS_8	I did not cause risks to myself and the cars around me.

Table 12
Takeover style inventory, modified from the Multidimensional Driving Style Inventory (Taubman-Ben-Ari et al., 2004).

Latent variables	Abbr.	Observed variables
takeover_style_reckless	RC_1	I misjudged the speed of the cars passing me when I was taking over car control.
	RC_2	I forgot to switch on the turn indicator before changing lanes.
	RC_3	I nearly crashed due to misjudging my distances from other cars.
	RC_4	I engaged in mind wandering from time to time when I was driving the car manually.
	RC_5	I tried to move into the left lane as soon as possible.
takeover_style_anxious	A_1	I felt nervous when I was taking over car control.
	A_2	Taking over car control frustrated me.
	A_3	It worried me when taking over car control after engaged in the n-back task.
	A_4	I drove at or below the speed limit when I was taking over car control.
	A_5	I used muscle relaxation techniques (such as taking deep breaths).
takeover_style_angry	AH_1	I swore at the automation when it asked me to take over car control.
	AH_2	I wanted to blow my horn or "flash" the car in front as a way of expressing frustrations.
	AH_3	I enjoyed the excitement of taking risks when I was taking over car control.
	AH_4	I took chances to merge into the adjacent lane.
	AH_5	I removed at least one hand from the steering wheel when I was driving the car manually.
takeover_style_patient	PC_1	I waited for a proper gap to change lanes.
	PC_2	I based my takeover behaviours on the motto "better safe than sorry".
	PC_3	I took over car control from automation cautiously.
	PC_4	I shifted my focus from the game to taking over car control before the takeover requests.
	PC_5	I had to slam on the brake to avoid collisions [−].

[−] indicates reversed items.

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