ARTICLE TEMPLATE

Find My Friend: An Innovative Cooperative Approach of Real-Time Goal Collaboration in Automated Driving

Jun Zhang[a,b,c], Fang You[b], Jieqi Yang[b], Jie Zhang[d], Ping Wang[b], Hailiang Wang[c], and Yan Luximon[c],

[a] College of Design and Innovation, Tongji University, Shanghai, China; [b]College of Arts and Media, Tongji University, Shanghai, China; [c]School of Design, The Hong Kong Polytechnic University, Hong Kong SAR, China; [d] Faculty of Applied Sciences, Macao Polytechnic University, Macao SAR, China

ARTICLE HISTORY
Compiled September 30, 2024

ABSTRACT
Real-time goal collaboration represents a promising approach to human-vehicle cooperative driving; however, it remains underexplored. To address this gap, we introduced an innovative human-vehicle cooperative approach and designed four interactive types with increasing autonomous levels to implement it. Additionally, we proposed seven interface design principles to design three increasing levels of transparency for the four interactive types, aiming to enhance collaboration. Experimental results demonstrate the favorable reception of the proposed cooperative approach by users. Furthermore, higher interactive autonomous levels result in reduced workload, and higher interface transparency levels lead to increased satisfaction, trust, and mutual dependence. Notably, the combination of the highest interactive autonomous level and interface transparency level, which exhibited the best performance, is recommended for practical application. This collaborative approach expands the research domain of human-vehicle cooperative driving and offers extensive potential applications across various relevant scenarios.

KEYWORDS
Cooperative interface, goal collaboration, Automated driving, Human-machine interface

1. Introduction

Before fully achieving autonomous driving technology, humans and Automated Vehicles (AVs) will collaboratively engage in driving tasks (Chen et al., 2022; International, 2018; Xing et al., 2021; You et al., 2024). During the process of achieving common goals, humans and AVs exhibit autonomous cognitive, decision-making, and action capabilities while relying on each other to complete tasks (Campion et al., 1993; Figalová et al., 2024; Salas et al., 1992). For example, humans and AVs can cooperate with each other at the operational level of driving tasks (such as lateral and longitudinal movement) and at the tactical level (e.g., overtaking, lane changing, etc.) to achieve mutual intervention effects (Jiang et al., 2018; Kamezaki et al., 2022; Wang et al.,

CONTACT: Yan Luximon (yan.luximon@polyu.edu.hk)

2020). Despite extensive research on various collaboration modes, such as shared control (Flemisch et al., 2016, 2014; Nguyen et al., 2021) and planned cooperation (Walch et al., 2016; Wang et al., 2020), there are still some critical collaboration approaches that may not have received sufficient attention. One of these approaches is real-time goal collaboration.

Although long-term goals in driving typically remain relatively stable, short-term real-time goals often change. For instance, while traveling, we might discover a beautiful landmark and decide to make a temporary stop, or we might encounter a friend while driving and choose to offer them a ride, requiring a temporary halt at the roadside. Such situations are relatively straightforward in a manual driving environment but present challenges in an autonomous driving context. This is because when goals change, negotiation between humans and vehicles is necessary to establish new directions (Barnes et al., 2015; Hoc, 2001; Salas et al., 2005). Taking a taxi ride as an example, we can negotiate with the driver who has control over the vehicle to request them to stop at specific locations, facilitating changes in our real-time goals. However, in current research on human-vehicle cooperative driving, collaboration for such real-time goals seems to have received relatively less attention. Moreover, many of these goals cannot be directly set through navigation systems or may not allow sufficient time for navigation planning due to their proximity. This further leads to a dilemma of a lack of appropriate interaction interface for cooperative navigation between humans and vehicles.

In addressing these issues, the current solution is takeover (Philipp et al., 2014). However, this takeover strategy has several drawbacks. For instance, during autonomous driving, the driver's cognitive engagement with the driving task decreases, leading to a disconnection from the driving environment and a reduced level of situation awareness (Merat et al., 2019; Onnasch et al., 2014; Woide et al., 2023b). Additionally, the driver might shift their attention to secondary tasks, resulting in delayed response times to critical events (Biondi et al., 2018; Eriksson and Stanton, 2017; Jazayeri et al., 2021). Therefore, the takeover strategy has evident limitations in practical application. Exploring more effective strategies is essential to facilitate cooperative handling of these real-time goals.

From the perspective of human-vehicle cooperation, there are two main scenarios when real-time goals change: The first scenario involves human drivers guiding AVs towards new goals. One challenge here is ensuring that drivers can accurately convey real-time goals and intentions to the AV (Huang and Mutlu, 2016). Multi-modal interaction techniques seem capable of meeting the interactive demand for real-time transmission of target orientation information. For instance, Wang et al. (2020) employed gaze-voice interaction (Jiang et al., 2018) to convey driver intentions, notifying the AV to pay attention to certain vehicle behaviors and generate new execution plans. The second scenario envisions AVs as members of a cooperative team that can recognize goals and proactively adjust real-time destinations. For instance, through facial recognition technology, vehicles could rapidly identify specific individuals. By leveraging big data or social networks, AVs could identify suitable parking locations near tourist spots. However, the challenge lies in the level of autonomy of the AV, which could influence how interactions with humans occur. Highly autonomous AVs might execute autonomously without prior notification to humans (Chen and Barnes, 2014; Parasuraman et al., 2000), whereas AVs with medium autonomy might require human approval before taking action (Parasuraman et al., 2000; Woiceshyn et al., 2017). Yet, the autonomy level of AVs impacts interface design and human perception and decision-making regarding the AVs (Rau et al., 2013; Saha and Motuba, 2023). Hence, when real-time goals change, there are numerous possibilities for collaboration between humans and vehicles. Nevertheless, challenges within these scenarios are closely tied to autonomy levels, interface design, and how humans perceive and decide regarding AVs.

Motivated by this issue, the objective of this study is to explore real-time goal collaboration, including the interactive types and interface designs that support such cooperation. In this collaborative context, two fundamental situations exist: (1) the human driver first discovers and confirms the real-time goal, and (2) the AV first discovers and confirms the real-time goal. Therefore, the research questions **(RQs)** can be summarized as follows:

- **RQ1: What interactive types and interface designs are better when the human driver first discovers the goal?**
- **RQ2: What interactive types and interface designs are better when the AV first discovers the goal?**

These two research questions are explored in two separate studies. Fig. 1 illustrates the process and steps of our research. We adopted a scenario using "finding a friend" as an example, which can be extended to other objects or locations. The primary steps of the research involve humans providing target object information (such as a photo) to the AV and requesting the AV to locate the target while driving. In Study 1, we assume that humans first discover their friend, at which point the driver can choose to take control of the vehicle or command the vehicle to proceed to the friend's location. In Study 2, we assume that the vehicle first discovers the friend, allowing the vehicle to ask the human driver for approval to go to the new destination or to autonomously navigate to the target location. This research thoroughly investigates the interaction type and interface design between humans and AVs for these four potential scenarios.

This study represents the first attempt to explore novel cooperation approach that cater to the potential demands of real-time goal collaboration, thereby broadening the research scope of cooperative driving. The main contributions of this paper are summarized as follows:

(1) We developed an innovative human-vehicle cooperative approach and designed four interactive types with increasing autonomous levels to implement it.
(2) We proposed seven interface design principles to design three increasing transparency levels for four interactive types to enhance collaboration.
(3) We confirmed the optimal combinations of interactive types and transparency levels through two subject-with experiments with interface prototypes.

The structure of the following sections is as follows: Part 2 reviews relevant theories and research findings, discusses their roles, limitations, and relevance to this study. Part 3 constructs the architecture for real-time goal collaboration, and proposes a set of principles and methods for cooperative interface design. Parts 4 and 5 provide detailed descriptions of the two independent studies, outlining the steps and methods of interaction design, presenting verification results, and discussing the outcomes. Parts 6 and 7 delve into the findings and limitations of this study, extracting design insights from them. Finally, the Conclusion section summarizes the main contributions of this paper and offers prospects for future research in this field.

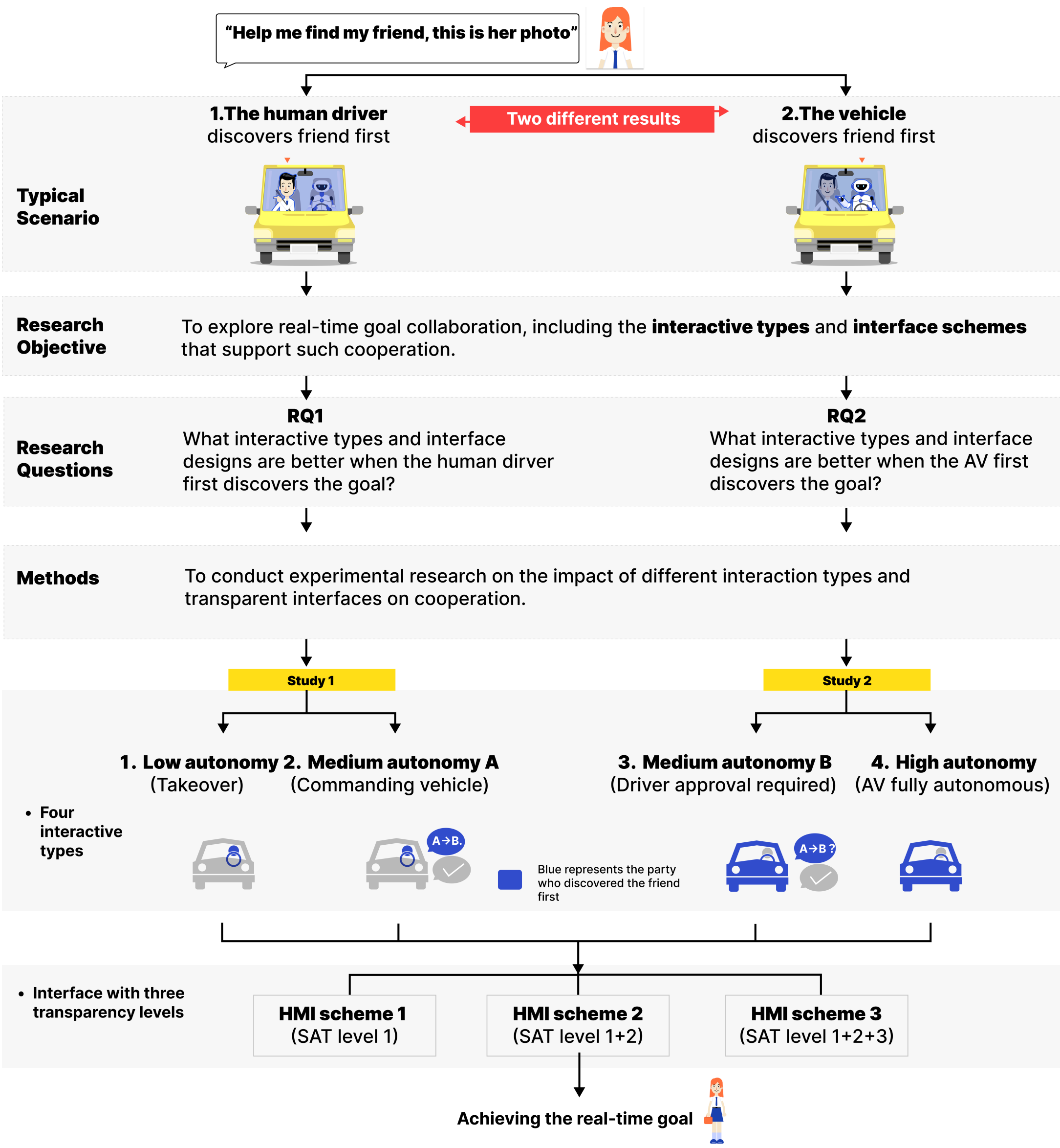

Figure 1.: Process and steps of research. Human drivers and autonomous vehicles (AVs) jointly search for a target (e.g., the driver's friend) on the road. One of the parties, either the driver or the AV, discovers the target first (indicated in blue). In Study 1, the human driver first identifies their friend. The driver can choose to take control of the vehicle or give commands for the vehicle to drive to the friend's location. In Study 2, we assume that the vehicle detects the driver's friend first. At this point, the vehicle can either actively seek the human driver's input for approval to head to the new destination or make autonomous decisions and drive directly to the target location. We also investigated which level of transparency interface among the four types mentioned above is more effective.

2. Background and Related Works

In this section, we introduce relevant theoretical concepts and prior research related to human-vehicle cooperative driving, interacting with vehicle agents with different levels of autonomy, transparent interfaces, and collaborative interdependence. We analyze the deficiencies of existing theories and research, highlighting the connection between our research and the existing body of knowledge.

2.1. Human-Vehicle Cooperative Driving

In conditional automated driving, humans and AVs collaborate as a team to operate the vehicle (Brandt et al., 2017; International, 2018; Merat et al., 2018; Walch et al., 2017; Xing et al., 2021). According to the minimum requirements for collaborative teamwork proposed by Hoc (2001):

- (1) Each one strives towards goals and can interfere with the other on goals, resources, procedures, etc.
- (2) Each one tries to manage the interference to facilitate the individual activities and/or the common task when it exists.

This implies that team members have autonomous abilities for perception, understanding, decision-making, and action. They work interdependently towards a shared goal, and they can interfere with each other's goals, resources, and procedures to facilitate the common task (Salas et al., 1992). Additionally, members can dynamically coordinate their behaviors in response to changes in team goals (Allen et al., 1999; Barnes et al., 2015; Salas et al., 2005). In the context of driving tasks, both humans and vehicles can collaborate across three levels of driving tasks defined by Michon (1985): the operational level, tactical level, and strategical level (Kamezaki et al., 2022).

2.1.1. Operational Level

Real-time control of the vehicle's lateral and longitudinal movement is referred to as the Operational level (Michon, 1985). In automated driving beyond Level 2, the automated driving system has full control over vehicle motion unless a human driver takes over. This switching of control has a binary nature. However, when human drivers take over, they need to re-engage with the driving environment, leading to diminished situation awareness, longer takeover times, and delayed response to critical events due to human factors issues. These problems impact the safety of driving (Biondi et al., 2018; Eriksson and Stanton, 2017; Merat et al., 2012; Wang et al., 2021, 2024; White et al., 2019).

2.1.2. Tactical Level

Path planning during travel, such as overtaking, lane changing, and obstacle avoidance, falls under the category of the Tactical level (Song et al., 2024). However, challenges exist in this collaboration because humans and intelligent systems might have different understandings, intentions, or path planning strategies for the same scenarios. Conflicts can arise when the behavior of an AV contradicts human expectations (Woide et al., 2023a, 2021). Interaction design is used to address these issues. For instance, in overtaking scenarios, the system can provide multiple path planning options to the driver, allowing them to choose one through a touch interface (Walch et al., 2016). Additionally, due to the differing cognitive capabilities of humans and AVs, in complex or uncommon situations, humans often make predictions based on various factors, while machines struggle to engage in advanced reasoning, particularly concerning social cues or implicit intent communication (Wang et al., 2020).

2.1.3. Strategical Level

The strategic level refers to long-term route planning and destination collaboration through navigation. Automated driving systems may recommend the most economical route based on factors such as traffic congestion or distance. However, once a human driver confirms the destination, adjustments are usually infrequent. Since strategic-level collaboration often involves longer duration (minutes) and has less impact on safety, research on human-vehicle cooperation at the strategic level is relatively limited (Guo et al., 2019).

A review of these studies indicates that current research on human-vehicle cooperative driving predominantly focuses on the operational and tactical levels. These two levels involve mid-term vehicle behavior control under unchanged destinations. However, in real-world driving, situations where destinations need real-time adjustments are quite common. For instance, during a journey, one might suddenly decide to pull over and pick up a friend. Currently, if a human driver has such a requirement, they typically have to take control of the vehicle, which has numerous drawbacks. Therefore, we propose that in the context of automated driving, a real-time cooperative approach can be designed to address short-term destination adjustments.

2.2. Interacting with Vehicle Agents

Although the SAE has categorized automation levels into six based on vehicle capabilities (International, 2018), it does not specify what level of intelligence vehicles should exhibit when interacting with humans within each level. Different autonomy levels have varying capabilities for perceiving the environment and performing tasks (Rau et al., 2013). For instance, agents with medium autonomy need to await operator commands before executing actions, whereas highly autonomous agents can perform actions directly without notifying the operator (Allen et al., 1999; Peng et al., 2019). Therefore, different autonomy levels correspond to distinct human-machine interaction methods. Parasuraman et al. (2000) divided automation into 10 levels, which has been applied in human-machine interaction research, such as studying autonomy levels in human-robot interaction (Beer et al., 2014; Peng et al., 2019; Rau et al., 2013). We can classify agents into three autonomy levels: low autonomy, medium autonomy, and high autonomy.

2.2.1. Low Autonomy

Control remains with humans. In level 1 automation, the task is performed entirely manually, with no automation assistance. In levels 2 to 4 automation, control still lies with humans, but automation provides some informational assistance, such as narrowing down choices, offering decision and action recommendations, and issuing danger warnings. In Study 1 of this research, one option for human drivers to choose after changing the target is taking over the vehicle, aligning with the low autonomy interaction scenario. The challenge lies in the fact that before taking over, drivers are likely to be disengaged due to low task involvement or engaging in other activities (Endsley, 2017; Endsley and Kiris, 1995; Kaber and Endsley, 1997; Onnasch et al., 2014). Additionally, considering that the interface can provide relevant cognitive information to enhance human situation awareness after taking over, the interface after takeover has also been designed and evaluated in Study 1.

2.2.2. Medium Autonomy

Control remains with the agents. In automation levels 5 and 6, the automation possesses control, but execution of actions requires human approval or, if there's no human veto within a certain time, execution proceeds. In level 7, the automation can act autonomously but needs to inform humans. Agents with medium autonomy need to wait for human commands or propose decisions and wait for human approval before executing tasks (Allen et al., 1999; Chen and Barnes, 2014; Woiceshyn et al., 2017). The downside is that it demands humans to make the final decisions, thereby increasing workload (Miller and Parasuraman, 2007). This corresponds to the scenario in Study 1 of this research where the vehicle is commanded to head to a new destination and in Study 2 where the vehicle proposes a change in destination but requires human approval.

2.2.3. High Autonomy

Control lies in the hands of the agent. In Levels 8 to 9 automation, automation can inform humans when needed or when asked. In Level 10 automation, automation can autonomously execute without notifying humans at all. This implies that the actions and plans of AVs require no human input (Chen and Barnes, 2014; Fisher et al., 2020). However, research indicates that the behavior of highly proactive intelligent agents can compromise user perception and excessive proactivity might not be well-received by humans (Huang et al., 2015; Sun et al., 2017). In contrast, humans tend to prefer agents with medium proactivity (Peng et al., 2019).

In summary, different interactive types not only influence task execution itself but also impact human perception of intelligent agents (Barnes et al., 2015). These various interactive types might coexist before full autonomous driving is achieved. Therefore, through two studies, we investigate the effects of different interactive types in real-time goal collaboration. In Study 1, we compare the interactive types of takeover (low autonomy) and executing human commands (medium autonomy). In Study 2, we compare interactive types that require human approval (medium autonomy) and those that require no human intervention (high autonomy).

2.3. Transparency

Once the interaction approach is determined, it is essential to consider how to design interfaces to facilitate real-time goal collaboration. In situations where intelligent systems can observe, predict environmental changes, and make autonomous decisions (Wooldridge and Jennings, 1995), their behavior becomes unpredictable. Hence, humans need to accurately comprehend the internal model of intelligent systems, including perception, understanding, decision-making, and reasons for actions, through transparent interfaces. At the same time, intelligent systems need to show their understanding of the current situation, along with the reasoning and decision-making processes behind it to humans (Chen and Barnes, 2014; Lyons, 2013; van de Merwe et al., 2022).

Based on Situation Awareness theory (Endsley, 1995), Chen et al. (2014) proposed the Situation Awareness-based Agent Transparency (SAT) model. The SAT model defines agent transparency as the descriptive quality of the interface that allows operators to understand the agent's intent, reasoning process, and future plans. Specifically, the SAT model presents three levels of agent transparency:

- SAT Level 1: Refers to perception of agent's plan. Agents should provide relevant information about their goals and actions to operators, including the agent's current state, behavior, plans, and perception of the environment, while also suggesting action alternatives.
- SAT Level 2: Refers to understanding the agent's logic. Agents should provide the reasoning behind their actions, including the constraints and feasibility considered during planning.
- SAT Level 3: Refers to predicting potential outcomes of the agent's plan. Agents should provide predictive information about future states, including expected outcomes, likelihood of success or failure, and associated uncertainties or additional reasoning.

Existing research based on SAT indicates its significant impact on human trust in the system, workload, team performance, and situation awareness (Bass et al., 2013; Chen and Barnes, 2014; Helldin et al., 2014; Joseph et al., 2016; Zhou and Chen, 2015). Higher transparency in intelligent agents increases operator trust (Joseph et al., 2016). Furthermore, improved transparency aids operators in maintaining accurate situation awareness (Chen and Barnes, 2014; Miller, 2014; Stubbs et al., 2007). While increasing transparency might introduce more information on the interface, potentially increasing workload (Chen and Barnes, 2014; Wickens, 2008), the presentation of information supporting transparency, particularly the reasoning and predictive information provided in SAT Level 2 and 3 transparency, significantly impacts workload reduction (Chen and Barnes, 2014; Parasuraman et al., 2000).

Although transparency provides guidance, how to apply it in the interaction design of human-vehicle cooperation lacks established principles. To address this gap, researchers have attempted to extract design principles applicable to autonomous driving interfaces. Based on Lyons' transparency model (Lyons, 2013), Pokam et al. (2019) extracted 12 design principles. However, Lyons' model does not differentiate cognitive process levels as explicitly as the SAT model. Therefore, in our study, we opted for the SAT model and extracted seven design principles to guide interface design for real-time goal collaboration.

2.4. Interdependence: Conflict, Mutual Dependence

In social interactions, the cooperative relationship between individuals is characterized by mutual interdependence, and a similar dynamic exists between humans and AVs. The Interdependence theory emphasizes that in specific contexts, an interactive relationship is defined by the perception of each individual's behavior, motives, thoughts, and needs towards each other (Gerpott et al., 2018; Kelley and Thibaut, 1978). Thus, dimensions of the Interdependence theory such as Mutual Dependence, Power, Conflict, Future Interdependence, and Information Certainty can be used to evaluate people's perceptions, trust, and willingness to cooperate in interactive relationships (Gerpott et al., 2018; Woide et al., 2023a, 2021). Recently, the Interdependence theory has gained attention within the autonomous driving community, encouraging its application to measure drivers' perceptions of cooperation with vehicles (Woide et al., 2022, 2023b).

2.4.1. Conflict

The outcomes pursued by each partner can either be aligned or conflicting (Woide et al., 2021). In the context of cooperative driving, both the driver and the vehicle pursue common goals. Conflict arises when one partner disagrees with the other's actions or opinions regarding these shared goals (Woide et al., 2021). Research suggests that reduced conflict leads to increased trust between partners (Gerpott et al., 2018; Kelley and Thibaut, 1978). In the context of achieving cooperative goals, finding a new goal by one party affects the other's search for the goal, and sometimes, mutual agreement is required for new goals (across different autonomy levels). Poorly designed interactions may lead to misunderstandings of each other's intentions and purposes, resulting in conflict. Hence, we also examine whether transparency information in interface design can mitigate potential conflict issues.

2.4.2. Mutual Dependence

Mutual dependence refers to how the outcomes of each person are determined by their actions in certain circumstances (Gerpott et al., 2018). Partners' actions may increase or decrease the individual outcomes (Rusbult and Van Lange, 2008). Mutual dependence operates in two directions: (1) if outcomes are entirely independent of the other's actions, then interactions are independent; (2) if one person's decisions can alter the other's outcomes, then they are interdependent (Gerpott et al., 2018; Woide et al., 2021). Furthermore, one person's behavior can serve as a prerequisite for the partner's actions in that situation (Hoc, 2000). Woide et al. (2021) argue that the concept of mutual dependence is applicable to measuring how drivers perceive the distribution of dependencies in human-vehicle cooperation. For instance, whether a driver independently operates a vehicle or both the driver and the AV drive interdependently.

In our two studies, scenarios where humans take control (low autonomy) and vehicles drive directly to the goal (high autonomy) represent extreme cases of mutual independence, where their actions are independent of each other. On the other hand, scenarios where humans give instructions to the vehicle (medium autonomy A) and the AV waits for human approval (medium autonomy B) reflect characteristics of mutual dependence, as the actions of the AV depend on the driver's actions. Therefore, different autonomy levels may influence how drivers perceive the mutual dependence between themselves and AVs.

3. Architecture for Real-time Goal collaboration and HMI Design

To describe various forms of collaboration possibilities, we propose an architecture for real-time goal collaboration. Subsequently, we present seven interface design principles tailored to different transparency levels, aiming to facilitate human-machine interaction in this type of cooperation.

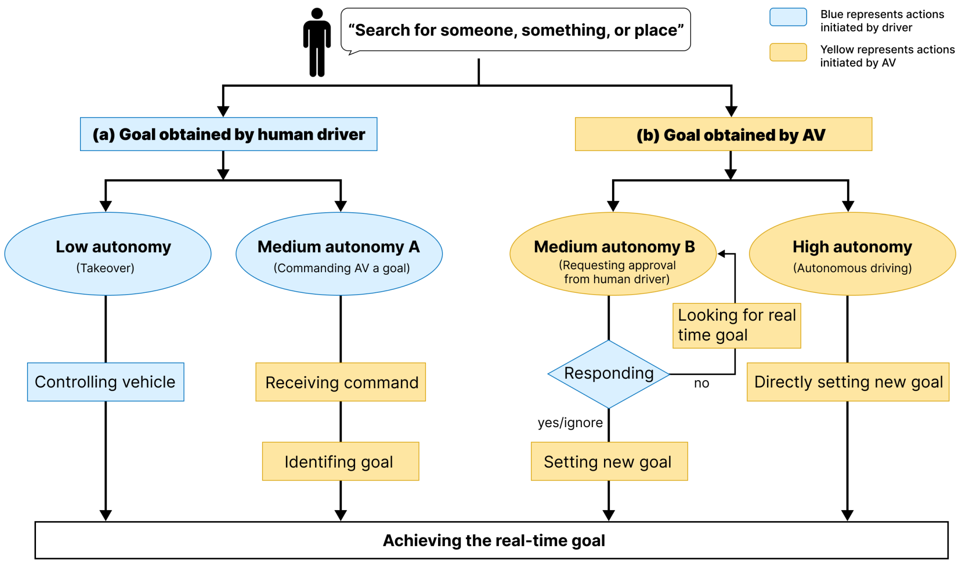

Figure 2.: Architecture for real-time goal collaboration. In the context of autonomous driving, the human driver instructs the AV to search for a specific goal (person, object, or location) along the route. Then, both the human and AV search for the goal simultaneously. (a) When the goal is obtained by the human driver, there are two options: low autonomy (takeover) or medium autonomy A (commanding the vehicle to a new goal) through gaze and voice commands. (b) When the goal is obtained by the AV, there are two options: medium autonomy B (the AV can request the driver's approval/disapproval to proceed to the new goal). If denied, it continues searching, or high autonomy (the AV can autonomously drive to the new goal).

3.1. Architecture for Real-time Goal Collaboration

We designed a cooperative architecture for real-time collaborative goal achievement (see Fig. 2). This architecture classifies four interactive types based on potential scenarios. Human drivers initially input target feature information, such as a photo or description, requesting the AV to search for the goal (person, object, or location) during the journey. Subsequently, during the simultaneous search process by both humans and the AV, two possible scenarios exist:

(a) When the goal is obtained by the human driver, there are two operational modes to choose from:

- Low autonomy: The driver can take control and manually drive the vehicle to the goal location.
- Medium autonomy A: The driver can indicate the AV to proceed to the goal location using gaze and voice commands (replaced by buttons in the experiment).

(b) When the goal is obtained by the AV, the following operational modes are available for selection:

- Medium autonomy B: The AV requests approval from the driver to proceed to the new goal location. The driver can approve, ignore, or deny the request. If approved or ignored, the AV drives to the new goal location. If denied, the AV continues searching for the goal.
- High autonomy: The AV can autonomously drive to the real-time goal location.

Table 1.: AV's information design for real-time goal collaboration adapted from SAT model(Chen et al., 2014). We have formulated seven design principles that align the three layers of transparency information for the agent with the information design requirements for the AV. These requirements are categorized into understanding of the environment and the internal status of the AV.

Situation Awareness-based Agent Transparency (SAT)	**Agent's information details**	**Principles**	**AV's information details**	
			Understanding of the environment	**Internal states**
Level 1: Goal and action	Purpose: Desire (Goal selection)	P1	x	Selection of real-time objectives
	Process: Intentions (Planning/Execution); Progress	P2	x	Illustration of task execution
	Performance	x	x	x
	Perception (Environment/Teammates)	P3	Indications of dangers from the environment to the vehicle	Task outcomes, response to driver
Level 2: Reasoning	Reasoning process (Belief/Purpose)	P4	Basis for inferring dangers	Reasoning of task progress, reasoning of task outcomes
	Motivations	P5	x	Goal constraints
Level 3: Projections	Projection of future outcomes	P6	Predictions of arrival time and destination	Predictions of task outcomes
	Uncertainly and potential limitations, Likelihood of success/failure	P7	Potential limitations of the destination	Uncertainty of results, accuracy of task outcome predictions
	History of Performance	x	x	x

3.2. Designing HMI with Transparency

As previously discussed, real-time cooperative goals can correspond to different autonomy levels of the AV, i.e., low, medium, and high autonomy. However, it remains unclear what kind of information interfaces should be provided for each autonomy level. Therefore, we refer to the SAT requirements proposed by **?** and propose relevant interface design principles based on the needs of real-time cooperative goals in autonomous driving (see Table 1). We map the three SAT levels of information provision from agents to AVs, categorized as AV's understanding of the environment and AV's internal states.

(1). In SAT Level 1, AVs should convey relevant information about their goals and actions to the drivers. AVs need to inform about their objectives and plans, assess the current state, provide perceptual information, and enable the driver to understand how the AV accomplishes tasks and perceives the environment and teammates. Therefore, the following design principles can guide AV interaction design:

- **Principle 1:** AVs should inform about their purpose and intentions, such as goal selection. When AVs change goals, highly autonomous AVs should inform the driver, while medium autonomous AVs should ask the driver to ensure the driver fully understands the AV's purpose.
- **Principle 2:** AVs should inform about the current task planning and progress to help the driver understand how the AV will accomplish tasks.
- **Principle 3:** AVs should inform about their perception of the environment and tasks to assist the driver in making decisions. AVs should provide perception of teammates, respond to driver commands, and help the driver confirm whether the AV has received commands.

(2). In SAT Level 2, AVs should convey the reasons and motivations behind their decisions and actions to the drivers. AVs should explain their reasoning process and considerations of the environment, constraints, and affordances during planning. Hence, the following design principles can be formulated:

- **Principle 4:** AVs should explain their beliefs and purposes. When recommending or taking decision options, AVs should provide explanations for the reasons behind those decisions. When acting, AVs should explain the underlying reasoning. When completing tasks, drivers should understand how AVs accomplished and determined task outcomes.
- **Principle 5:** AVs should promptly inform about constraints or affordances encountered during task completion. This prevents drivers from being surprised when there are interruptions or changes in AV tasks.

(3). In SAT Level 3, AVs should provide drivers with predictive information, including outcomes and uncertainties. AVs should convey predictions about future outcomes and additional reasoning behind decisions. AVs should inform about the possibility of task success or failure, uncertainties in predictions, and potential task limitations. Historical performance data can support predictive outcomes and uncertainties. Therefore, the following design principles can guide AV interaction design:

- **Principle 6:** AVs should communicate predictions about future states or task outcomes, enabling drivers to understand task results and adjust actions based on predictive information.
- **Principle 7:** AVs should inform about the uncertainty of information, likeli-

hood of task success or failure, and potential limitations, helping drivers fully understand the reliability of provided information. If uncertainty or failure rates are high, drivers should have the ability to verify independently.

These seven design principles can guide information design for interfaces with different levels of transparency in real-time collaborative goals. We apply these principles in the design of interfaces at different transparency levels for each interaction.

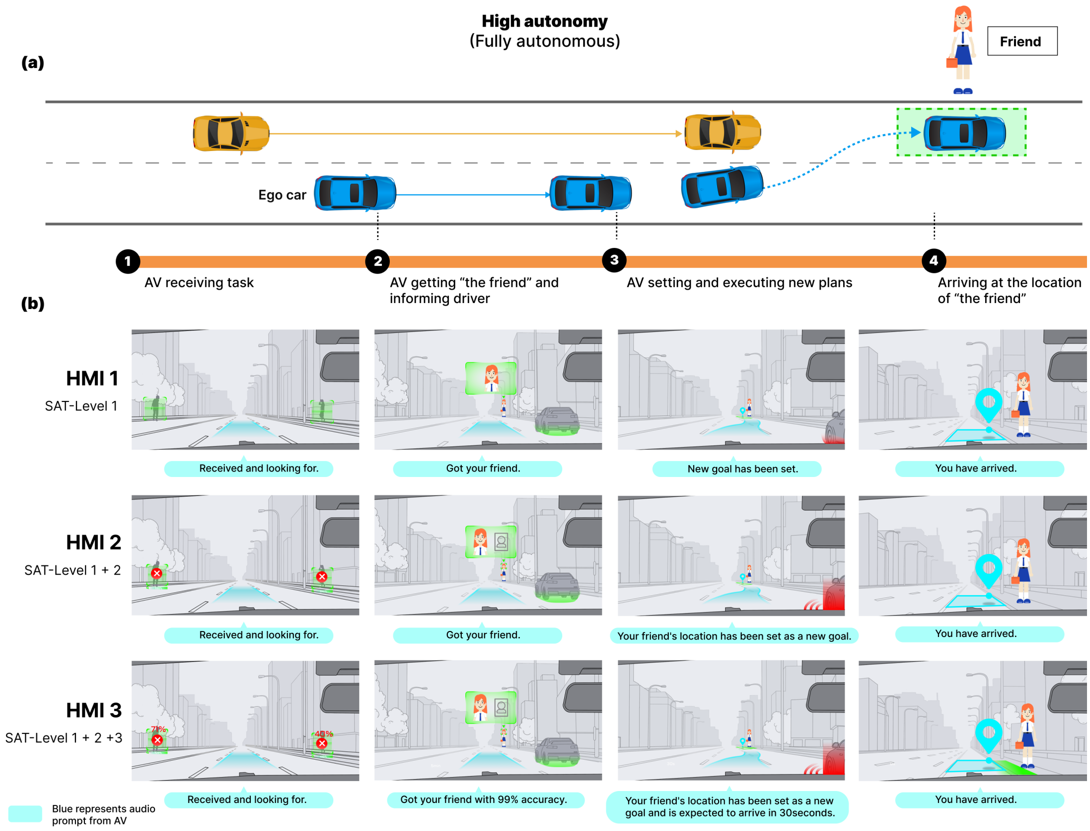

Figure 3.: HMI schemes design (using high-autonomy interface design as an example, the top image is reversed in orientation compared to the actual experimental setup for visual clarity). (a) Describes the different stages of the current scene. Initially, the human driver requests the vehicle's help in finding a friend through voice and shows the vehicle a picture of the friend. The vehicle then goes through four stages of cooperation: (1) Vehicle accepts the task. (2) Vehicle finds the friend. (3) Vehicle sets and executes a new plan. (4) Vehicle arrives at the friend's location. (b) Explains the design of the three transparency level interfaces for each stage of the cooperative process, including necessary voice responses. Scheme 1 follows principles 1, 2, and 3; Scheme 2 adds principles 4 and 5; Scheme 3 adds principles 6 and 7.

3.3. Interface Design Overview

Using the principles above, we designed interfaces for three levels of transparency in cooperation. Figure. 3 illustrates the design proposal for the high autonomy scenario. In the different stages, the current scenario unfolds as follows: (a) Initially, the human driver requests the vehicle's assistance in finding a friend through voice command and displays a photo of the friend. Then, the vehicle enters four stages of cooperation: 1). Vehicle accepts the task. 2). Vehicle finds the friend. 3). Vehicle sets and executes a new plan. 4). Vehicle arrives at the friend's location. (b) It outlines the design of the three transparency interface options for each stage in the cooperative process. HMI 1 follows principles 1, 2, and 3. HMI 2 adds principles 4 and 5. HMI 3 includes principles 6 and 7.

4. Study 1: Real-Time Goals Perceived by Human Drivers

4.1. Research Question and Hypotheses

Study 1 was conducted to address **RQ1: What interactive types and interface designs are better when the human driver first discovers the goal?** Drawing from the research question and the related work, we formulated the following hypotheses:

- **H1:** Drivers prefer commanding the vehicle to move towards the target rather than taking over control.
- **H2:** Taking over control results in higher workload compared to commanding the vehicle.
- **H3:** Commanding the vehicle leads to a better perception of mutual dependence, fewer conflicts, and increased satisfaction compared to taking over control.
- **H4:** Higher transparency leads to higher trust in both interactive types.
- **H5:** Higher transparency leads to a reduction in conflicts in both interactive types.

4.2. Participants

We recruited a total of 28 drivers to participate in the experiment, ranging in age from 19 to 30 years (M = 23.6, SD = 3.4). All participants held valid driver's licenses and had a minimum of one year of driving experience. Before the commencement of the experiment, participants completed demographic information and provided informed consent by filling out the necessary forms.

4.3. Scenarios and Tasks

The experiment utilized an urban road scenario where the AV (self-driving car) was traveling in the medium lane at a speed of 40 km/h (due to the maximum speed limit of 60 km/h on city roads in China and reduced speed during target search). Other vehicles were present in the left lane. The sidewalk had numerous pedestrians, and the experimental target person, referred to as "friend," would randomly appear at distances ranging from 110 to 350 meters from the vehicle. The "friend" was visible within the driver's field of view, and a parking space was located ahead on the road where the "friend" was present. We established the scenario where the driver discovered the "friend" before the vehicle did. Participants were required to perform tasks upon detecting the "friend." The different stages of the two interactive types are described in Figure 4.

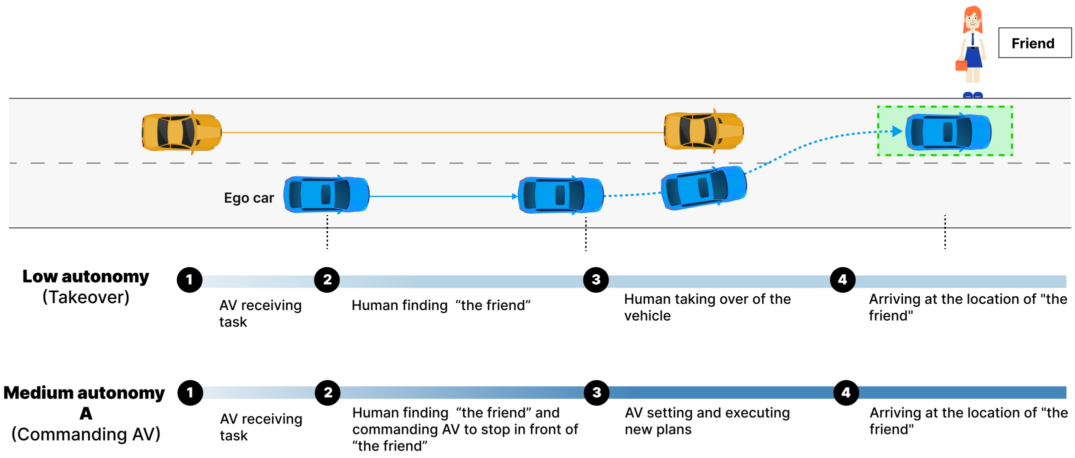

Figure 4.: Scenarios and tasks of Study 1: (For clarity of presentation, the top image is reversed from the actual experimental setup). In the takeover mode, four phases are experienced: (1) AV receives the task, (2) Human driver detects the friend, (3) Driver takes control of the vehicle, (4) Drives towards the target location. In the commanding mode, four phases are also experienced: (1) AV receives the task, (2) Human driver detects the friend and commands the vehicle to stop in front of the friend, (3) AV sets and executes a new plan, (4) AV drives towards the target location.

- **Low autonomy (takeover):** Participants took over control of the vehicle and manually drove it to park in the parking spot ahead of the "friend."
- **Medium autonomy A (commanding AV):** Participants commanded the vehicle to park in the parking spot ahead of the "friend" by pressing a button (the button replaced gaze-based and voice-based commands).

4.4. Experimental Design

We conducted a two-factor repeated-measures experiment. Participants experienced two interactive types and were randomly assigned to use three different interfaces to complete specific tasks. The description of the independent variables is as follows:

Interactive types. The interactive types include low autonomy (takeover) and medium autonomy A (commanding the vehicle to drive to a new destination). Fig. 4 illustrates the different stages of these two interactive types.

Interface. The term "interface" refers to three different interface designs created based on transparency levels. HMI 1 follows principles 1, 2, and 3; HMI 2 follows principles 4 and 5; and HMI 3 follows principles 6 and 7. The design elements in the schemes are explained as follows (see Fig. 5):

- **HMI 1:**
  (a) Searching for a target (dynamic scanning frame, see Fig.5 **1a**)
  (b) Obtaining the target (target discovered prompt, see Fig.5 **1b**, voice prompt for destination change prompt)
  (c) Warning of danger (vehicle danger prompt, see Fig.5 **1c**)
  (d) Reaching the destination (destination annotation, see Fig.5 **1d**)
- **HMI 2:**

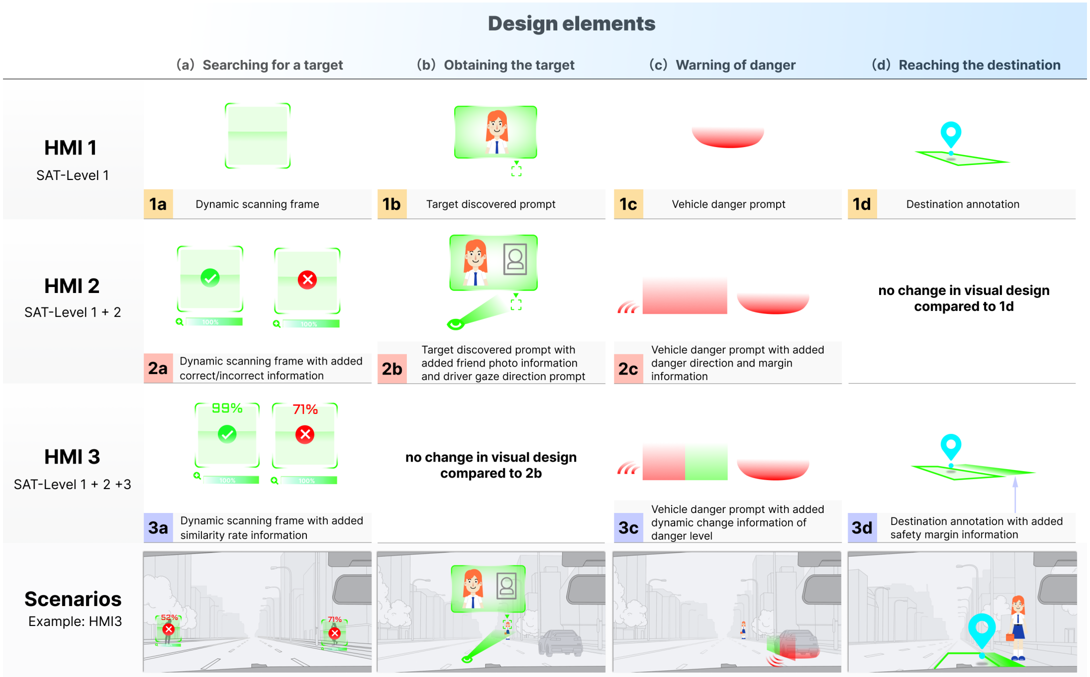

Figure 5.: HMI schemes design and elements of Study 1: We have aligned the seven proposed design principles with our implementation objectives for collaborative tasks, guiding the interface design with varying levels of transparency for each type of interaction. Across different stages of collaboration, distinct design principles have been applied to four main segments: (a) Searching for a target—Upon receiving a task, the AV provides a prompt indicating its active search for the target. (b) Obtaining the target—When a human identifies a target before instructing the AV, the AV responds accordingly. (c) Warning of danger—Upon detecting impending danger, the AV issues a warning. (d) Reaching the destination—As the vehicle approaches the destination, the AV presents cues related to target point establishment.

(a) Searching for a target (dynamic scanning frame with added correct/incorrect information, see Fig.5 **2a**)
(b) Obtaining the target (target discovered prompt with added friend's photo information and driver gaze direction prompt, see Fig.5 **2b**, voice prompt for destination change prompt with added location information)
(c) Warning of danger (vehicle danger prompt with added danger direction and margin information, see Fig.5 **2c**)
(d) Reaching the destination (destination annotation)

- **HMI 3:**
(a) Searching for a target (dynamic scanning frame with added similarity rate information, see Fig.5 **3a**)
(b) Obtaining the target (target discovered prompt with added friend's photo information and driver gaze direction prompt, voice prompt for destination change prompt with added estimated parking position and time information)
(c) Warning of danger (vehicle danger prompt with added dynamic change information of danger level, see Fig.5 **3c**)
(d) Reaching the destination (destination annotation with added safety margin

information, see Fig.5 **3d**)

4.5. Dependent Variables and Measurements

In order to comprehensively measure the effects of interactive types and interface transparency on drivers, this study's dependent variables include: usability and satisfaction, workload, interdependence, and trust.

- **Usability and Satisfaction.** The System Usability Scale (SUS) (Brooke, 1996) was employed to assess the interface's usability. A 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree) was used. The Acceptance Scale's 2.4.6.8 items were used to measure satisfaction (Laan et al., 1997).
- **Workload.** The impact of different cooperation modes on driver workload was measured using the Driving Activity Load Index (DALI), a revised version of NASA-TLX tailored for driving tasks (Pauzié, 2008). DALI assesses workload across dimensions such as effort of attention, visual demand, auditory demand, temporal demand, interference, and situational stress.
- **Interdependence.** The Human-Machine-Interaction-Interdependence (HMII) questionnaire developed by Woide et al. (2021) was employed to measure conflict and mutual dependence. The conflict dimension consists of 5 items, e.g., "Our preferred outcomes in this situation are in conflict." (Cronbach's alpha = 0.84). The mutual dependence dimension comprises 6 items, e.g., "We are dependent on each other in this situation." (Cronbach's alpha = 0.87). Both dimensions were scored on a 5-point Likert scale.
- **Trust.** Participants' trust in the autonomous driving system was measured using the scale developed by Jian et al. (2000), which includes 12 items representing factors influencing trust in the interaction with autonomous driving systems. Each item is rated on a scale from 1 to 7, with higher scores indicating higher levels of trust.

4.6. Materials and Equipment

The experiment was conducted on a self-developed driving simulation simulator system (see Fig. 6). This system consists of three 60-inch TVs and a car driving cabin, providing a panoramic view. The experiment was developed using Unity 3D, creating a 3D scene that simulates a real driving environment. Design elements were displayed on the screen (simulating a full windshield effect). The duration of experiencing each experimental scenario was approximately 72 seconds. The simulator software included a module for collecting vehicle data, allowing the recording of relevant data during the experiment.

4.7. Procedure

Each participant's experiment lasted approximately 40 minutes and consisted of the following steps: **(1)** Researchers introduced the experimental tasks and requested participants to read and sign informed consent forms. **(2)** Participants provided a photograph of the "friend" and engaged in simulated driving practice within a scene devoid of interface design elements. When the "friend" appeared, researchers instructed participants to ensure their recognition of the friend within the scene. **(3)** Researchers in-

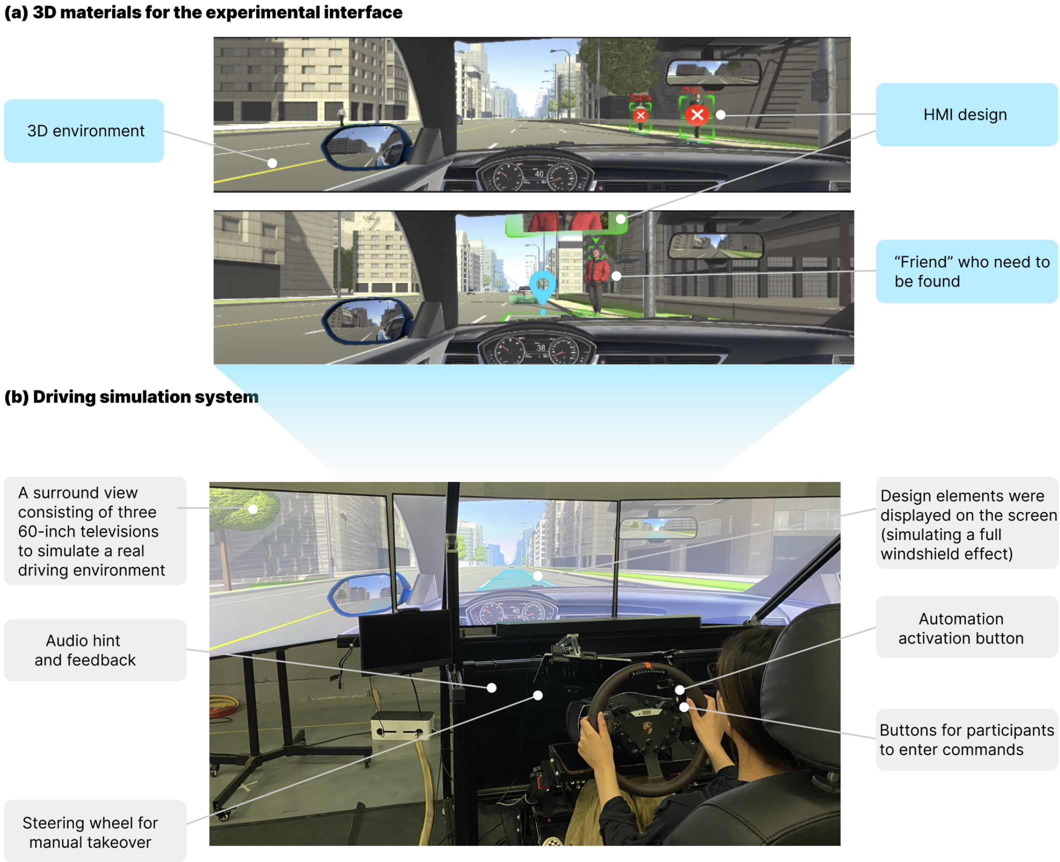

Figure 6.: Materials and equipment. (a) 3D materials for the experimental interface: The 3D scene of the experiment simulates a real driving environment. The scene depicts a three-lane urban road with other vehicles in motion. Pedestrians can be seen standing or walking on both sides of the road. Experiment target characters randomly appear between 110 to 350 meters from the vehicle, with a parking space ahead of them. Design elements are displayed on the full windshield for the driver's observation. (b) Driving simulation system: The driving simulation simulator system consists of three 60-inch TVs and a car driving cabin, providing a panoramic view. Design elements are displayed on the screen (simulating a full windshield effect). In addition to visual displays, the system also provides audio cues and feedback. The simulator can switch between manual and autonomous driving modes. When the driver toggles the automation activation button, the system switches to autonomous driving mode. When the driver starts turning the steering wheel, pressing the accelerator or brake, the system switches to manual driving mode. There is a button on the steering wheel that, when pressed, can execute voice and gaze commands in place of the driver. The seat can be personalized to meet the needs of different drivers.

troduced each participant to the interface design elements and their meanings, ensuring participants understood the design elements on the interface. **(4)** At the commencement of the formal experiment, participants randomly viewed three HMI schemes for two tasks, totaling six schemes. Prior to each task, researchers informed participants of the task objectives. **(5)** Following the conclusion of each task, participants completed relevant scales. **(6)** After all experiments were completed, a semi-structured interview was conducted, providing participants with the opportunity to offer detailed context-relevant verbal feedback on any design elements they encountered during the experiment.

4.8. Analysis and Results

The Shapiro-Wilk test was utilized to assess the normality of the data with small samples. Based on their results, the majority of dimensions were found to follow a normal distribution. Consequently, in the case of normal data, two-way repeated measures ANOVA was applied to examine the differences among the three SAT-based HMIs with two interactive types (low autonomy and medium autonomy A) and their interaction effects. The Hotelling's T-squared test (Hotelling, 1931), as a multivariate counterpart of the T-test, was used to examine the differences of performance among two interactive types in three HMIs and three HMIs with two interactive types. The post-hoc tests, using the pairwise T-tests for paired samples, were then conducted to further investigate specific group differences; In this study, two Python packages, namely Pingouin and Plotnine (Vallat, 2018), were utilized to perform various tests and visualize the results, respectively. In these figures, *p $=\leqslant 0.05; **p =\leqslant 0.01; ***p =\leqslant 0.001; ****p =\leqslant 0.0001$.

4.8.1. Usability and Satisfaction

In terms of usability, the two-way repeated measures ANOVA revealed no significant difference among interactive types and the interaction effects of two variables, but a significant difference was found among SAT-based HMIs: $F(2, 60) = 8.50$, $p < 0.001$. Conversely, there were significant differences in satisfaction for both variables: $F(1, 30) = 5.73$, $p = 0.023$, and $F(2, 60) = 24.47$, $p < 0.0001$. Furthermore, the results of the Hotelling's T-squared test indicated a significant improvement in satisfaction across the three HMIs with two interactive types: HMI 1 < HMI 2 < HMI 3, and their corresponding Hotelling's T-squared tests were $T^2 = 25.61$, $p < 0.001$ (HMI 1-HMI 2) and $T^2 = 7.91$, $p = 0.033$ (HMI 2-HMI 3). Figure 7(a) illustrates an increasing trend in usability and satisfaction for the HMIs, from 1 to 3. Post-hoc tests further confirmed that the combination of HMI 3 and medium autonomy A exhibited the highest usability and satisfaction.

4.8.2. Trust

The results of the two-way repeated measures ANOVA indicated no significant difference in trust among interactive types and the interaction effetcs of two variables, but a significant difference was observed for SAT-based HMIs: $F(2, 60) = 19.51$, $p < 0.0001$. Additionally, there was a significant improvement in trust across the three HMIs with two interactive types: HMI 1 < HMI 2 < HMI 3, and their corresponding Hotelling's T-squared tests were $T^2 = 21.42$, $p < 0.001$ (HMI 1-HMI 2) and $T^2 = 7.38$, $p = 0.041$ (HMI 2-HMI 3). The multiple comparison results presented in Figure 7(b) demonstrated that both the HMI 3 with low autonomy and the HMI 3 with medium autonomy elicited the highest level of trust from the users.

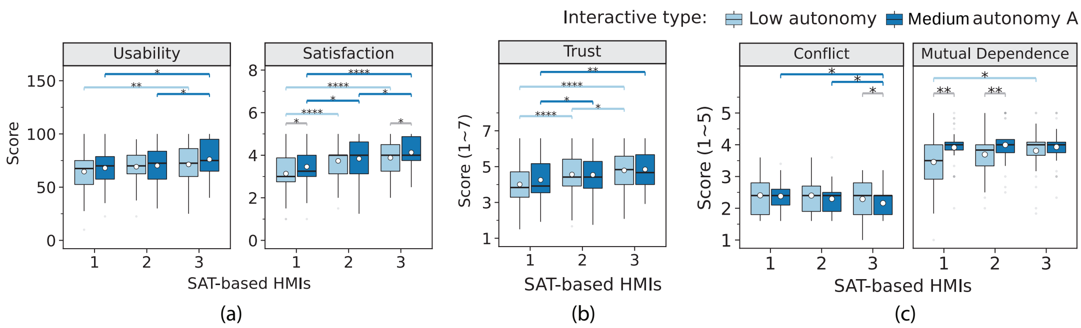

Figure 7.: Multiple comparison across three main groups of dimensions with the significance labels of pairwise T-tests results: two interactive types and three SAT-based HMIs. The comparisons were made for the following dimensions: (a) Usability and satisfaction. (b) Trust. (c) Interdependence: conflict and mutual dependence. Notably, the combination of medium autonomy A and HMI 3 yielded the highest usability, satisfaction, trust, and mutual dependence, while simultaneously resulting in the lowest conflict.

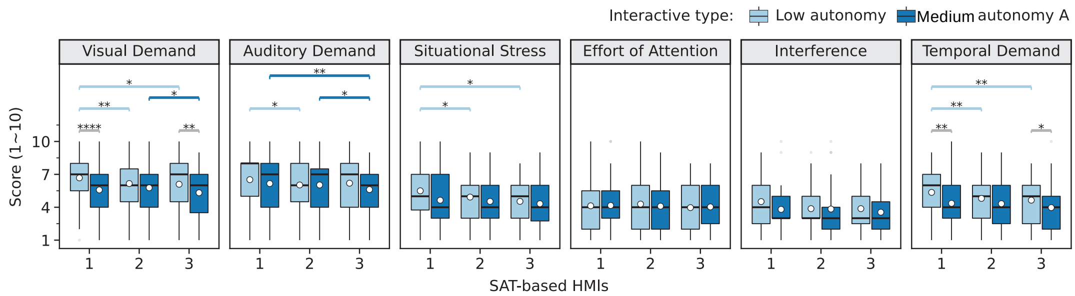

Figure 8.: Multiple comparison across workload's six dimensions with the significance labels of pairwise T-tests results: two interactive types and three SAT-based HMIs. Notably, the medium autonomy A outperformed low autonomy significantly, and a consistent increasing trend was observed among the HMIs, from 1 to 3.

4.8.3. Interdependence: Conflict, Mutual dependence

As shown in Figure 7(c), the two-way repeated measures ANOVA revealed no significant difference only in conflict for interactive types: F(1, 30) = 2.22, p = 0.146, and the interaction effects of two variables. Moreover, the results of the Hotelling's T-squared test revealed that HMI 3 exhibited the lowest conflict (T^2 = 7.71, p = 0.036 for HMI 3 - HMI 1 and T^2 = 9.01, p = 0.022 for HMI 3 - HMI 2). Additionally, medium autonomy A displayed higher mutual dependence compared to low autonomy (T^2 = 17.32, p = 0.004 for mutual dependence, although no significant difference was observed in conflict, T^2 = 5.51, p = 0.187). Notably, Figure 7(c) displayed a consistent decreasing trend in conflict and an increasing trend in mutual dependence as the HMIs progressed from 1 to 3. Furthermore, a more detailed analysis using pairwise T-tests revealed that the combination of medium autonomy A and HMI 3 resulted in the lowest conflict and highest mutual dependence.

4.8.4. Workload

The two-way repeated measures ANOVA indicated significant differences in interactive types or SAT-based HMIs for almost all dimensions, with the exception of effort of attention (F(1, 30) = 0.04, p = 0.838, F(2, 60) = 0.58, p = 0.563) and interference (F(1, 30) = 3.27, p = 0.080, F(2, 60) = 2.34, p = 0.105). However, there was no significant difference observed in their interaction effects across all dimensions. Additionally, the Hotelling's T-squared test results revealed noteworthy findings. Specifically, medium autonomy A exhibited significantly lower scores than low autonomy in three HMIs for two dimensions, namely visual demand (T^2 = 23.03, p = 0.001) and temporal demand (T^2 = 14.25, p = 0.011). Furthermore, HMI 3 demonstrated significantly lower scores than HMI 1 using two interactive types for all dimensions, except for effort of attention (T^2 = 0.51, p = 0.783) and interference (T^2 = 5.23, p = 0.097). Interestingly, these workloads displayed a consistent decreasing trend with the order of the HMIs, from 1 to 3. Moreover, a more detailed analysis using pairwise T-tests (see Figure 8) revealed that the combination of medium autonomy A and HMI 3 yielded the lowest workload.

4.8.5. Interview Results

After the conclusion of the experiment, we conducted semi-structured interviews with the participants, focusing primarily on their perceptions of the interaction types and their experiences using the interface. The interview results are presented below:

interactive types. When asked about their preferences for these two interactive types, several participants expressed dissatisfaction with the takeover mode, generally believing that it didn't allow them to experience the superiority of autonomous driving and intelligent recognition. Some participants mentioned: *"I don't like taking over; it feels a bit troublesome."* (p15) *"I don't like taking over. I feel like I can't experience the advantages of autonomous driving and intelligent recognition in this way."* (p2) These feedback comments indicate issues with the takeover mode in terms of user experience.

Workload. User feedback from the interviews emphasized that the takeover mode added additional cognitive and situational pressures to users, including the need to monitor changes in road conditions and handle various driving-related information. One participant pointed out, *"There are too many manual intervention parts in taking over. I need to pay more attention to driving, which defeats the purpose of autonomous driving."* (p6). *"In the case of manual takeover, I need to pay attention to road information, whether my friend is on the roadside, and after spotting my friend, I still* *need to be aware of oncoming vehicles on the roadside. I need to see if I can park on the roadside. It feels too bothersome."* (p20).

Interfaces. When participants were asked about which design elements from the experienced interfaces left the deepest impression, the information design of transparency resonated with users. Particularly during the pedestrian scanning process, some users in the interviews mentioned the following points: *"The display of correct and incorrect decisions (HMI 2) is important. If it's not provided (HMI 1), I would feel like it's just a pedestrian detector, and I wouldn't know if it excluded anyone."* (p13) *"Providing the accuracy rate is crucial (HMI 3). I can make a judgment again for the group of people with a relatively high similarity rate. This prevents situations where I accidentally exclude someone who is actually my friend."* (p13) These responses indicate that during the process of searching for friends, drivers utilize cognitive information provided by the vehicle, rather than solely searching on their own.

Suggestions. In the final stage of the interviews, participants provided insightful suggestions. They expressed appreciation for the "Find Friends" feature, but some users also voiced concerns about privacy issues. One participant stated, *"I would like the vehicle to have this feature, but I think it could bring a lot of problems. For example, uploading photos could lead to privacy concerns."* (p19). Furthermore, participants proposed ideas for feature expansion, especially in scenarios where drivers need to find unfamiliar passengers, such as ride-sharing and business receptions. One participant mentioned, *"This feature might be more suitable for Uber's target scenario, where the driver needs to pick up someone they don't know at all, or in situations where they need to entertain business clients. This feature would be very useful."* (p11). These suggestions highlight the promotion and application scenarios of this feature.

4.9. Discussion of Study 1

In Study 1, we examined the differences in satisfaction, workload, and interdependence between the low autonomy (takeover) and medium autonomy A (commanding the vehicle to drive to a new destination) interactive types in real-time goal collaboration when the human driver first detected the target. Using quantitative methods, we compared the performance of these two interactive types. Additionally, we investigated whether the transparency of the interface influenced the trust and interdependence of human drivers towards the AV.

The results for both interactive types supported **H1**, indicating that the command mode exhibited advantages over the takeover mode in terms of perceived usability and satisfaction by participants. Through interviews, we observed higher satisfaction among users with the command mode, as they believed it better aligned with their expectations of the autonomous driving system. Conversely, participants generally expressed dissatisfaction with the takeover mode, feeling it hindered them from experiencing the superiority of the autonomous driving system and made it almost indistinguishable from manual driving. Furthermore, **H2** was supported, suggesting that the command mode potentially had an advantage in reducing participants' cognitive workload during the interaction. User feedback in interviews emphasized the cumbersome and less intelligent nature of the takeover mode, requiring users to divert more attention to the driving task. The results also indicated that while there was no significant difference between the takeover mode and command mode in terms of conflict, there was a significant difference in terms of mutual dependence, thus partially supporting **H3**. Specifically, the command mode demonstrated a higher level of mutual dependence, possibly due to the fact that the AV required human commands to execute the next action, leading to stronger mutual dependence.

Regarding transparency, **H4** was supported, suggesting that interface transparency significantly influenced human drivers' trust in the autonomous driving system. The study further revealed that increased interface transparency was significantly associated with higher levels of trust among human drivers towards the AV, irrespective of whether it was in the takeover or command mode. This finding underscores the importance of interface design in establishing trust. Additionally, **H5** was partially supported. While no significant impact of transparency on conflict was observed in the manual driving mode, an increase in transparency was positively correlated with reduced conflict in the command mode. This finding suggests that increased transparency can provide more information about AV behavior, aiding drivers in better understanding the system's intent and subsequently reducing conflicts, especially in medium autonomy driving modes. It is noteworthy that we also observed a gradual increase in participant satisfaction with higher transparency levels in both interactive types. This finding aligns with prior research (Wang et al., 2020). Furthermore, the use of high transparency interfaces reduced visual and auditory demands during the interaction process, as well as contextual pressure, in both interactive types, consistent with prior research (Chen and Barnes, 2014; Parasuraman et al., 2000).

The results indicate that, when the human driver detects the target first, the command mode has advantages over the takeover mode in terms of usability, satisfaction, and cognitive workload. The transparency of the interface also plays an important role in trust and conflict in the context of autonomous driving systems.

5. Study 2: Real-time Goal Perceived by AV

5.1. Research Question and Hypotheses

In Study 2, we aim to compare the collaborative modes of medium autonomy B (driver approval required) and high autonomy (AV fully autonomous), as well as different transparency interfaces under specific conditions when the AV initially detects a target. This study is designed to address **RQ 2: What interactive types and interface designs are better when the AV first discovers the goal?** The following hypotheses are proposed:

- **H6:** Drivers exhibit higher satisfaction with medium autonomy B compared to high autonomy.
- **H7:** Drivers experience higher workload with medium autonomy B compared to high autonomy.
- **H8:** medium autonomy B results in lower driver conflict and higher mutual dependence compared to high autonomy.
- **H9:** Higher transparency interfaces in both autonomy levels lead to greater driver trust in the AV.

5.2. Participants

We recruited 31 drivers for the experiment, aged between 18 and 31 (M = 23, SD = 3.2). All participants held valid driver's licenses and had at least one year of driving experience. Before the experiment, they provided demographic information and signed

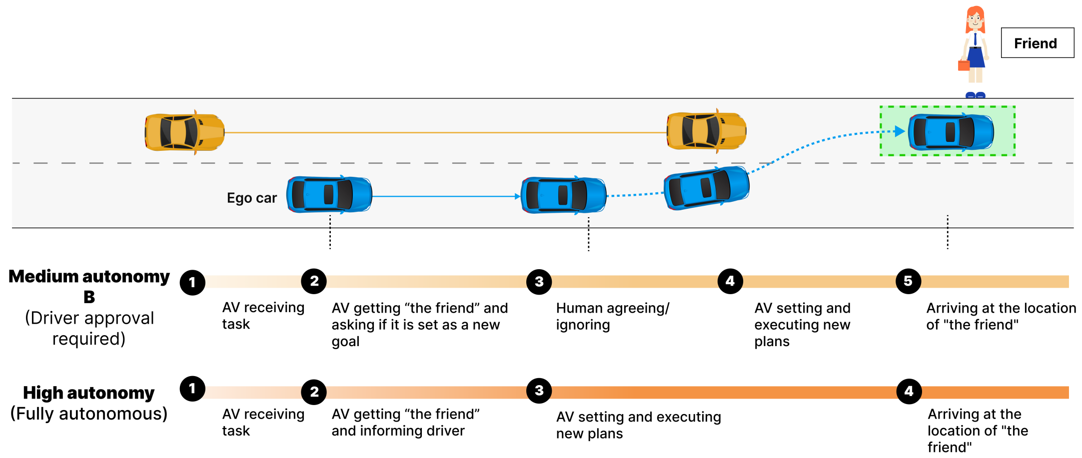

Figure 9.: Scenarios and tasks of Study 2: The top image illustrates the driving process after the human driver discovers the "friend" (for clarity of illustration, the top image is reversed compared to the actual experimental setup). In the medium autonomy B mode, participants went through five stages: (1) AV accepts the task, (2) AV discovers the friend and requests driver approval, (3) Driver approves, (4) AV sets a new execution plan, and (5) AV drives to the target location. In the high autonomy mode, participants also went through four stages: (1) AV accepts the task, (2) AV discovers the friend and informs the driver, (3) AV sets and executes a new plan, and (4) AV drives to the target location.

informed consent.

5.3. Scenarios and Tasks

The scenario setup is the same as in Study 1 (see Section 4.3), with the difference being that in this case, the vehicle discovers the "friend" first (see Fig. 9). We instructed participants to complete the following two tasks when the vehicle issued a signal indicating that it had found the "friend." Fig. 4 illustrates the different stages of the two interactive types:

- **medium autonomy B (driver approval required):** When the AV detects the "friend," it sends a prompt to the driver indicating the discovery of the target (enlarged image of the target person) and a request to change the target (voice query asking if the new target should be set). Participants need to approve the vehicle by pressing a button, and once approved, the vehicle drives to the parking spot near the "friend."
- **High autonomy (AV fully autonomous):** When the AV detects the "friend," the driver receives a prompt from the vehicle indicating the discovery of the target (enlarged image of the target person). The vehicle then directly drives to the parking spot near the "friend," and the driver does not need to perform any additional tasks.

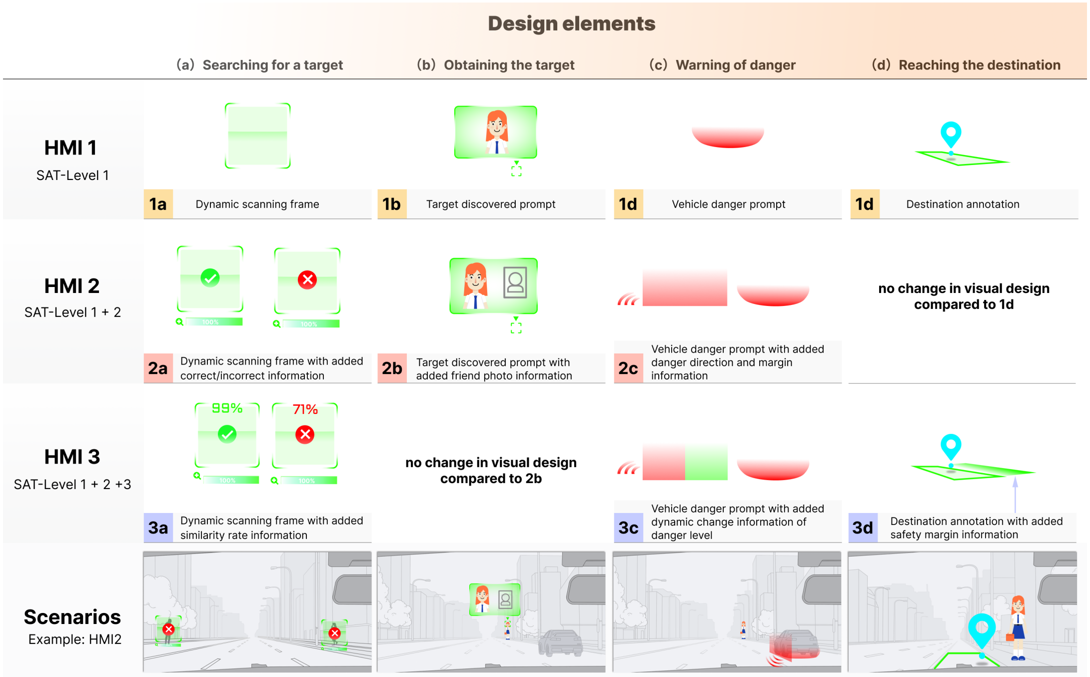

Figure 10.: HMI schemes design and elements of Study 2. We have correlated the seven proposed design principles with the objectives of our collaborative task implementation, guiding the interface design with different levels of transparency for each interaction type. Across various stages of collaboration, distinct design principles have been primarily applied to four components: (a) Searching for a target—Upon receiving a task, the AV informs the driver that it is searching for the target friend. (b) Obtaining the target—When the AV locates the target friend, it notifies the driver. (c) Warning of danger—In the event of detected danger, the AV provides alerts. (d) Reaching the destination—As the vehicle nears the destination, the AV offers cues for setting a target point.

5.4. Experimental Design

We conducted a two-factor repeated-measures experiment. Participants engaged in two interactive types and experienced three different interfaces in random order to complete tasks. The dependent variables measured is the same as in Study 1, including satisfaction and usability, workload, Interdependence, and trust (see Section 4.5). The description of the independent variables is as follows:

interactive types. The interactive types consisted of medium autonomy B (driver approval required) and high autonomy (AV fully autonomous). Fig. 9 illustrates the distinct stages of these two interactive types.

Interface. According to the transparency levels, we designed three different interfaces. HMI 1 follows principles 1, 2, and 3. HMI 2 follows principles 4 and 5. HMI 3 follows principles 6 and 7. The design elements in the schemes are explained as follows (see Fig. 10):

- **HMI 1:**
  (a) Searching for a target (dynamic scanning frame, see Fig.10 **1a**)
  (b) Obtaining the target (target discovered prompt, see Fig.10 **1b**, voice

prompt for destination change prompt)

(c) Warning of danger (vehicle danger prompt, see Fig.10 **1c**)

(d) Reaching the destination (destination annotation, see Fig.10 **1d**)

- **HMI 2:**

  (a) Searching for a target (dynamic scanning frame with added correct/incorrect information, see Fig.10 **2a**)

  (b) Obtaining the target (target discovered prompt with added friend's photo information, see Fig.10 **2b**, voice prompt for destination change prompt with added location information)

  (c) Warning of danger (vehicle danger prompt with added danger direction and margin information, see Fig.10 **2c**)

  (d) Reaching the destination (destination annotation)

- **HMI 3:**

  (a) Searching for a target (dynamic scanning frame with added similarity rate information, see Fig.10 **3a**)

  (b) Obtaining the target (target discovered prompt with added voice prompt for accuracy information, voice prompt for destination change prompt with added estimated parking position and time information)

  (c) Warning of danger (vehicle danger prompt with added dynamic change information of danger level, see Fig.10 **3c**)

  (d) Reaching the destination (destination annotation with added safety margin information, see Fig.10 **3d**)

5.5. Materials, Equipment and Procedure

The materials, equipment, and procedure were identical to those used in Study 1 as described in Section 4.6 and Section 4.7.

5.6. Analysis and Results

The experimental data was analyzed using the same method as that in Section 4.8 of the study 1.

5.6.1. Usability and Satisfaction

As illustrated in Fig. 11(a), the two-way repeated measures ANOVA indicated no significant difference in usability and satisfaction among the two variables (namely interactive types and SAT-based HMIs), and the interaction effects of two variables.

5.6.2. Trust

The results of the two-way repeated measures ANOVA showed no significant difference in trust among interactive types and the interaction effects of two variables. However, a significant difference was observed for SAT-based HMIs: $F(2, 60) = 6.88$, $p = 0.002$. Additionally, the results of the Hotelling's T-squared test indicated that HMI 3 with two different interactive types exhibited significantly higher levels of trust compared to HMI 1 and HMI 2: $T^2 = 9.38$, $p = 0.019$; and $T^2 = 19.71$, $p < 0.001$, respectively. The multiple comparison results in Figure 11(b) demonstrated that the HMI 3 with high autonomy or medium autonomy yielded the highest levels of trust for the users.

5.6.3. Interdependence: Conflict, Mutual dependence

The two-way repeated measures ANOVA revealed significant differences only in interactive types for mutual dependence: F(1, 30) = 9.67, p = 0.004. There was also no significant difference in the interaction effects of two variables. Additionally, the results of the Hotelling's T-squared test and the multiple comparison analysis (see Figure 11(c)) demonstrated that medium autonomy B displayed significantly higher levels of mutual dependence compared to high autonomy across the three SAT-based HMIs: $T^2 = 9.72$, p = 0.046.

5.6.4. Workload

The two-way repeated measures ANOVA indicated significant differences in interactive types or SAT-based HMIs for three dimensions: visual demand, auditory demand, and situational stress (F(1, 30) = 8.37, p = 0.007, F(2, 60) = 5.05, p = 0.009), (F(1, 30) = 5.01, p = 0.033, F(3, 60) = 4.12, p = 0.021), and (F(1, 27) = 8.86, p = 0.006, F(2, 54) = 4.27, p = 0.019), respectively. However, there was no significant difference observed in their interaction effects across all dimensions. Additionally, the Hotelling's T-squared test results revealed noteworthy findings. Specifically, high autonomy exhibited significantly lower scores than medium autonomy B in three HMIs for two dimensions, namely visual demand ($T^2 = 16.98$, p = 0.005) and situational stress ($T^2 = 11.44$, p = 0.029). Furthermore, HMI 3 demonstrated significantly lower scores than HMI 1 using two interactive types for three dimensions: visual demand ($T^2 = 10.98$, p = 0.011), auditory demand ($T^2 = 7.95$, p = 0.033), and temporal demand ($T^2 = 8.84$, p = 0.024). Interestingly, these workloads displayed a consistent decreasing trend with the order of the HMIs, from 1 to 3. Moreover, a more detailed analysis using pairwise T-tests (see Figure 12) revealed that the combination of HMI 3 with high autonomy yielded the lowest workload in terms of workload.

5.6.5. Interview Results

After the experiments, we conducted semi-structured interviews with participants to gather their preferences regarding the interactive types and their subjective perceptions of the interface design elements. The main interview findings are as follows:

Interactive types. We found supporters for both interactive types among the users. Some participants mentioned that the medium autonomy B made them feel more in control and engaged, especially in confirming the vehicle's intentions. Among them, Participant p1 stated: *"In the scenario of finding a friend, if the vehicle asks me after finding them, it would make me feel that it's ready and also bring my attention to it."* On the other hand, some users expressed a preference for the high autonomy type. *"I like fully autonomous driving, where I don't need to be involved throughout and can reduce the need to judge road conditions while driving. If the vehicle asks me and then I confirm, it would feel like I have to pay attention to both the road conditions and the vehicle's inquiries, which could be a bit bothersome."* (p24) Overall, both interactive types have their own supporters, which could be related to users' different expectations and preferences regarding the level of intelligence in autonomous driving technology.

Regarding mutual dependence, we found that in the high autonomy interaction, users highly desired similar information prompts as those in the medium autonomy B. This also indicated a stronger reliance on the medium autonomy B mode. Participant p9 stated: *"In fully autonomous driving, I can't determine the vehicle's intent. Without my confirmation, I'm concerned about the vehicle misidentifying something."*

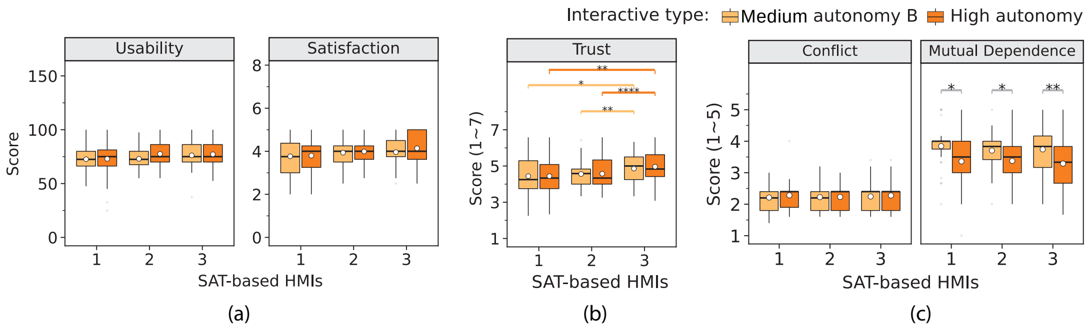

Figure 11.: Multiple comparison across three main groups of dimensions with the significance labels of pairwise T-tests results: two interactive types and three SAT-based HMIs. The comparisons were made for these dimensions: (a) Usability and satisfaction. (b) Trust. (c) Interdependence: conflict and mutual dependence. Notably, the combination of HMI 3 with high autonomy or medium autonomy B yielded highest trust and there was no significant difference between high autonomy or medium autonomy B.

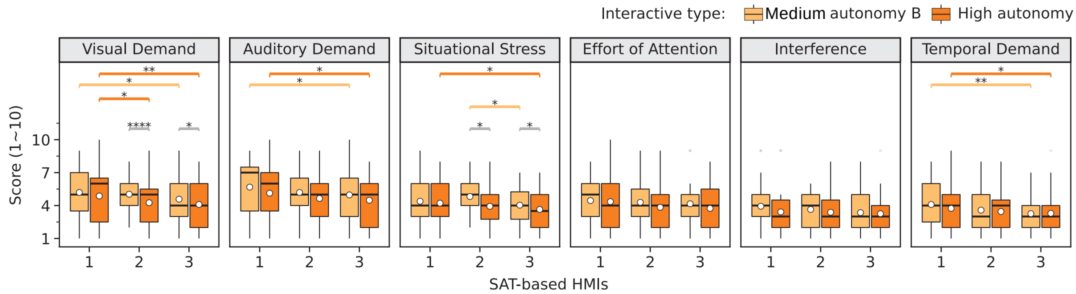

Figure 12.: Multiple comparison across workload's six dimensions with the significance labels of pairwise T-tests results: two interactive types and three SAT-based HMIs. Notably, the high autonomy outperformed medium autonomy B significantly, and a consistent increasing trend was observed among the HMIs, from 1 to 3.

Participant p22 also mentioned: *"Confirming after the vehicle asks me would make me feel that if the vehicle identifies something incorrectly, I can correct it. If the vehicle is fully autonomous, I would feel completely controlled without any initiative of my own."* These viewpoints indicate that even with highly autonomous driving, some users still wish to have a certain level of control to rectify potential errors and ensure safety.

Workload. Participants generally believed that the goal of autonomous driving technology is to reduce human intervention, ideally allowing the vehicle to autonomously handle most tasks and minimizing visual and auditory attention during the driving process. Participant p5 stated: *"If the vehicle's autonomy increases, I can minimize my intervention as much as possible and reduce my visual and auditory involvement."* Participant p20 mentioned: *"Full autonomous driving achieves not needing my involvement throughout, reducing the need to judge road conditions while I drive. I think this is what future autonomous driving should be like."*

Interface. Based on users' interview feedback on interface usability, we noticed a strong interest in the presentation of reasoning process information. For example, in HMI 1, only a green box represents the scanning process, while in MHI 2, the scanning result (correct or incorrect) is included. Participant p24 said: *"After the vehicle finds my friend, enlarging their appearance and adding a photo (HMI 2) makes me feel better than just enlarging their appearance (HMI 1). It gives me more peace of mind and makes me more certain that this is the person I'm looking for."* Another participant, p26, mentioned: *"If the vehicle provides symbols for correct and incorrect decisions, I only need to verify its results, and I don't need to start from scratch to determine if this person is my friend. I think the reaction process would be slightly shorter and more convenient."* In HMI 3, deterministic information (percentage accuracy) played a crucial role in enhancing driver trust, whereas HMI 2 only included the scanning result. Users believed that accuracy information helps eliminate errors, reducing visual burden and increasing driver trust in the autonomous driving system. Participant p5 stated: *"The most useful one should be accuracy (HMI 3). If it's just scanning (HMI 1), I would still subconsciously check the status inside the scanning box. Because, with just scanning, I can't be sure if its judgment is correct."* These feedback comments suggest that interface transparency can help users better confirm and verify the vehicle's judgment results, reducing cognitive load and enhancing user trust in the autonomous driving system.

Suggestions. In the end, participants also provided many interesting suggestions, some of which included scenarios we hadn't previously considered. Firstly, they hoped for more voice prompts, believing that it would enhance the overall system. Additionally, they raised questions about certain confusing situations. For instance, *"If their friend has their back turned to them, can the vehicle still recognize them? In adverse weather conditions like rain, snow, or fog, would the accuracy of the vehicle's recognition be affected? If they give the vehicle a photo of their friend standing, but in reality, the friend is crouched on the roadside, would the vehicle be able to recognize it?"* (p10) Furthermore, they suggested some feature expansion ideas. Some participants believed, *"The connection between the vehicle and the friend is still relatively weak. If methods for positioning and location sharing could be added, it would be better (via mobile positioning software)."* (p7) Other suggestions involved applying this feature to other scenarios. For example, *"When a colleague invites you to dinner, they can take a picture to show you they're near a certain location with a landmark. But both you and your colleague might not know what that place is. You can give this photo to the vehicle, and it can find the landmark from the photo."* (p5) These suggestions demonstrate that real-time collaborative targeting has extremely diverse application scenarios and aligns with people's expectations for future intelligent living.

5.7. Discussion of Study 2

In Study 2, we focused on the differences between the medium autonomy B (driver approval required) and high autonomy (AV fully autonomous) interactive types of AV when the AV first detects a real-time target. We examined these differences in terms of driver satisfaction, workload, and mutual dependence. We employed quantitative methods to compare the performance of these two interactive types in the context of real-time goal collaboration. Additionally, we investigated whether the transparency level of the interface would affect human drivers' trust and perception of mutual dependence on the AV. The following sections detail our research findings.

H6 was not supported. Our quantitative results indicated no significant differences in usability and satisfaction between the medium autonomy B and high autonomy interactive types. This finding contrasts with previous studies(Huang et al., 2015; Sun et al., 2017). The divergence might be due to the fact that both medium autonomy B and high autonomy modes have their respective advocates. Some participants, as revealed in interviews, felt more empowered and engaged with the medium autonomy B interaction type, while others favored the high autonomy mode, envisioning minimal intervention in line with their expectations of autonomous driving. **H7** was supported. Our quantitative results showed that the medium autonomy B interactive type exhibited higher workload in terms of visual demands and situational stress. Some participants expressed a preference for the high autonomy interaction type, as they anticipated reduced intervention from the autonomous driving system during the driving process. **H8** received partial support. Quantitative data did not demonstrate a significant difference in conflict perception between the medium autonomy B and high autonomy interactive types. This might be attributed to the experimental scenario's predefined goals, as prior research suggested that conflicts primarily arise from differing objectives and expectations(Woide et al., 2023a). While conflicts arising from AV recommending or autonomously heading towards an incorrect target were not considered in this study, a significant difference in mutual dependence was observed between the two interactive types. The medium autonomy B mode exhibited stronger mutual dependence, likely because it required the driver's approval for the AV's subsequent actions, fostering a sequential cooperation dynamic. Furthermore, participants stated that the medium autonomy B mode offered them a greater sense of control. **H9** was supported. The results indicated that both the medium autonomy B and high autonomy interactive types saw increased driver trust with enhanced transparency levels. This finding aligns with previous research(Chen and Barnes, 2014; Helldin et al., 2014; Joseph et al., 2016). This discovery underscores that higher transparency levels enhance driver trust regardless of the chosen interactive type.

6. Comprehensive Discussions and Design Implications of Two Studies

This study explores a novel collaboration mode termed real-time goal collaboration. In the paper, we introduce a framework that categorizes this cooperation into two scenarios: human-first detection and AV-first detection of the target. Subsequently, we propose seven transparency-based principles to guide the interface design for such cooperation. Finally, we compare different interactive types and interfaces through two studies.

6.1. Key Findings

The study results highlight several significant findings. Firstly, regardless of whether the target is detected by humans or by the AV, participants tend to prefer more autonomous interactive types, evident from their overall aversion to takeover scenarios. Although opinions differ when the AV first detects the target, participants express that high autonomy may lack a sense of control and involvement, suggesting room for improvement through design interventions. Secondly, when pursuing the same target, conflicts between humans and AVs are absent. However, the command mode (medium autonomy A) exhibits stronger mutual dependence compared to the takeover mode (low autonomy), and requiring human approval (medium autonomy B) demonstrates stronger mutual dependence than autonomous execution (high autonomy). This implies that not only during fully independent scenarios but also during varying levels of cooperation, a certain degree of mutual reliance exists(Gerpott et al., 2018; Woide et al., 2021). Lastly, irrespective of the interaction type, trust is closely tied to the transparency of the interface(Chen and Barnes, 2014; Helldin et al., 2014; Joseph et al., 2016). Hence, to gain drivers' trust, the AV's internal state should be promptly conveyed through the interface. This also signifies that the seven transparency design principles proposed in the study demonstrate efficacy.

Overall, these findings hold significant implications for the interaction design between humans and AVs in real-time goal collaboration scenarios. They underscore preferences for more autonomous interactive types, emphasize the importance of interface transparency for mutual dependence and trust-building, and validate the effectiveness of the proposed transparency design principles. These insights offer valuable guidance for human-vehicle cooperation interface design.

6.2. Design Implications

To enhance the efficiency and user experience of real-time goal collaboration between humans and AVs, drawing from our findings and qualitative results, we propose several design considerations:

(1) **Provide customizable autonomous interactive types.** People tend to favor more autonomous interactive types. Therefore, when designing human-machine interfaces, consider offering customizable settings and personalized driving preferences to achieve this.

(2) **Enhance sense of control and involvement.** In cases where the AV first detects the target, participants expressed a lack of control and involvement. Interface design can address this by involving drivers in decision-making processes, such as providing suggestions or choices, thereby increasing their sense of participation and control over the entire driving experience.

(3) **Mutual dependence.** When pursuing a common goal, conflicts between humans and AVs are minimal, and a certain degree of mutual dependence exists. Hence, in interface design, drivers should feel the cooperative relationship with the AV, with support and feedback provided to facilitate effective collaboration.

(4) **Elevate interface transparency.** Trust is closely linked to interface transparency. To establish drivers' trust in AVs, interfaces should promptly convey the AV's underlying internal state and decision-making processes. This can be achieved through visualizing the AV's perception information, behavioral intentions, decision processes, and providing explanations and understandable feedback.

7. Limitations

While our study provides meaningful insights, there are still some limitations. (1) Our research primarily focuses on a specific real-time goal collaboration scenario, so the applicability in other driving contexts requires further validation. (2) Although our interface design framework demonstrated favorable performance in system evaluations, its real-world effectiveness in broader driving scenarios needs to be verified. (3) Future research may need to consider additional factors, such as drivers' cultural backgrounds and individual differences. (4) This study did not take into account the issue of overtrust in trust measurement. Changes in trust require multiple and prolonged interaction experiences, which the current experimental conditions do not accommodate. Future studies could explore trust variations through long-term observation and tracking to examine how trust evolves with extended use of autonomous driving systems.

8. Conclusion and Future research

This study proposes a novel collaborative mode aimed at fulfilling the real-time goal realization requirements in human-vehicle cooperative driving. This collaborative mode introduces innovative ideas to the field of collaborative driving between humans and vehicles. Based on the principles of transparency interface design, we establish an interactive interface design framework suitable for real-time collaboration and develop a set of interface design solutions, which are systematically evaluated. The research findings indicate that our study outcomes have the potential for generalized application in real-time goal collaboration scenarios. Future research can further expand and optimize the proposed collaborative mode and interface design framework to better meet the demands of practical applications.

Acknowledgement

This work was supported partially by P0050655 and P0042701 from Non-PAIR Research Centres of The Hong Kong Polytechnic University.

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About the authors

Jun Zhang is a PhD at College of Design and Innovation, Tongji University and School of Design, The Hong Kong Polytechnic University. His research interests include augmented reality, human-agent interaction, human factors and user experience.
Fang You is a professor at College of Arts and Media, Tongji University. Her research interests include user experience design, traffic safety, interactive design and human factors.
Jieqi Yang is postgraduate student at College of Arts and Media, Tongji University. Her research interests include user experience design, human-agent interaction and traffic safety.
Jie Zhang is a lecturer at the Faculty of Applied Sciences, Macao Polytechnic University. His research interests include AI for design and graphics, ergonomic design, and human-computer interaction.
Ping Wang is postgraduate student at College of Arts and Media, Tongji University. Her research interests include user experience design, augmented reality and human-agent interaction.
Hailiang Wang is an Assistant Professor at the School of Design, The Hong Kong Polytechnic University. His research mainly focuses on Human Factors and Ergonomics, Human-Computer Interaction, Gerontechnology Design, Design Intelligence, and Human Psychosocial Behaviors.
Yan Luximon is a professor at School of Design, The Hong Kong Polytechnic University. Her current research interests include graphics, 3D human modeling and CAD, and ergonomic design.

Appendix: Pairwise T-tests results

Table 1.: Pairwise T-tests results of Fig.7 and Fig.11. To reduce the paper space, only the comparisons with the significant difference are shown in the table.

Study	ID	Iterm	Group1	Group2	Mean Difference	Lower Bounds	Upper Lounds	Cohen's d	P-value	Symbol
1	1	Usability	1-Low autonomy	3-Low autonomy	-6.774	-11.311	-2.237	-0.548	0.005	**
1	2	Usability	1-Medium autonomy A	3-Medium autonomy A	-8.145	-14.423	-1.868	-0.476	0.013	*
1	3	Usability	2-Medium autonomy A	3-Medium autonomy A	-4.597	-9.096	-0.098	-0.375	0.046	*
1	4	Satisfaction	1-Low autonomy	1-Medium autonomy A	-0.323	-0.640	-0.005	-0.372	0.047	*
1	5	Satisfaction	3-Low autonomy	3-Medium autonomy A	-0.250	-0.496	-0.004	-0.373	0.047	*
1	6	Satisfaction	1-Low autonomy	2-Low autonomy	-0.597	-0.853	-0.341	-0.856	< 0.0001	****
1	7	Satisfaction	1-Medium autonomy A	2-Medium autonomy A	-0.379	-0.717	-0.041	-0.411	0.029	*
1	8	Satisfaction	1-Low autonomy	3-Low autonomy	-0.742	-0.990	-0.494	-1.098	< 0.0001	****
1	9	Satisfaction	1-Medium autonomy A	3-Medium autonomy A	-0.669	-1.019	-0.319	-0.702	< 0.0001	****
1	10	Satisfaction	2-Medium autonomy A	3-Medium autonomy A	-0.290	-0.525	-0.056	-0.454	0.017	*
1	11	Trust	1-Low autonomy	2-Low autonomy	-0.554	-0.833	-0.275	-0.727	< 0.0001	****
1	12	Trust	1-Medium autonomy A	2-Medium autonomy A	-0.282	-0.520	-0.045	-0.436	0.022	*
1	13	Trust	1-Low autonomy	3-Low autonomy	-0.782	-1.046	-0.519	-1.089	< 0.0001	****
1	14	Trust	1-Medium autonomy A	3-Medium autonomy A	-0.589	-0.992	-0.186	-0.536	0.006	**
1	15	Trust	2-Low autonomy	3-Low autonomy	-0.228	-0.452	-0.005	-0.375	0.046	*
1	16	Conflict	3-Low autonomy	3-Medium autonomy A	0.129	0.011	0.247	0.402	0.033	*
1	17	Conflict	1-Medium autonomy A	3-Medium autonomy A	0.219	0.042	0.396	0.454	0.017	*
1	18	Conflict	2-Medium autonomy A	3-Medium autonomy A	0.135	0.012	0.259	0.403	0.032	*
1	19	Mutual Dependence	1-Low autonomy	1-Medium autonomy A	-0.457	-0.767	-0.147	-0.541	0.005	**
1	20	Mutual Dependence	2-Low autonomy	2-Medium autonomy A	-0.301	-0.503	-0.099	-0.546	0.005	**
1	21	Mutual Dependence	1-Low autonomy	3-Low autonomy	-0.355	-0.644	-0.066	-0.451	0.018	*
2	1	Trust	1- Medium autonomy B	3- Medium autonomy B	-0.417	-0.810	-0.024	-0.389	0.038	*
2	2	Trust	1-High autonomy	3-High autonomy	-0.522	-0.874	-0.169	-0.543	0.005	**
2	3	Trust	2- Medium autonomy B	3- Medium autonomy B	-0.298	-0.499	-0.098	-0.546	0.005	**
2	4	Trust	2-High autonomy	3-High autonomy	-0.387	-0.570	-0.205	-0.778	< 0.0001	****
2	5	Mutual Dependence	1- Medium autonomy B	1-High autonomy	0.484	0.117	0.851	0.483	0.012	*
2	6	Mutual Dependence	2- Medium autonomy B	2-High autonomy	0.328	0.055	0.601	0.440	0.02	*
2	7	Mutual Dependence	3- Medium autonomy B	3-High autonomy	0.452	0.128	0.776	0.511	0.008	**

Table 2.: Pairwise T-tests results of Fig.8 and Fig.12. To reduce the paper space, only the comparisons with the significant difference are shown in the table.

Study	ID	Iterm	Dimension	Group1	Group2	Mean Difference	Lower Bounds	Upper Lounds	Cohen's d	P-value	Symbol
1	1	Workload	Visual Demand	1-Low autonomy	1-Medium autonomy A	1.097	0.534	1.660	0.714	< 0.0001	****
1	2	Workload	Visual Demand	3-Low autonomy	3-Medium autonomy A	0.774	0.249	1.299	0.541	0.005	**
1	3	Workload	Visual Demand	1-Low autonomy	2-Low autonomy	0.516	0.139	0.893	0.502	0.009	**
1	4	Workload	Visual Demand	1-Low autonomy	3-Low autonomy	0.581	0.139	1.023	0.482	0.012	*
1	5	Workload	Visual Demand	2-Medium autonomy A	3-Medium autonomy A	0.452	0.099	0.804	0.470	0.014	*
1	6	Workload	Auditory Demand	1-Low autonomy	2-Low autonomy	0.484	0.031	0.937	0.392	0.037	*
1	7	Workload	Auditory Demand	1-Medium autonomy A	3-Medium autonomy A	0.548	0.148	0.948	0.503	0.009	**
1	8	Workload	Auditory Demand	2-Medium autonomy A	3-Medium autonomy A	0.419	0.009	0.830	0.375	0.045	*
1	9	Workload	Situational Stress	1-Low autonomy	2-Low autonomy	0.571	0.009	1.134	0.394	0.047	*
1	10	Workload	Situational Stress	1-Low autonomy	3-Low autonomy	0.964	0.207	1.722	0.494	0.014	*
1	11	Workload	Temporal Demand	1-Low autonomy	1-Medium autonomy A	1.000	0.432	1.568	0.645	0.001	**
1	12	Workload	Temporal Demand	3-Low autonomy	3-Medium autonomy A	0.677	0.114	1.241	0.441	0.02	*
1	13	Workload	Temporal Demand	1-Low autonomy	2-Low autonomy	0.548	0.148	0.948	0.503	0.009	**
1	14	Workload	Temporal Demand	1-Low autonomy	3-Low autonomy	0.710	0.189	1.230	0.500	0.009	**
2	1	Workload	Visual Demand	2- Medium autonomy B	2-High autonomy	0.774	0.376	1.173	0.713	< 0.0001	****
2	2	Workload	Visual Demand	3- Medium autonomy B	3-High autonomy	0.484	0.072	0.895	0.431	0.023	*
2	3	Workload	Visual Demand	1-High autonomy	2-High autonomy	0.613	0.133	1.093	0.468	0.014	*
2	4	Workload	Visual Demand	1- Medium autonomy B	3- Medium autonomy B	0.613	0.063	1.163	0.409	0.03	*
2	5	Workload	Visual Demand	1-High autonomy	3-High autonomy	0.774	0.294	1.254	0.591	0.003	**
2	6	Workload	Auditory Demand	1- Medium autonomy B	3- Medium autonomy B	0.710	0.080	1.339	0.413	0.028	*
2	7	Workload	Auditory Demand	1-High autonomy	3-High autonomy	0.645	0.139	1.151	0.468	0.014	*
2	8	Workload	Situational Stress	2- Medium autonomy B	2-High autonomy	0.893	0.223	1.563	0.517	0.011	*
2	9	Workload	Situational Stress	3- Medium autonomy B	3-High autonomy	0.393	0.054	0.732	0.449	0.025	*
2	10	Workload	Situational Stress	1-High autonomy	3-High autonomy	0.571	0.083	1.060	0.454	0.024	*
2	11	Workload	Situational Stress	2- Medium autonomy B	3- Medium autonomy B	0.786	0.115	1.456	0.454	0.023	*
2	12	Workload	Temporal Demand	1- Medium autonomy B	3- Medium autonomy B	0.839	0.247	1.431	0.520	0.007	**
2	13	Workload	Temporal Demand	1-High autonomy	3-High autonomy	0.452	0.009	0.894	0.374	0.046	*