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Uncertainty in Human–Machine Shared Driving and Takeover Decision-Making

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Abstract. In human–machine shared driving, takeover decision-making is affected by multi-source uncertainty from the environment, driver, and system. Existing studies lack integration of uncertainty modeling, evaluation, and the takeover process. This paper presents a focused review of recent literature from four aspects: uncertainty types, modeling methods, takeover decision-making process, and evaluation frameworks. It summarizes four sources of uncertainty: environment and perception, driver state, system and interaction, and situation. Modeling methods are grouped into probabilistic and Bayesian modeling, learning-based uncertainty quantification, cognitive modeling, and decision-theoretic methods. Research progress on pre-takeover risk prediction, takeover request timing, authority allocation, and trust calibration is reviewed. Current limitations include inconsistent evaluation metrics, poor cross-scenario generalization, and constraints on real-time deployment and explainability. Future work should strengthen multi-source fusion and online updating, human-adaptive takeover support, and standardized evaluation to improve the safety and timeliness of takeover decisions.

Keywords: human–machine shared driving, takeover decision-making, uncertainty modeling, automated driving, takeover safety and timeliness

1. Introduction

As automated driving moves from controlled environments to real-world deployment, human–machine shared driving has become an important transitional form of vehicle control [1, 2]. With increasing levels of automation, the driver's role gradually shifts from active control to system supervision [2, 3]. However, when the automated driving system reaches its operational limits, control may need to be transferred back to the driver, making takeover a critical safety issue [1, 2].

Takeover risks arise from multiple sources. Adverse environments may impair perception, while prolonged supervision, fatigue, and distraction can reduce driver readiness [1, 4, 5]. System limitations and inappropriate takeover timing may further compromise the safety of control transitions [1, 4]. These factors make takeover particularly challenging because environmental conditions, driver states, and system capabilities are inherently uncertain.

Effective takeover decision-making should therefore seek to resolve three key questions: when to initiate a takeover, whether the driver is ready, and how to ensure a safe transfer of control. Existing

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research reveals limitations in real-time decision-making, personalized adaptation, and the integration of trust into takeover systems [1]. Moreover, passive takeover rules may overestimate the driver's ability to rapidly resume control in emergencies [6]. These limitations highlight the need to incorporate uncertainty more systematically into takeover decision-making.

Accordingly, this paper examines the role of uncertainty in takeover decision-making, with particular attention to its sources, modeling methods, and evaluation metrics. It further discusses current limitations and future directions for uncertainty-aware takeover systems.

2. Uncertainty in automated driving takeover: sources, modeling, and evaluation

2.1. Sources of uncertainty in takeover scenarios

Uncertainty in takeover scenarios arises from multiple interacting sources, including the environment, driver, automated system, and driving situation. At the environmental and perception levels, adverse conditions such as rain, snow, glare, and tunnel transitions can degrade sensor performance and perception reliability. Out-of-distribution (OOD) objects or scenarios may further increase the risk of perception errors and subsequently affect system decisions [7, 8]. Indicators such as time-to-collision (TTC) can therefore provide useful information for assessing takeover urgency and risk [9].

Driver-related uncertainty primarily arises from variations in cognitive and physiological states. Takeover requires drivers to redirect attention, reconstruct situation awareness, and regain vehicle control, all of which can be affected by cognitive load, fatigue, and non-driving-related tasks [1, 5]. Compared with environmental uncertainty, these internal states areharder to observe directly and may fluctuate substantially over time.

System- and interaction-related uncertainty stems from both algorithmic limitations and human–machine interaction design. Perception and decision algorithms may perform less reliably in complex or previously unseen scenarios [7]. Meanwhile, the timing and modality of takeover requests influence how quickly and effectively drivers resume control [9, 10]. Appropriate warning strategies can improve drivers' preparedness and reduce takeover risk.

Situational uncertainty concerns factors such as takeover urgency, available time budget, and traffic complexity [9, 10]. Rather than acting independently, these factors often interact with environmental, driver, and system uncertainties. For example, dense or complex traffic may increase cognitive workload and reduce takeover quality, whereas preparatory warnings may facilitate situation understanding and improve takeover readiness [9].

2.2. Modeling and quantification of uncertainty

Existing approaches to uncertainty modeling can be broadly classified into probabilistic and Bayesian methods, learning-based uncertainty quantification, cognitive modeling, and decision-theoretic methods [7, 11, 12].

Probabilistic and Bayesian methods provide a general framework for representing uncertainty and dependencies among relevant factors. Bayesian belief networks (BBNs) can model probabilistic relationships among driver, system, and environmental variables, while dynamic Bayesian networks (DBNs) extend this approach to temporal risk inference [11]. Partially observable Markov decision processes (POMDPs) further represent latent driver states and update their estimates through sequential observations, enabling adaptive takeover prediction and decision-making [12].

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Learning-based methods are particularly suitable for high-dimensional driving data. Deep ensembles and MC Dropout estimate predictive uncertainty through repeated predictions, while conformal prediction provides statistically valid prediction intervals [7, 8]. OOD detection can further identify scenarios that differ substantially from the training distribution, allowing the automated system to adopt more conservative strategies when uncertainty is high [7, 8].

Cognitive modeling focuses on uncertainty in the driver's internal state. For example, active inference models represent drivers as agents who continuously update their beliefs and actions based on perceived information. Model parameters have been associated with cognitive fatigue, trust, and situation awareness, providing a formal framework for explaining individual differences in takeover behavior [5].

Decision-theoretic methods integrate uncertainty directly into authority allocation. In this framework, control authority can be dynamically adjusted according to the system's confidence in driver intention, driver state, and environmental conditions. Such approaches provide a computational basis for adaptive human–machine authority allocation under uncertainty.

2.3. Metrics for takeover decision-making

The effectiveness of uncertainty-aware takeover decision-making can be evaluated from three complementary dimensions: uncertainty representation, takeover performance, and human factors [10, 13].

Uncertainty representation concerns whether model outputs accurately reflect actual uncertainty. Common metrics include calibration error, Brier score, negative log-likelihood, prediction interval coverage, and AUROC or AUPRC for OOD detection [7, 8, 14]. Although widely used in machine learning, these metrics have not yet been consistently incorporated into takeover research.

Takeover performance evaluates whether control transitions are safe and timely.Takeover time is one of the most widely used measures and reflects how rapidly drivers respond to and complete a takeover request [2, 10, 15]. Takeover quality is typically assessed using vehicle-control measures, such as lateral and longitudinal acceleration, lane-position variability, and steering behavior [16]. Together, these measures capture both the timeliness and stability of the control transition.

Human-factor measures assess how takeover strategies affect drivers' cognitive and psychological states. Common measures include subjective workload, situation awareness, and trust in automation, typically assessed using standardized scales such as NASA-TLX and established trust measures [17, 18]. These indicators are particularly important because improvements in system safety may be accompanied by increased cognitive workload or inappropriate changes in trust.

However, evaluation metrics remain inconsistent across studies, limiting direct comparisons [1, 10, 14]. Most evidence is also based on short-term simulator experiments, with limited real-world and long-term validation. A standardized, multidimensional evaluation framework is therefore still needed.

3. Uncertainty-driven takeover decision-making

3.1. Pre-takeover: risk prediction and driver readiness

Before takeover, two things must be determined: when risk increases and whether the driver is ready. Both are subject to uncertainty.

For risk prediction, TTC remains the most commonly used metric. One study found that TTCmin correlates with takeover risk at −0.81, indicating its practical value for takeover demand prediction

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[9]. However, TTC reflects only the current collision risk; takeover decision-making also needs to predict how risk will change. Trajectory prediction models can fill this gap by predicting the movement trends of surrounding vehicles, providing richer input for risk prediction [19]. Such models construct dynamic graphs via spatiotemporal indexing and combine LSTM encoders–decoders, achieving stable short- and long-term prediction in highway scenarios, with RMSE as low as 1.95 and accuracy up to 98.12% [19]. However, trajectory prediction itself is uncertain—the longer the prediction horizon, the larger the error. Combining prediction uncertainty with risk prediction is a direction worth attention in the pre-takeover stage.

Driver readiness assessment is another key issue. Takeover comprises three stages: attention reorientation, situation awareness reconstruction, and motor control recovery [1]. Eye movements, hand position, and head orientation can reflect current state. Yao et al.'s structural equation model showed that saccade time within one second has the strongest explanatory power for eye behavior, with a standardized path coefficient of 0.859 [20]. However, these indicators only reflect the current state and cannot directly answer whether the driver can complete takeover within X seconds. The mapping from state to capability is itself an uncertainty problem.

3.2. Takeover request and timing

The timing of takeover requests is the most core decision variable. Too early, the driver may feel disturbed; too late, takeover may fail. Zhang et al.'s meta-analysis found that 70% of studies set the takeover time threshold between 5 and 7 s [15]. However, this range is only a reference; the actual optimal value depends on scenario complexity and driver state.

Takeover time budget significantly affects takeover performance. Longer budgets generally mean better lateral control and shorter minimum TTC [2]. Yet longer is not always better. Excessive budget can distract the driver and even create unnecessary trust issues、.The modality of takeover requests is also important. Auditory and tactile modalities are more effective than visual ones, because visual requests require the driver to shift gaze from non-driving tasks to the screen. Multimodal combinations are generally better than unimodal ones, but more modalities are not always better. Three modalities are not always better than two, and seat haptics may even worsen takeover performance [2]. This indicates that design requires trade-offs, not simple stacking.

Adaptive takeover requests are a recent trend. The CBTOR-Design framework decomposes takeover into posture, perception, and cognition stages, identifies real-time bottlenecks, and generates customized requests for the bottleneck stage [9]. Experimental results show that bottleneck identification accuracy exceeds 90%, and reaction time is reduced by up to 0.48 s [9]. This suggests that takeover requests should not be fixed templates but should be dynamically adjusted according to driver state.

3.3. Authority allocation, interaction, and trust calibration

The core issue of authority allocation is determining when and to what extent control should be transferred to the driver. Human–machine trust is critical in this process: excessive trust may lead to over-reliance and insufficient takeover preparedness, whereas insufficient trust may result in unnecessary intervention [21]. Therefore, appropriate trust calibration is essential for effective authority allocation.

Uncertainty communication provides an important means of calibrating trust. Clearly communicating system uncertainty can help drivers better understand system limitations and takeover requests, thereby supporting appropriate responses [9, 22]. However, excessive uncertainty

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information may increase cognitive workload, requiring a balance between transparency and information complexity.

From this perspective, dynamic authority allocation can be understood as an uncertainty-based decision process. The level of control assigned to the driver or automation should be adjusted according to uncertainties related to system capability, driver intention, and driver state. Factors such as fatigue and distraction may therefore serve as important inputs for adaptive authority allocation.

3.4. Datasets and benchmarks

In terms of datasets, BATON provides 380 routes, 127 drivers, and 136.6 hours of naturalistic driving data, synchronized with forward video, in-cabin video, CAN bus signals, and GPS route context, defining three tasks: driving action understanding, handover prediction, and takeover prediction [23]. ViE-Take supplements the emotional dimension, including facial expressions, eye movements, body posture, and heartbeat data, with evaluation metrics including takeover readiness, reaction, and quality [23]. However, the current evaluation system is not unified; different studies use very different trust scales, takeover performance metrics, and experimental conditions, making results difficult to compare [1, 14].

4. Main limitations of existing research

First, takeover data remain limited and often rely on subjective labeling, as most studies are conducted in simulators or controlled environments. Second, cross-scenario generalizability remains insufficient, with models often showing reduced performance in unfamiliar driving conditions. Third, real-time performance and interpretability are difficult to balance. Complex uncertainty models may impose high computational costs, whereas black-box models often lack transparent decision logic. Fourth, ethical, legal, and regulatory issues remain unresolved, particularly regarding responsibility for takeover failures and acceptable levels of system conservatism. Finally, the lack of consistent uncertainty definitions and evaluation metrics limits comparison across studies and slows methodological development.

5. Conclusion

This paper reviews how uncertainty affects the safety and timeliness of takeover decision-making in SAE L2–L4 automated driving and how existing studies model uncertainty to optimize takeover decisions. Uncertainty arises from system randomness, incomplete knowledge, environmental perception, driver state, system capability, and interaction processes, and it affects all takeover stages. The review shows that uncertainty modeling can support more reliable and timely takeover decisions, but current methods remain fragmented and often focus on single sources or isolated stages.

Several limitations remain. Many studies rely on simulated or limited datasets, lack standardized evaluation, and insufficiently address individual driver differences and real-time adaptation. Future research should therefore move toward multi-source fusion and online updating, human-oriented adaptive takeover support, explainable and causal uncertainty, and human-in-the-loop learning. Standardized evaluation and application translation are also needed. In addition, uncertainty modeling in foundation models and world models deserves attention, especially how to estimate model reliability and transmit it to takeover decisions. Addressing these directions can improve takeover safety, timeliness, and human-machine cooperation.

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