Explaining Takeover Requests: The Role of Hazard Type and Explanation Strategy in Conditionally Automated Driving

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Abstract*—In conditionally automated vehicles (CAVs), takeover requests (ToRs) must re-engage drivers quickly and effectively. This study examines how the type of ToR explanation (action-only, precursor-only, hazard-only, precursor+hazard) and hazard type (behavioral vs. environmental) jointly affect driver's situation awareness, situational trust, and cognitive workload. In a driving simulator experiment using a 4×2 within-subjects design, 12 participants experienced all conditions while engaged in non-driving tasks. The findings suggest that while more informative explanations significantly improved situational awareness, trust, and satisfaction, they also imposed a greater cognitive workload. Behavioral hazards consistently led to better outcomes, whereas environmental hazards were more sensitive to explanation quality. Significant interaction effects emerged across most measures. This study underscores the importance of adaptive, context-aware ToR interfaces that adjust information to both the driving environment and cognitive demands. Balancing informativeness with mental workload is key to enhancing safety and trust in automated driving systems.

I. Introduction

Conditionally automated vehicles (CAVs) at SAE (Society of Automotive Engineers) Level 3 allow drivers to disengage from the driving task and perform non-driving-related tasks (NDRTs) such as reading, watching videos, or texting. While this autonomy grants driver's relief from constant vigilance, it also creates a cognitive gap between the driver and the driving context. When the system reaches the limits of its operational design domain (ODD), it must issue a takeover request (ToR), requiring the driver to reassume control under potentially urgent and complex conditions [1]. The time-critical nature of such transitions, coupled with the driver's potentially diminished situation awareness (SA), poses a significant risk to safety and human-automation coordination. To mitigate these risks, prior research emphasized the need for takeover interfaces that rapidly restore driver situation awareness. Endsley's work on SA [2, 3] defines SA as the driver's perception of elements in the environment, comprehension of their meaning, and projection of their status into the near future. These three levels of SA provide a structured framework to analyze how ToR interfaces might support driver cognition during takeovers. Several prior studies have investigated how the content and modality of ToR explanations influence drivers' SA and performance.

For example, Koo [4] explored explanation framing by providing "how," "why," and "how+why" explanations of automation behavior. Their results demonstrated that combined how+why explanations led to improved understanding and trust but also increased mental workload, highlighting the trade-off between informativeness and cognitive burden. Similarly, explanations were operationalized based on Endsley's three situation awareness levels, and performance was compared across visual and visual+auditory modalities [5]. They found that level 2 (comprehension-level) explanations significantly enhanced situational trust but were also associated with higher NASA-TLX workload scores. These studies underscore the need for explanation strategies that are informative yet cognitively efficient.

However, a major limitation of these prior works is their assumption that all driving situations are equally conducive to the same explanation strategy. Most studies applied a one-size-fits-all explanation model across varied driving contexts without accounting for how the nature of the underlying hazard might mediate the effectiveness of explanation design. For instance, driver interaction with automation was examined under conditions of varying criticality and hazardousness [6]. While they did consider scenario characteristics, their explanation content was not tailored to match scenario-specific cognitive demands, nor did they explicitly incorporate Endsley's SA framework into their design. In reality, hazards differ substantially in the perceptual cues they provide and the cognitive reasoning they require.

Crundall [7] proposed that hazard anticipation can be categorized into behavioral prediction (BP) hazards and environmental prediction (EP) hazards. BP hazards involve agents such as vehicles or pedestrians whose behavior must be inferred based on observable precursors, like a car waiting at a junction. In contrast, EP hazards involve risks emerging from the environment without direct behavioral cues, such as a hidden pedestrian emerging from behind a parked vehicle. This taxonomy was further elaborated, noting that hazard types differ in salience, visibility, and predictability, all of which affect the cognitive demands placed on the driver [8].

Given these distinctions, it is problematic to assume that identical ToR explanations would be equally effective for BP and EP scenarios. For BP hazards, the precursor and hazard are often co-located in space and time, making them easier to interpret with simpler cues. In contrast, EP hazards involve spatial or temporal occlusion, requiring drivers to engage in higher-level inference, which could benefit more from enriched explanations. This study aims to address this theoretical and practical gap by examining how ToR explanations should be tailored to the type of hazard present. Through this framework, the present study investigates the following research question:

Research Question: How does tailoring ToR explanation type to hazard type (BP vs. EP) affect drivers' situation awareness, cognitive workload, and situational trust?

II. METHODS

A. Experimental Design

This study employed a 4 (Hazard Type: two Behavioral Prediction Hazard [BP] vs. two Environmental Prediction Hazard [EP]) × 4 (Explanation Type: E1 (Action-only), E2 (Precursor-only), E3 (Hazard-only), E4 (Precursor+Hazard)) within-subjects design. The experiment was conducted in room 336 of building 39 at Seoul National University. Forum 8 UC winroad ver.10 was applied for operating driving scenarios.

Each participant experienced all four experimental conditions in counterbalanced order using a Latin square design to control for order effects and learning effects. All scenarios were implemented in a high-fidelity driving simulator with automated driving functionality and sudden transitions to manual control via a Takeover Request (ToR). For each scenario, participants were required to do a non-driving-related task (NDRT) involving smartphone use. Informed by prior studies indicating that mobile phone usage is one of the most frequently preferred non-driving-related activities (NDRAs) during automated driving scenarios [9, 10], participants in this experiment were instructed to engage freely with their smartphones during the simulations of autonomous driving. Participants could freely monitor the driving environment.

B. Participants

Twelve licensed drivers (3 in each counterbalanced group by Latin square) with normal or corrected-to-normal vision and hearing were recruited via researchers' face-to-face requests. Participation was voluntary, and no compensation was provided in compliance with the university's ethics guidelines.

C. Scenario

Four dynamic takeover scenarios were constructed based on Crundall's [7] hazard taxonomy and Zhang's [8] extensions as shown in Table I:

BP1: A car waits at a nearside road and pulls into the ego vehicle's lane.

BP2: A motorcycle drives ahead of the ego vehicle and slows down.

EP1: A motorcycle emerges from behind a parked truck.

EP2: A car emerges from behind a roadside construction site.

Each scenario featured a pre-ToR autonomous driving period of 5 minutes, followed by a ToR issued at 6,000 meters with a fixed takeover lead time (ToRlt) of 7 seconds and time-to-collision (TTC) of 10 seconds. All events were designed to be non-critical to avoid criticality affecting the results.

TABLE I. HAZARD TYPES WITH DIFFERENT PRECURSORS AND HAZARDS

Type	Precursor	Hazard
Behavioral hazard 1 (BP1)	A car waits at a nearside road	The car pulls into the ego vehicle's lane
Behavioral hazard 2 (BP2)	A motorcycle moves ahead of the ego vehicle	The motorcycle slows down in the ego vehicle's lane
Environmental hazard 1 (EP1)	A truck is parked at a nearside road	A motorcycle emerges from behind a parked truck
Environmental hazard 2 (EP2)	A construction site is visible at a nearside road	A car emerges from behind the construction site

D. Takeover Request Explanations

The ToR messages were delivered in four explanation types: action-only, precursor-only, hazard-only, and precursor+hazard. All messages were delivered in Korean. Action-only message stated just the action for the driver to do, which was to takeover. Precursor-only message indicated the precursor of the behavioral precursor hazard or environmental precursor hazard. Hazard-only message indicated the hazard of the behavioral precursor hazard or environmental precursor hazard. Precursor+hazard message indicated both the precursor and hazard of the behavioral precursor hazard or environmental precursor hazard. The messages below are the examples for the hazard type BP1. Here, E1 corresponds to the action-only message, E2 to the precursor-only message, E3 to the hazard-only message, and E4 to the precursor+hazard message.

1) Action-only (E1): "Please take over"

2) Precursor-only (E2): "A car is waiting at a side road."

3) Hazard-only (E3): "A car may pull into your path."

4) Precursor + Hazard (E4): "A car is waiting at a side road and may pull into your path."

E. Modality and Design

All takeover explanations were delivered via a combined visual and auditory modality. This design choice is grounded in multiple resource theory and empirical evidence showing that multimodal presentation enhances reaction time, driver trust, and situation awareness more effectively than either modality alone [5].

Visual cues were designed following the human factors guidelines provided by the U.S. National Highway Traffic Safety Administration (NHTSA) [11]. The content was displayed on a central screen located within the driver's natural field of view to minimize attentional redirection.

For auditory ToRs, to maximize efficiency in auditory delivery, we employed spearcons, which are algorithmically time-compressed speech cues. Spearcons retain semantic content while significantly reducing duration, averaging around 40% of the corresponding TTS length [12]. For example, a 1-second spoken phrase is reduced to ~400 milliseconds without losing interpretability [13, 14].

Spearcons were generated by adjusting TTS tempo while keeping pitch constant using a MATLAB-based compression script [15]. This technique has shown superior performance in interface navigation tasks and is increasingly applied to automated driving contexts.

In addition to the technical efficiency of spearcons, the speech style was carefully designed to foster trust. As supported by Lee [16], natural human-like speech improves user trust in agent-based vehicle interactions. Accordingly, all auditory messages were recorded using a female voice actor, based on findings regarding voice-based agent acceptance [17]. Recordings were made in a neutral and friendly tone using a high-quality Dictaphone, rather than relying on synthesized speech, to ensure greater naturalness and intelligibility [18].

The average duration of each explanation in its final spoken form was approximately 3.5 seconds, consistent with prior work evaluating user compliance to auditory ToRs in conditionally automated driving systems.

F. Measures

The study evaluated four key dependent variables: situation awareness, situational trust, explanation satisfaction, and cognitive workload, using validated instruments and protocols suited to the automated driving context. Since participants were all Korean, self-report measures mentioned in the sections below were all employed in Korean.

Situation awareness. Situation awareness (SA) was assessed using the Situation Awareness Global Assessment Technique (SAGAT) developed by Endsley [2]. SAGAT is a direct and objective method that involves freezing the simulation at pre-defined moments and asking the participant three structured probe questions, each targeting one of Endsley's SA levels: (1) Perception, (2) Comprehension, and (3) Projection. Sample questions for each level are shown in Table II. This approach has been widely used in automated driving research [5, 19], and is considered appropriate for assessing cognitive state transitions during takeovers [20].

TABLE II. SITUATION AWARENESS GLOBAL ASSESSMENT TECHNIQUE

Level of Situation Awareness	**Question**	**Options**
Perception	The simulation has suddenly stopped. What kind of road user/site was in front of the ego vehicle?	1) Bus 2) Truck 3) Motorcycle 4) Passenger car 5) Construction site 6) Unknown 7) Other
Comprehension	What was the cause of this situation requiring your attention?	1) A motorcycle cutting into the ego vehicle's lane 2) A truck cutting into the ego vehicle's lane 3) A passenger car cutting into the ego vehicle's lane 4) A pedestrian trying to cross the street 5) Adjacent car speeding up 6) Unknown 7) Other
Projection	When the simulation resumes from the paused state, under what circumstance do you expect your additional attention or actions might be required?	1) Illegal actions by other road users 2) Movement of the ego vehicle that may endanger a pedestrian 3) Movement of the ego vehicle that may endanger a motorcycle 4) Movement of the ego vehicle that may endanger a passenger car 5) Movement of the ego vehicle that may endanger a truck 6) Unknown 7) Other

TABLE III. SITUATIONAL TRUST SCALE FOR AUTOMATED DRIVING

Situational Trust Factor	**Scale Item**
Trust	I trust the automation in this situation
Performance (reverse scored)	I would have performed better than the automated vehicle in this situation
Non-Driving Related Task (NDRT)	In this situation, the automated vehicle performs well enough for me to engage in other activities (such as reading)
Risk (reverse scored)	The situation was risky
Judgement (reverse scored)	The automated vehicle made an unsafe judgement in this situation
Reaction	The automated vehicle reacted appropriately to the environment

Situational trust. Situational trust in the automation was measured using the Situational Trust Scale for Automated Driving (STS-AD) developed by Holthausen [21]. The scale captures scenario-specific trust responses and was administered immediately after each trial. Items include statements such as "I trusted the system to warn me in time," rated on a Likert scale. The STS-AD is particularly suited for within-subjects studies involving multiple takeover scenarios. Six questions for STS-AD are shown in Table III.

Explanatory satisfaction. Participants rated their satisfaction with each ToR explanation using a five-item questionnaire [22] designed to capture dimensions of clarity, helpfulness, appropriateness, and informativeness. Example items include: "This explanation of how the system works has sufficient detail," and "This explanation of how the system works is useful to my goals." Responses were recorded on a 5-point Likert scale ranging from Strongly Disagree to Strongly Agree. The items are shown in Table IV.

TABLE IV. EXPLANATORY SATISFACTION

Scale Item
From the explanation, I know how the system works
This explanation of how the system works is satisfying
This explanation of how the system works has sufficient detail
This explanation of how the system works seems complete
This explanation of how the system works tells me how to use it
This explanation of how the system works is useful to my goals
This explanation of the system shows me how accurate the system is

Cognitive workload. Cognitive workload was assessed using the Driving Activity Load Index (DALI) developed by Pauzié [23], which was chosen over NASA-TLX due to its superior contextual validity in driving tasks. DALI evaluates workload along six dimensions (e.g., visual demand, auditory demand, time pressure) that are particularly relevant to real-time decision-making in vehicular environments. The DALI questionnaire was administered once after the final scenario, with participants reflecting on their cumulative experience.

The datasets used in this study are publicly available at https://github.com/iamjustabeginner/takeover-request-dataset to promote transparency and reproducibility.

III. RESULTS

A. Situation Awareness

There were significant main effects of both Hazard Type ($F = 1279.77$, $p < .001$) and Explanation Type ($F = 161.00$, $p < .001$). A significant interaction effect was also found between the two factors ($F = 35.65$, $p < .001$). This indicates that both the type of hazard and the explanation type strongly influenced participants' situational awareness, and their combination produced varying effects.

TABLE V. ANOVA FOR SITUATION AWARENESS

Independent variable	F	p-value
Hazard Type	1279.77	p < 0.001
Explanation Type	161.00	p < 0.001
Interaction	35.65	p < 0.001

Situational awareness increased with more informative explanations of hazards and precursors. The effect was particularly strong under behavioral hazards. A clear interaction pattern emerged, with the explanation type affecting awareness differently depending on hazard type.

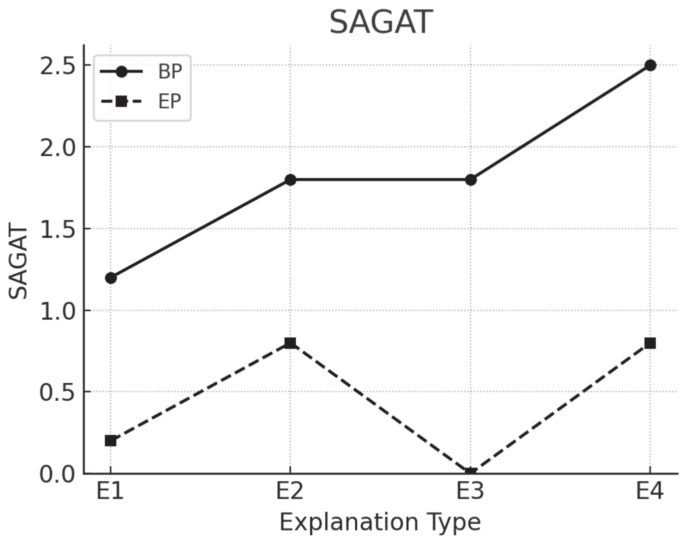

Fig. 1. Interaction Plot for Situation Awareness

All pairwise comparisons showed statistically significant differences. E4 significantly increased situational awareness compared to all other explanation types. E1 resulted in the lowest awareness, significantly lower than E2, E3, and E4. Awareness improved progressively as more context (precursor, hazard) was included in the explanation

B. Situational Trust

Significant main effects were found for Hazard Type ($F = 10.64$, $p = .001$) and Explanation Type ($F = 6.00$, $p < .001$). A significant interaction was also observed ($F = 5.22$, $p = .001$). These findings suggest that trust levels vary with both the hazard condition and the explanation provided, and their combination further influences trust.

TABLE VI. ANOVA FOR SITUATION TRUST

Independent variable	F	p-value
Hazard Type	10.64	p = 0.001
Explanation Type	6.00	p < 0.001
Interaction	5.22	p = 0.001

Overall, trust was higher for behavioral hazards. Under E3 (hazard only), trust dropped more sharply for environmental hazards, suggesting sensitivity to explanation relevance.

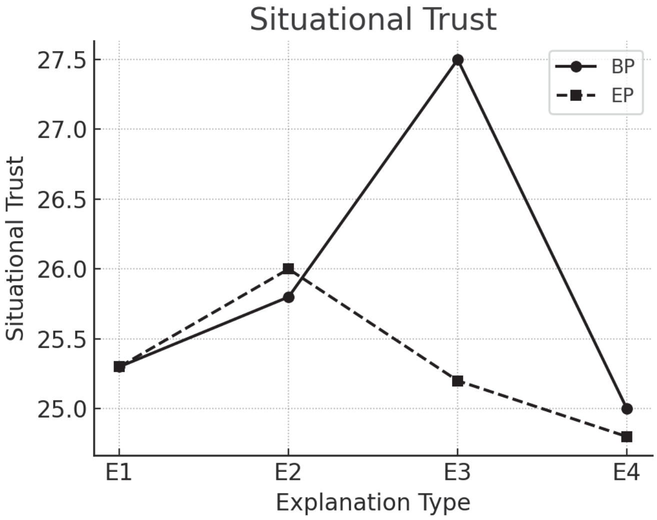

Fig. 2. Interaction Plot for Situation Trust

Only a few comparisons reached significance: E4 led to significantly lower trust than E2 and E3. Other pairwise differences (e.g., E1 vs. E2, E1 vs. E3) were not statistically significant. This suggests that while trust varies across explanation types, the effect is mainly driven by differences involving E4 (precursor + hazard).

C. Explanatory Satisfaction

Both Hazard Type ($F = 73.77$, $p < .001$) and Explanation Type ($F = 95.23$, $p < .001$) had significant main effects. A significant interaction effect was also present ($F = 16.22$, $p < .001$). This implies that users' satisfaction with the explanation depends not only on the explanation type but also on the hazard condition and their combined context.

TABLE VII. ANOVA FOR EXPLANATORY SATISFACTION

Independent variable	F	p-value
Hazard Type	73.77	p < 0.001
Explanation Type	95.23	p < 0.001
Interaction	16.22	p < 0.001

E2, E3, and E4 yielded higher satisfaction than E1 (action only). Satisfaction was consistently higher for behavioral hazards. A pronounced interaction was observed, indicating that the satisfaction level is jointly influenced by both factors.

Significant differences were found only between E1 and the other explanation types: E1 yielded significantly lower satisfaction than E2, E3, and E4. No significant differences were found among E2, E3, and E4. This implies that the presence of any contextual explanation (beyond action-only) is sufficient to improve explanatory satisfaction.

D. Cognitive Workload

Hazard Type did not have a significant effect on workload ($F \approx 0$, $p = 1.000$). The $F \approx 0$ result indicates a complete absence of variance across hazard types in workload ratings.

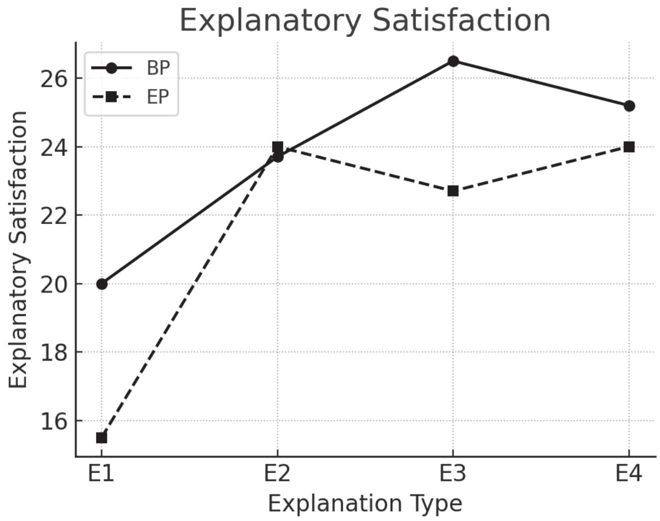

Fig. 3. Interaction Plot for Explanatory Satisfaction

Given the small participant pool (n=12) and the limited number of workload items, this likely reflects a ceiling or floor effect rather than a true null relationship. Explanation Type had a significant main effect ($F = 9.61$, $p < .001$), and the interaction was also significant ($F = 20.39$, $p < .001$). This indicates that cognitive workload is unaffected by hazard type alone, but increases depending on the complexity of the explanation and its interaction with hazard context.

TABLE VIII. ANOVA FOR COGNITIVE WORKLOAD

Independent variable	F	p-value
Hazard Type	0	p = 1.000
Explanation Type	9.61	p < 0.001
Interaction	20.39	p < 0.001

E2 and E4 conditions were associated with higher workload. There was little difference between hazard types, consistent with the non-significant main effect of hazard. The pattern indicates that more detailed explanations increase workload, but hazard type does not moderate this effect.

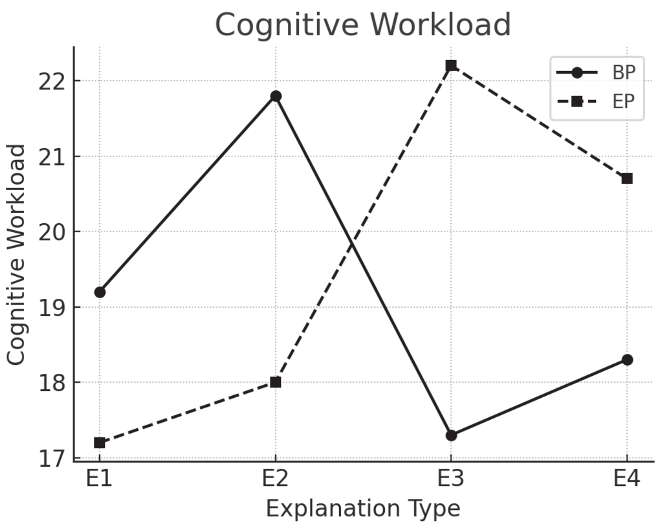

Fig. 4. Interaction Plot for Cognitive Workload

Only comparisons involving E1 showed significant effects: E1 had significantly lower workload than E2 and E3. The difference between E1 and E4 was marginal ($p = .056$). No significant differences were observed between E2, E3, and E4. This suggests that minimal explanation (E1) is cognitively least demanding, but more informative explanations increase cognitive effort.

IV. DISCUSSION

This study investigated the effects of explanation types and hazard types on situational awareness, explanatory satisfaction, situational trust, and cognitive workload in the context of takeover requests in conditionally automated driving. The findings provide several important insights into how explanation strategies can shape human responses in safety-critical contexts.

First, explanation type significantly influenced all four dependent variables. More informative explanations, particularly those including both precursor and hazard information, consistently led to higher situational awareness and explanatory satisfaction. These results suggest that users benefit from contextualized explanations that provide both predictive and diagnostic cues, enhancing their understanding and perception of the driving situation.

Second, situational trust was also affected by explanation type, though to a lesser degree. Explanations that omitted critical hazard information (e.g., action-only) were associated with reduced trust, particularly under environmental hazard conditions. This highlights the importance of tailoring explanations to hazard type to maintain appropriate trust in automated systems.

Third, cognitive workload increased with the complexity of the explanation. While informative explanations improved awareness and satisfaction, they also demanded greater mental effort. This trade-off suggests that designers must balance informativeness and cognitive demand when constructing explanations for real-time decision-making.

Finally, the interaction effects observed across all variables (except for workload's main effect of hazard type) indicate that the impact of explanation type cannot be fully understood without considering the hazard context. For example, behavioral hazards generally led to better outcomes across measures, possibly due to their higher salience or perceived urgency.

Taken together, these findings emphasize that effective takeover communication in conditionally automated driving should be adaptive and context-sensitive, particularly by adjusting the explanation strategy according to the type of hazard in the external environment. Future work may further explore how explanation systems can dynamically tailor the amount and type of information to different hazard categories (e.g., behavioral vs. environmental), in order to optimize drivers' awareness, trust, and workload balance.

For the limitations of this study, some non-significant results, such as the negligible main effect of hazard type on workload, may reflect the limited sample size. Also, the small sample size limits the generalizability of the findings and possibility to detect subtle effects. Future studies with larger and more diverse samples are needed to validate and generalize these findings to ensure robustness. Also, it should incorporate objective performance indicators such as driving performance and eye-tracking to provide a more comprehensive understanding of cognitive and behavioral responses.

VII. CONCLUSION

This study examined how takeover request (ToR) explanation types and hazard types jointly influence drivers' situation awareness, situational trust, explanatory satisfaction, and cognitive workload in conditionally automated driving. The results showed that more informative explanations, particularly those including both precursor and hazard information, substantially improved awareness and satisfaction, while also increasing cognitive workload. Hazard type further moderated these effects, with behavioral hazards producing generally better outcomes and environmental hazards proving more sensitive to explanation quality.

These findings highlight the importance of tailoring ToR explanation strategies to both situational context and cognitive demands. Designing adaptive and context-aware interfaces can improve safety, enhance trust, and balance mental workload during critical transitions in automated driving. Future work should explore personalization techniques and dynamic explanation systems that can adjust content in real time to support diverse driver states and environments.

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