MoTUI: Personalization of In-Vehicle Tactile Interfaces for People With Vision Impairments and the Blind

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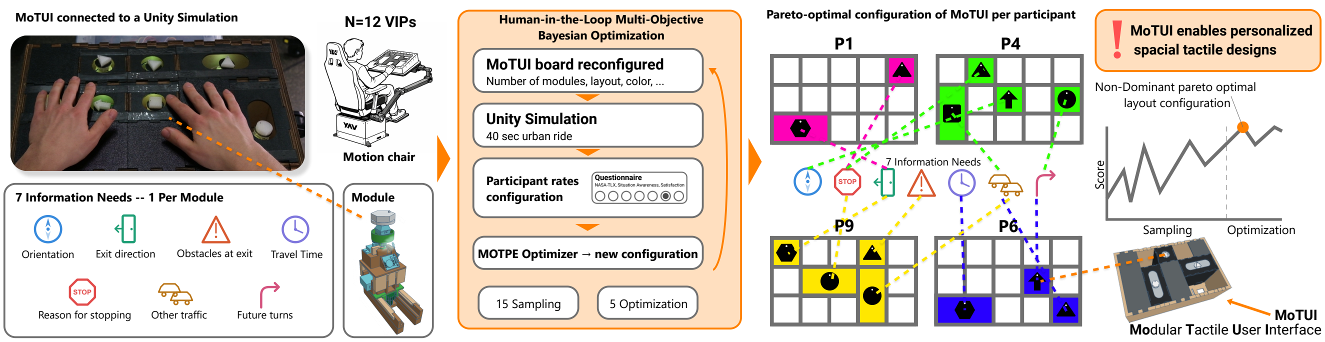

Figure 1: MoTUI pairs a reconfigurable modular tactile interface with HITL-MOBO to personalize in-vehicle interfaces for people with vision impairments. Over 20 HITL trials (N=12), optimized configurations significantly outperformed a static baseline and an LLM-generated design on situation awareness, workload, and ownership—while revealing divergent preferences.

Abstract

Configuring in-vehicle interfaces for people with vision impairments (VIPs) requires jointly tuning buttons, feedback modalities, layout, and speech parameters. This defines a design space too large for manual exploration, with inherently conflicting objectives such as maximizing situation awareness while minimizing cognitive load. Prior work recognizes personalization as critical but offers no systematic method to achieve it. We contribute **MoTUI**, an open-source **Mo**dular **T**actile **U**ser **I**nterface with reconfigurable hardware and software for runtime exploration of this design space and replication of existing designs. MoTUI is configuration-agnostic and supports multiple personalization strategies; we instantiate and evaluate one, pairing it with Human-in-the-Loop Multi-Objective Bayesian Optimization (HITL-MOBO) to navigate the space efficiently. In a within-subject study (N = 12 VIPs), HITL-optimized configurations outperformed a static baseline and an LLM-generated design on situation awareness, perceived workload, and satisfaction, with significant gains over the LLM-based approach. For psychological ownership, optimized configurations were rated significantly higher than both baselines. Importantly, optimization converged on substantially different configurations across participants, indicating strong individual differences; qualitative findings further explain these personalized outcomes.

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CCS Concepts

• **Human-centered computing** → **Accessibility systems and tools**; **Accessibility technologies**; **Empirical studies in accessibility**; **Haptic devices**.

Keywords

Accessibility, Personalization, Tactile Interface, Multimodal Interface, Automated Vehicles, Situation Awareness, Optimization

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1 Introduction

Globally, over 2.2 billion individuals are affected by visual impairment, and 45 million are considered legally blind [60]. For people with vision impairments (VIPs), independent mobility is crucial for social inclusion where they anticipate that vehicle automation could significantly reduce their reliance on others [39]. However, studies have revealed apprehensions among VIPs about whether highly automated vehicles (HAVs) will adequately accommodate their specific needs, for example the ability to maintain awareness of their surroundings, the exit direction or how long a journey will take [6, 10, 12, 14]. Recent work highlights the need for multimodal interfaces for VIPs, as they want to use tactile and auditory channels [53]. While Meinhardt et al. [51] observed that engagement with non-visual interfaces increased as visual acuity decreased, substantial individual differences remained across all acuity levels. Meinhardt et al. [53] further examined this relationship between interface design and visual acuity by separating participants into blind and low-vision groups while evaluating multimodal interfaces. However, their results similarly reveal that preferences differ substantially even within these subgroups. Together, these findings suggest that categorizing VIPs solely by visual acuity risks overlooking individual needs, as factors such as the onset of impairment, residual peripheral vision, or personal familiarity with tactile media shape preferences that coarse groupings cannot capture [53]. Personalization, therefore, emerges as an essential design goal [5, 29]. Fink et al. [29] reports that participants "*wanting to be able to customize several features, including the speech rate, volume, units of measure*" [29, p. 11]. While workshops are a widely adopted methodology for designing such interfaces [11, 33, 51, 53], these works highlight the need for approaches that can systematically and scalably support personalized interface configurations. This limitation is further exacerbated in group-based workshops, where participants may suppress their individual needs in order to align with others [8]. What remains open is how to appropriately personalize a multimodal interface in which buttons and visual, auditory, and tactile feedback must be jointly configured.

To address this gap, and complement workshops as a primary means of identifying user needs and configurations, we present a Modular Tactile User Interface (MoTUI). MoTUI enables tactile interface configurations through reconfigurable software and hardware, and can be used to replicate existing designs. MoTUI is a standalone platform: its value as a reconfigurable test-bed is independent of any particular configuration method, and it can be driven by workshops, manual customization, expert heuristics, or automated optimization. In this work we focus on one such method. However, configuring such a multimodal interface requires jointly tuning auditory, tactile, and visual parameters, resulting in a design space too large for manual exploration. Moreover, the objectives inherently conflict: richer information may improve situation awareness but increase mental workload, while aesthetic preferences may favor configurations that compromise informativeness. To navigate these trade-offs systematically, we employ Multi-Objective Bayesian Optimization (MOBO), which iteratively explores the design space to identify Pareto-optimal solutions, meaning configurations where no single objective can be improved without degrading another [15, 41, 64]. Because our objectives, namely situation awareness, mental workload, and perceived satisfaction, depend on subjective human judgment, we adopt a Human-in-the-Loop (HITL) approach [22] in which the VIP repetitively provides feedback while a Multi-Objective Tree-structured Parzen Estimator (MOTPE) [2] dynamically refines the parameter space. While prior work has applied HITL MOBO to optimize visual interface parameters for sighted users [38, 52], we extend this paradigm to multimodal tactile interfaces for VIPs. In a user study, we compared a static configuration inspired by Meinhardt et al. [51] against personalization via a large language model (LLM) prompt based on user characteristics and interface parameters, and our HITL MOTPE approach.

Our work answers the following research questions:

RQ1 *How do personalized HITL-optimized configurations compare to a static one-size-fits-all design and an LLM-generated configuration in terms of situation awareness, mental workload, and user satisfaction?*

RQ2 *What individual differences in information needs, modality preferences, and layout requirements emerge among VIPs, and how does this inform the necessity of personalization?*

Our results show that MOTPE-based HITL-MOBO produced significantly better-rated configurations in the exploitation phase than in the initial exploration phase β_{phase}, and that for every participant a non-dominated configuration was available for the final comparison. Quantitatively, HITL-optimized configurations were rated higher than both baselines on situation awareness, perceived workload, and perceived satisfaction, with statistically significant improvements relative to the LLM baseline, and significantly higher psychological ownership than both baselines.

Qualitative analysis revealed strong individual differences in information needs, layout preferences, and modality use, indicating that participants converged on personalized configurations that were well-matched to their needs. This work offers a practical approach to optimizing tactile interfaces for VIPs, particularly those with explicit auditory and tactile needs. We also corroborate and extend the existing body of work on situation awareness for VIPs in HAVs.

Contribution Statement [74]

- **Artifact Contribution** MoTUI (GitHub: **[Link]**) MoTUI, an open-source, reconfigurable modular tactile UI platform that enables runtime exploration and replication of in-vehicle tactile interface designs, independent of any particular configuration method.
- **Method** A demonstration that MoTUI can be paired with HITL-MOBO to personalize configurations per user, extending HITL-MOBO from visual interfaces for sighted users to multimodal tactile interfaces for VIPs
- **Empirical Study about People** An empirical study (N=12) demonstrated how MoTUI paired with HITL-MOBO, improves situation awareness, lowers mental workload, and increases perceived satisfaction, and highlights trade-offs between optimization and one-size-fits-all approaches.

2 Related Work

This work is situated at the intersection of two research areas. First, we review interfaces for VIPs, with a particular emphasis on tactile and multimodal solutions for HAVs. Second, we introduce MOBO as an approach to navigate the complex design space when configuring such interfaces.

2.1 Non-Visual Interfaces for People With Vision Impairments

Many VIPs anticipate that vehicle automation could substantially reduce their reliance on others [39], yet qualitative investigations revealed concerns about whether HAVs will adequately accommodate their needs [6, 10, 12, 14], particularly regarding the ability to maintain awareness of their surroundings. Studies have identified information needs spanning orientation assistance upon arrival [14, 28], exit direction [28] and obstacles at the exit [14, 34, 53]. Addressing these needs has motivated the exploration of diverse interface modalities.

Auditory interfaces have been among the most common approaches for VIPs to navigate their surroundings [17]. In the AV context, Brinkley et al. [13] developed the ATLAS system, which translates a vehicle's camera-based surroundings into vocalized descriptions, thereby increasing trust and perceived reliability among VIPs. Tactile interfaces have also shown considerable promise because of their non visual nature. On-body tactile cues have been found to effectively support situation awareness in HAVs [21, 49]. Fink et al. [27] explored an ultrasonic haptic device for HAVs and found that it supported spatial awareness among VIPs, with follow-up work demonstrating that a multimodal gestural-audio and haptic mid-air interface enabled VIPs to navigate driving scenarios effectively [29].

A recurring finding is that multimodal interfaces outperform single-modality solutions [29]. For instance, VIPs maintain better spatial awareness when tactile and auditory feedback are combined [76]. This aligns with the multiple resource theory [73], which posits that distributing information across modalities reduces attentional competition. Building on this, Meinhardt et al. [53] developed PathFinder, a multimodal interface that combines visual, auditory, and tactile modalities to assist VIPs in exiting an HAV. Yet, their previous work also showed that visual acuity influences their preferences for interface designs [51]. Hence, related work explicitly identified a need for tailored interfaces for VIPs [5, 29, 51, 53].

However, personalizing a multimodal interface requires jointly configuring auditory, tactile, and visual parameters, a challenge that quickly exceeds the capacity of manual testing. Moreover, an effective interface must balance competing objectives, such as maximizing situation awareness, while minimizing mental workload [52]. To navigate these trade-offs systematically, we adopted HITL MOBO.

2.2 Multi-Objective Optimization for UI Design

Configuring multimodal interfaces can be formulated as a high-dimensional optimization problem, in which heterogeneous design parameters (e.g., layout, modality, and feedback characteristics) must be jointly tuned to satisfy competing objectives such as maximizing situation awareness while minimizing cognitive load. Exhaustive manual exploration of such design spaces is infeasible. MOBO addresses this challenge by modeling the relationship between design parameters and outcomes under limited evaluations, enabling efficient exploration of complex and mixed parameter spaces [15, 64]. Instead of optimizing a single objective, MOBO identifies Pareto-optimal solutions, capturing trade-offs where improving one objective would degrade another [46]. When objectives depend on subjective human judgments, the user can be integrated directly into the optimization loop. In such HITL processes [22, 41], the optimizer proposes configurations, users evaluate them, and the feedback iteratively refines the model. Prior work has demonstrated that HITL MOBO can efficiently navigate large UI design spaces [38, 52] and has been applied to the mechanical design of haptic devices [32]. However, existing applications focus on visual interface parameters for sighted users. In contrast, multimodal tactile interfaces for VIPs introduce additional complexity due to heterogeneous parameter types and subjective evaluation criteria, requiring systematic exploration methods that can adapt to individual users.

3 Introducing MoTUI

To guide the design of MoTUI, we derived four requirements on non-visual in-vehicle interfaces for VIPs: (R1) support heterogeneous information needs, (R2) support multimodal and reconfigurable feedback, (R3) support personalized spatial layouts and interaction mappings, and (R4) support rapid reconfiguration for iterative exploration. MoTUI addresses these requirements through a modular, reconfigurable hardware–software system. MoTUI enables the encoding and runtime reconfiguration of tactile buttons and their parameters. Each button can move along one linear axis, rotate, extend vertically, illuminate, and vibrate. An interchangeable top element features a small raised tactile marker—similar to the homing bump found on the F and J keys of a standard keyboard—allowing users to locate and identify module orientation by touch (see Figure 2). This flexibility enables the replication of a wide range of tactile interface configurations identified in prior work (e.g., PathFinder [53] or OnBoard [51]). Moreover, MoTUI is highly configurable and can be adapted for workshops or alternative setups, as we demonstrate in our study. The system exposes 7 global parameters (color, button type, vibration intensity, vibration on-time, vibration off-time, servo speed, and speech speed) and 7 local parameters per module (x position, y position, vertical movement, top element, use vibration, and use rotation). Each module contains a movable button (Figure 2) housed in a laser-cut wooden chassis measuring either 88×88 mm or 88×176 mm (when vertical movement is included), with a cutout for the button mechanism. Modules are connected to an Arduino Mega 2560 via custom-designed connectors, with six PCA9685 PWM driver boards. A Unity-based simulation environment (Version 6000.0.53f1 LTS) that uses events in the scene to trigger responses on buttons, for example, raising a button that indicates obstacles at the exit when the arrival event is triggered. The modules respond to an ongoing traffic simulation [70]. Buttons can be arranged on a 5×3 base plate (47×30 cm), offering up to 15 possible positions.

3.1 Information Needs

MoTUI was designed to communicate environmental and navigational information, already extensively identified in related work, to VIPs in HAVs. Each module serves one functionality:

Orientation Assistance Upon Arrival: Upon arrival, VIPs indicated they required support with navigating from the vehicle to their destination. Clear orientation cues are therefore necessary to convey location and direction. Prior work reports concerns about

being dropped off in unfamiliar areas without guidance [14], and "information about accessing the destination" has been identified as a key environmental information need in autonomous ride-sharing contexts [28, p. 97].
Exit Direction: Guidance on the side of the vehicle, offering a safe exit, such as a sidewalk, is also requested. Entry and exit assistance is increasingly important as vision loss increases, underscoring the need for explicit exit-side cues [28].
Obstacles at Exit: To exit safely, VIPs require information about nearby static or moving obstacles around the vehicle [14]. Huff et al. [34] similarly emphasize that hazard awareness during vehicle exit is critical for user safety.
Time and Relationship to Destination: Information about route progress and proximity to the destination is essential for maintaining situational awareness. Participants in a study by Martelaro et al. [47] highlighted the importance of updates on route status and arrival time, a need also emphasized by Brewer and Kameswaran [10].
Reason for Vehicle Stopping: VIPs need to understand why the vehicle stops. Unexpected stops were frequently named as a source of concern [14], and prior work highlighted that explaining vehicle behaviour supports awareness and independence [28, 34].
Other Traffic Members: Beyond the vehicle's own actions, VIPs benefit from awareness of surrounding traffic participants. Brinkley et al. [14] report that understanding how the HAV interacts with other road users is important for maintaining situational awareness and trust, particularly given the unpredictability of human drivers.
Future Turns and Upcoming Maneuvers: Information about upcoming maneuvers, such as turns or lane changes, helps VIPs

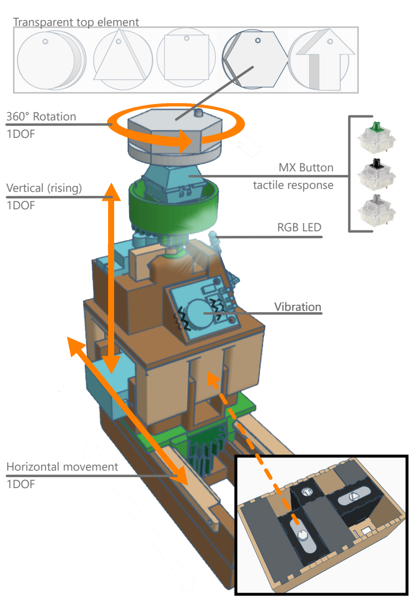

Figure 2: Interior module construction. Each module is housed in a wooden chassis with a black top and a cutout for the top element. The module can travel on a slide, extend vertically, and rotate. All functions can be controlled via the Arduino.

maintain predictability and control during the trip. Fink et al. [28] found route-based information, including turn-by-turn updates, to be among the most essential categories, enabling users to form a mental model of the vehicle's behaviour.

3.2 Parameterizing MoTUI

The design space is organized into **global** and **local** parameters. Global parameters define system-wide properties shared across all modules (e.g., color, vibration intensity, servo, and sound speed) and were introduced to reduce optimization dimensionality. Local parameters specify module-level properties, such as **whether a module is used at all** (thereby, some configurations are optimal for a person but only have 2 modules), its **position**, geometry, and interaction behavior (button type), and apply only to individual module instances.

Color: Element color is modeled as a global parameter using the hue component of the HSV color space (with saturation and value fixed at 100%), enabling continuous control via a single scalar. Color was included due to its demonstrated benefits for object recognition in low-vision users [75].
Buttons: Tactile feedback is provided via Cherry MX switches with three feedback profiles: linear (MX Black), tactile (MX Grey), and tactile with audible click (MX Green). No click-only option was included due to the lack of commercially available switches.
Vibration: Vibration feedback is defined by on/off timing parameters forming a square-wave signal, chosen for its fast response and ease of modulation [18]. Pulse durations were limited to [5, 200] ms and interpulse intervals to [10, 500] ms, following prior work on perceived urgency [43]. Vibration intensity is controlled via PWM duty cycle, with a minimum of 65% to ensure reliable motor activation.
Servo Speed: Servo speed controls the execution of rotational and translational movements. The range [100, 300] deg/s was selected to balance perceptibility with mechanical constraints.
Speech Output Speed: Auditory feedback speed is specified in words per minute (WPM). The range [100, 250] WPM reflects preferences of BVI users and known intelligibility limits [9, 30].
Modules and Layout: Module inclusion is also a boolean. Active modules are positioned on a discrete grid using x_i ($[0, 4]$) and y_i ($[0, 2]$). Absolute positions are not fixed to account for individual layout preferences [51].
Top Element Geometry: Module top elements can take one of five simple shapes (Circle, Triangle, Square, Hexagon, Arrow), selected to support fast tactile recognition [57, 62].
Functional Modalities: Each module may convey information via horizontal movement (1 degree of freedom (DOF)), vertical movement (1DOF), and rotation (1DOF). These boolean parameters, either active or not, allow systematic exploration of preferred modality–information mappings.

3.3 Merging Parameters and Needs

Seven identified information needs are encoded through each module's available output modalities—rotational, vertical, and horizontal movement, vibratory tactile feedback, and button interaction—as summarized in Table 1. These mappings are directly translated from related work (see Table 1; right column). **14 physical modules** were built. Since horizontal movement is a parameter, there are two versions for each information need. Modules that did not require horizontal movement used a compact 1×1 chassis to save space; otherwise, the 1×2 version is used. Figure 3 illustrates how a module's behavior unfolds over time, using the "Other traffic members" information need as an example. The mapping of information to modalities follows a consistent design logic that prioritizes spatial intuitiveness, tactile distinctiveness, and cross-module consistency:

Rotational movement conveys directional or angular information, leveraging the intuitive link between a tangible element's rotation and the orientation of the represented object in space.
Horizontal movement encodes continuous or proportional data such as progress or relative position, with the top element's linear displacement serving as a physically perceivable progress indicator.
Vertical movement signals the presence of an event. The module extends from the surface as a tactile pop-out to draw the user's attention.
Vibratory feedback notifies users of new events, providing an immediate alert without requiring continuous surface exploration.
Button interaction complements passive feedback (e.g., extracted button is pointing towards something) with on-demand access: pressing a module triggers a verbal explanation of its current state.

Table 1: Mapping of module functions to movement behaviours and corresponding auditory feedback.

Module	Rotational Movement	Vertical (rising) Movement	Horizontal Movement	Auditory Feedback	Ref.
Orientation to final destination	Points towards destination.	Extends at destination.	**Y-axis:** Reflects destination; center = HAV.	*"Your final destination is to the right behind you."*	[14, 29]
Exit direction	Points toward exit.	Extends at destination.	**X-axis:** Shifts per exit direction. (left or right side)	*"Safe exit direction on the right."*	[29]
Obstacles at exit	Points toward obstacle.	Extends if there is a obstacle.	**Y-axis:** Reflects obstacle; center = HAV.	*"Caution: a tree to your right in front."*	[14, 34]
Time to destination	Clock like movement.	Retracts at destination.	**X-axis:** Progress bar for time remaining.	*"45 seconds left to reach destination." / "You have reached your destination."*	[10, 47]
Reason for stopping	Points towards reason	Extends at HAV stop.	**X-axis:** Progress bar for stop duration.	*"Reason for stop: pedestrian crossing."*	[14, 29, 34]
Other traffic (see Figure 3)	Points towards traffic member.	Extends when traffic near.	**Y-axis:** Reflects position of traffic member upfront; in the back	*"Oncoming traffic on the left side."*	[14]
Future turns	Points per turn direction.	Extends if upcoming curve	**Y-axis:** Distance from top = distance to turn.	*"Upcoming left turn." / "Upcoming right turn."*	[29]

4 HITL Optimization of MoTUI

MoTUI is the first tool that allows HITL MOBO of tactile feedback in the in-vehicle context. Optuna (version 4.5.0) [2] with its Tree-structured Parzen Estimator (TPE) sampler (Python 3.12) was used to iteratively refine MoTUI's design parameters in our HITL-MOTPE setup. At a high level, the optimization is a guided search. In each trial the system proposes a candidate configuration, the participant experiences it in a roughly 40-second simulated ride and rates it on our three objectives, and these ratings tell the algorithm which regions of the design space to explore next. Over successive trials the proposals shift from broad coverage (exploration) toward configurations predicted to score well for that individual (exploitation). Between trials, a researcher physically reconfigures the board to match the proposal, and configurations placing two modules on the same grid cell are pruned. We use TPE, a BO algorithm that, unlike classical approaches using Gaussian Processes as surrogate models, models two separate probability distributions over the parameter space [7]:

$$l(x) = p(x \mid y < \hat{y}) \quad \text{and} \quad g(x) = p(x \mid y \geq \hat{y}),$$

where x represents a parameter configuration, y the observed objective value, and $\hat{y}$ a threshold separating good from bad outcomes. Intuitively, l(x) describes configurations that have tended to score well and g(x) those that have not; selecting configurations that maximize the ratio l(x)/g(x) steers sampling toward parameter regions associated with good ratings. New configurations are selected by maximizing the ratio $\frac{l(x)}{g(x)}$, thereby favoring promising regions of the search space [7]. This is important for MoTUI because the parameter space is heterogeneous and includes discrete, categorical, and conditional parameters. By replacing Gaussian Processes with non-parametric Parzen estimators, TPE efficiently handles high-dimensional, discrete, and categorical search spaces [7, 72]. Its tree-structured formulation naturally accommodates conditional dependencies between parameters by modelling distributions for each branch separately [72]. We chose TPE because MoTUI requires floating-point variables for continuous design parameters, integer variables for discrete settings, categorical variables for module and feedback choices, multi-objective optimization for jointly optimizing multiple user-centered objectives, conditional search spaces because module-specific parameters are only relevant when the corresponding module is active, and constraints to exclude invalid configurations [37, 59]. This was a better fit than algorithms such as MOBO BoTorch [4], where handling inactive modules would require additional workarounds. Comparative benchmarks confirm that Optuna's TPE achieves a strong balance between performance and runtime, particularly for complex, high-dimensional search spaces [37, 65].

5 Study

For our study, MoTUI was attached to the motion simulation chair YawVR 2 [67] using a monitor mount and placed on participants' laps with the electronics facing away from them. A 75" 4K monitor displayed a simulated HAV journey through an urban environment from a passenger's perspective to simulate the ride for our low vision participants. The route lasted ≈40 seconds and included realistic traffic events, including two turns, a stop at a pedestrian crossing, and one oncoming vehicle. The simulation was implemented in Unity using the Fantastic City Generator [48] and Urban Traffic System [1] assets. After a standardized introduction, participants provided informed consent (about GDPR regulated data storage) and were informed of their right to withdraw at any time. The study adhered to local and institutional ethical guidelines. Each trial lasted ≈150 minutes and was compensated with 35€. Participants were offered breaks but used them only as brief restroom

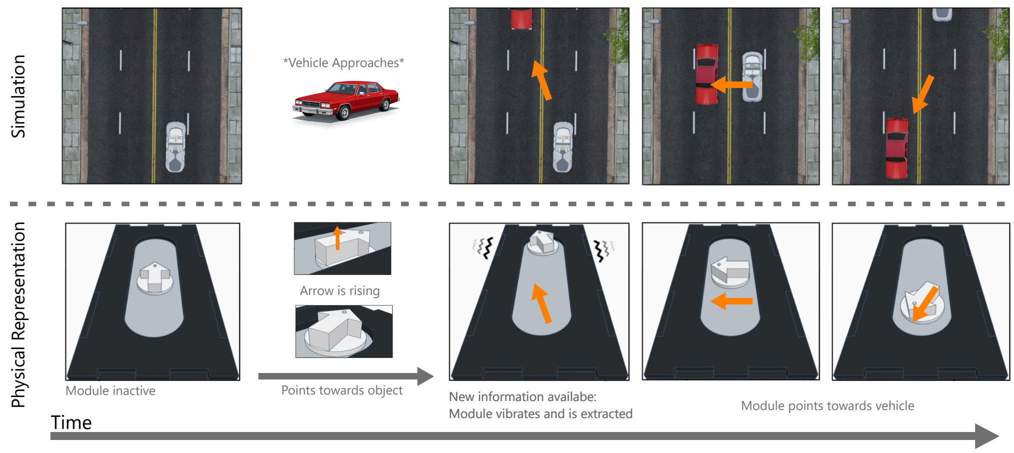

Figure 3: Mapping of the physical module to the Unity simulation. The "other traffic" visual cue is illustrated. The button is in the retracted state (left). When a vehicle approaches, the user is notified and the button becomes active, tracking the vehicle. When pressed, the speech output states: *"Oncoming traffic on the left side."*

pauses; there were no dropouts and no complaints about the iterative procedure.

Participants then saw 3 conditions in a counterbalanced within-subject order: Optimization, an OnBoard-inspired approach [51], and an LLM-based recommendation configuration (see subsection 5.2).

5.1 Measurements

Measurements were read aloud, and participants responded verbally. Situation awareness was measured on a 7-point Likert (low to high) scale using the item: *"To what extent did you feel you had a clear understanding of the situation and could predict what would happen next?"*, derived from the comprehension and projection components of the Situation Awareness Rating Technique [69]. Perceived workload was assessed using the six subscales of the raw NASA-TLX (*Mental Demand, Physical Demand, Temporal Demand, Own Performance, Effort, Frustration Level*) [31]. Perceived satisfaction was measured via agreement on a 7-point Likert scale (low to high) with the statement: *"Overall, how satisfying was this interface to use, and to what extent did it meet your needs and expectations?"*. We additionally assessed two related but distinct process constructs on a 7-point Likert scale once for each condition: perceived agency, capturing the sense of control over the optimization process (*"I felt that I had control over how the design changed."*), and psychological ownership, capturing the sense that the resulting artifact was one's own (*"I felt that the final design was my own."*). Concerns on the process (Process Satisfaction) *"Overall, I am satisfied with the design process."*, and perceived fit *"The final design meets my needs and preferences."* were also assessed.

To ensure comparability across measures, all objective values were normalized to the $[-1, 1]$ range, accommodating metrics defined on either a 0–1 scale or a 7-point Likert scale.

5.2 MoTUI Configuration

HITL MOTPE. The optimization began with a 15-iteration sampling phase using a fixed seed, ensuring that every module and its associated information appeared in at least 5 iterations. The same fifteen initial designs were used across all participants to ensure consistent starting conditions. Following this, the MOTPE conducted a five-iteration optimization phase using Optuna's MOTPE sampler, which probabilistically favored configurations predicted to perform better based on observed ratings. Designs in which two modules shared the same grid position were pruned (skipped) to enforce unique module placement. Between each iteration, a researcher swaps and configures (e.g., top element) the modules on the board. We employed the multivariate TPE variant, which models inter-parameter dependencies for more informed sampling [36], and set ($y^* = 0.4$) to balance exploration and exploitation [7]. An objective function maps a MoTUI design to a metric that the optimizer seeks to maximize. We aim to maximize two subjective metrics — situation awareness and perceived satisfaction — while minimizing perceived workload, all assessed via questionnaires after each trial. Local parameters are indexed by module (e.g., `x_i`, `y_i`, `shape_i`) and implemented as **conditional parameters**, sampled by Optuna only if the corresponding module is active (`use_module_i`). Together, these define the layout, appearance, and functionality of up to seven modules. After optimization, the package *emoa* [54] was used to identify a non-dominant Pareto-optimal solution, which was then assessed in an additional trial for our statistical comparison.

LLM Baseline. In addition to HITL, we used a LLM (ChatGPT-5.2, Nov. 2025) [58] as a heuristic baseline for personalized parameter selection. LLMs have been shown to capture key characteristics of visual impairments at a coarse level [56] and to adapt interface components to individual user needs in accessibility contexts [16, 19, 20, 71]. This makes them a plausible candidate for single-shot configuration without iterative feedback. For each participant, the model received a structured prompt (see *[GitHub]*) containing the results of standardized visual assessments (Amsler [3], Ishihara [35], Snellen [68], and Pelli-Robson [61]). These were selected following the recommendations of Rädler et al. [63],

Table 2: Participant demographics and vision. LV = low vision, B = legally blind. Amsler codes (effect on vision): CD (central dot), H (holes), B (blur), D (distortion), S (square size).

P	Age	G	Acuity (self-rep.)	Status	CVD	Amsler	Snellen	Pelli
1	66	M	3% BE	B	sev	CD,H,B,S,D	20/200	0.05
2	54	F	0% BE	B	–	–	–	–
3	61	M	n.a.	LV	sev	H	20/50	1.85
4	33	F	7%	LV	sev	CD,B,S	20/200	0.80
5	69	F	5% LE, ≤25% RE	LV	sev	CD,H,B,S,D	20/100	0.20
6	31	M	10% BE	LV	sev	CD,H,B	20/55	1.55
7	72	M	0% BE	B	–	–	–	–
8	61	M	0% RE, 6% LE	B	sev	CD,H,B,D	20/200	0.05
9	69	F	0% BE	B	–	–	–	–
10	46	F	1–2% BE	B	–	–	–	–
11	42	F	≤5% BE	LV	sev	CD,H	20/200	0.05
12	77	F	5–7% BE	LV	sev	CD,H,B,D	20/200	0.20

alongside a full description of MoTUI's adjustable parameters, their bounds, and expected perceptual effects. The model was instructed to propose a configuration maximizing situation awareness and perceived satisfaction while minimizing perceived workload (prompt in Appendix C). The resulting parameter values were evaluated using the same questionnaire as in the optimization procedure. This baseline thus represents an automated, single-shot configuration strategy that can be directly contrasted with feedback-driven optimization to isolate the added value of iterative, user-specific refinement.

OnBoard [51] inspired Baseline. As a second baseline, we implemented a MoTUI configuration derived from the OnBoard user interface proposed by Meinhardt et al. [51]. OnBoard [51] is a tactile in-vehicle interface for conveying traffic information to VIPs in HAVs, developed from a participatory workshop. It uses simple-shaped, expandable tactile elements that adapt to the current traffic situation. The original layout was recreated and adapted to MoTUI's available functionality, while preserving the overall spatial organization and interaction rationale of the reference design. Since our system uses a black background and the color of the upper elements is controlled by the hue parameter, we selected a yellow light-emitting diode color to ensure strong visual contrast in accordance with the principle of "highly contrasting colors" [51, p. 9]. All functionalities were directly translated except for the module displaying "time and relationship to the destination ", which can only be mounted horizontally in our setup. Consequently, it was placed in the upper-left region of the enclosure, following the recommendation that information of lower priority should be located toward the periphery [51, p. 9].

5.3 Participants

N=12 participants with a mean age of M=56.75 (SD=15.47) participated in our study. All of them either had low vision or were considered legally blind. Table 2 presents a detailed demographic overview, including remaining vision and test results.

6 Results

We first compare MOTPE HITL BO (non-dominant optimum configuration) against our baselines, then report on the optimization process itself. We also present qualitative findings from semi-structured interviews. For the analysis, we used R (ver. 4.5.1) and a package by Colley [25] that includes a pre-test for distribution and test selection.

6.1 Comparison of MoTUI Configurations: Subjective Questionnaires

6.1.1 Situation Awareness. A Friedman rank sum test found a significant effect of configuration on Situation Awareness ($\chi^2(2)$=6.82, p=0.033, r=0.28) see Figure 4. A post-hoc test found that Optimization was significantly higher (M=6.08, SD=0.67) in terms of Situation Awareness to LLM (M=4.42, SD=1.98); p_{adj}=0.022).

6.1.2 NASA-TLX. Analyses of the NASA-TLX subscales revealed a significant effect of configuration on *Mental Demand* ($F(1.78, 19.56) = 4.14$, p=0.035, r = 0.14). However, post-hoc analyses indicated no significant pairwise differences between conditions for *Mental Demand*.

No significant effects of configuration were observed for *Physical Demand*, *Temporal Demand*, or *Performance*.

For *Effort*, a significant effect of configuration ($F(1.54, 16.98) = 5.66$, p=0.018, r = 0.20) was found. Post-hoc comparisons showed higher *Effort* in the LLM condition (M=6.33, SD=5.02) compared to the Optimization condition (M=2.17, SD=1.90, p_{adj}=0.023).

A significant effect of configuration was also observed for *Frustration* ($F(1.40, 15.45) = 7.85$, p=0.008, r = 0.25). Participants reported higher *Frustration* in the LLM condition (M=6.50, SD=5.74) than in both the Optimization condition (M=2.00, SD=1.54) and the Static Design condition (M=1.67, SD=1.78, p_{adj}=0.023). Also, it was found that LLM was significantly higher in terms of *Frustration* compared to Static Design (M=1.67, SD=1.78); p_{adj}=0.027).

Finally, *Overall Workload* (RAW NASA-TLX) showed a significant effect of configuration ($F(1.85, 20.32) = 6.84$, p=0.006, r = 0.21) for reference see Figure 4. Overall workload was higher in the LLM condition (M=7.19, SD=4.72) than in the Optimization condition (M=2.82, SD=1.88, p_{adj}=0.014).

6.1.3 Perceived Satisfaction. A Friedman rank sum test found a significant effect of configuration on perceived satisfaction ($\chi^2(2)$=7.48, p=0.024, r=0.31) see Figure 4. A post-hoc test found that Optimization was significantly higher (M=5.92, SD=0.67) in terms of perceived satisfaction compared to LLM (M=4.42, SD=1.73); p_{adj}=0.014).

6.1.4 Process Related Questions. A Friedman rank sum test found a significant effect of configuration on Ownership ($\chi^2(2)$=8.67, p=0.013, r=0.36). A post-hoc test found that Optimization was significantly higher (M=5.83, SD=1.34) in terms of Ownership compared to LLM (M=4.17, SD=1.95); p_{adj}=0.015) and Static Design (M=4.58, SD=1.73); p_{adj}=0.015). No significant differences were found in Perceived Fit, Process Satisfaction, or Perceived Agency. For details, see Figure 4.

6.2 Personalized Outcomes and Process

As shown in Figure 6, we achieved positive outcomes during the exploitation phase of our optimization process, indicating that our HITL optimization worked. This aligns with the results of a linear mixed model on the combined score. Participants completed 20 HITL trials in a fixed-block design: exploration/seeding (first 15 trials) followed by exploitation/optimization (last 5 trials). For each outcome, we fit a linear mixed-effects model $Y \sim$

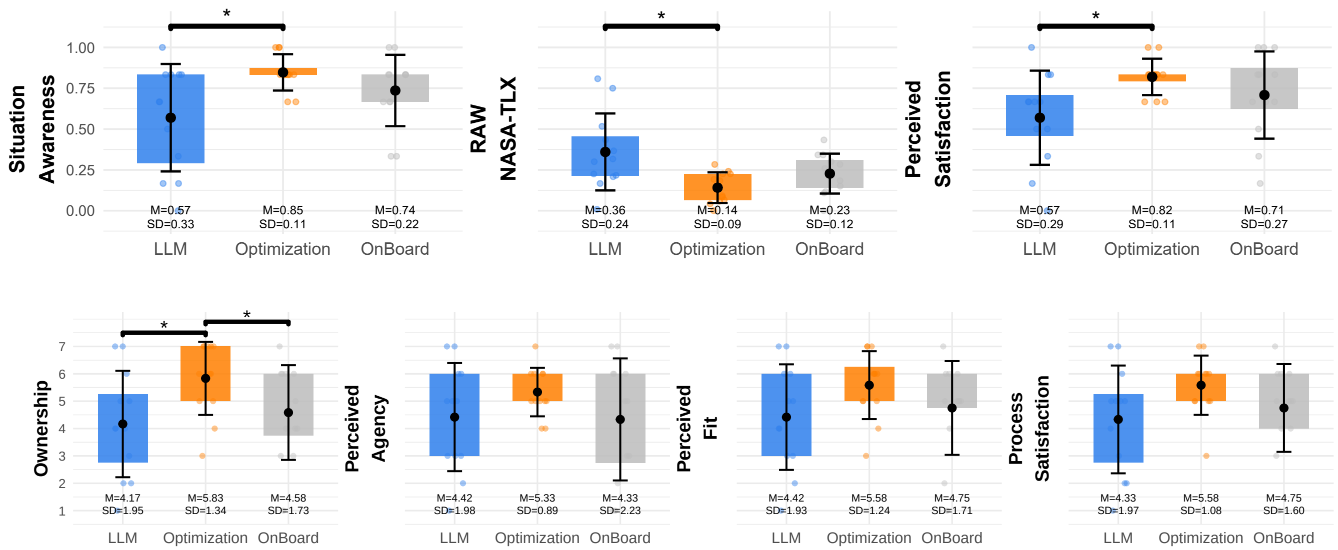

Figure 4: Overview of subjective evaluation results across conditions. Boxplots show distributions; points indicate individual observations; black markers and error bars denote mean and ±1 SD. Top row is normalized to 0—1 as the scale ranges differ. Asterisks indicate significant differences between LLM and Optimization (p < .05).

condition + trial_number + (1|participant). Exploration/seeding $M = 0.12$, $SD = 0.47$ on a -1 to 1 scale and exploitation/optimization $M = 0.41$, $SD = 0.42$. A linear mixed-effects model with a random intercept for participants and fixed effects of phase and trial number estimated a phase difference of $\beta_{\text{phase}} = 0.21$, $SE = 0.07$, $t = 2.85$, p = .004, and a linear trial effect of $\beta_{\text{trial}} = 0.00$, $SE = 0.00$, $t = 1.79$, p = .073. That indicates that the overall results during optimization were significantly better. Note that Figure 6 only shows that the optimization phase produced higher-rated configurations than seeding, not that full convergence occurred, which the limited number of optimization trials would not support. Notable are trials 1 and 15, which have especially high speech speeds and received negative ratings. For all participants, a non-dominant candidate could be found — for more details see Figure 7 — and for P10–12, maxed-out candidates (highest possible rating) could be identified. We observed a large discrepancy in the Pareto-optimal non-dominant configurations in our sample. Only a few similarities could be found. For the local parameters, given the sample size, statistical approaches were not feasible; however, Figure 5 shows how modules are distributed across all participants.

Global Parameter Convergence. We quantified dispersion using the coefficient of variation (CV = SD/M) for each global parameter (N=12).

Participants showed strongest convergence for *vibration_intensity* (M=84.5, SD=11.52, CV=0.14) and *sound_output_speed* (M=138.33, SD=34.89, CV=0.25). Moderate dispersion was observed for *servo_speed* (CV=0.36) and *hue* (CV=0.42). In contrast, vibration timing parameters exhibited substantially higher variability (*vibration_on_time*: CV=0.48; *vibration_off_time*: CV=0.62), and *(MX) Buttons/tactile feedback* showed the largest relative dispersion (CV=1.15). These

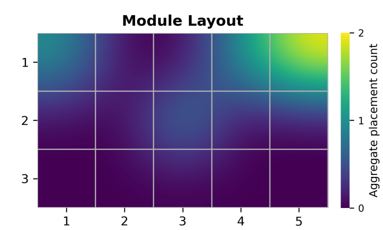

Figure 5: Spatial distribution of module placements (3×5 board). Each cell shows how often a module was placed at that location, summed across all participants and all of their active modules (N=12). The colorbar gives absolute counts; brighter cells were used more frequently. Because participants used different numbers of modules, counts reflect aggregate placement frequency rather than per-participant proportions.

results indicate convergence on intensity and speech-related parameters and higher dispersion for temporal and feedback settings. We caution that high dispersion within 20 trials does not by itself establish genuinely individual preferences: it may also reflect ongoing exploration of a high-dimensional space, or parameters that are perceptually irrelevant to a given participant (see subsection 7.2). Regarding overall model (information need) usage, the following ranking became apparent: Across the 12 participants, Exit direction (Module 1) and Reason for the vehicle stopping (Module 4) were most frequently selected (9/12 each) by the optimizer, indicating a strong preference for clear directional guidance and contextual explanations. Mid-level usage was observed for Orientation assistance at arrival (Module 0), Time & relationship to destination (Module 3), and Future turns & upcoming maneuvers (Module 6) (5/12 each).

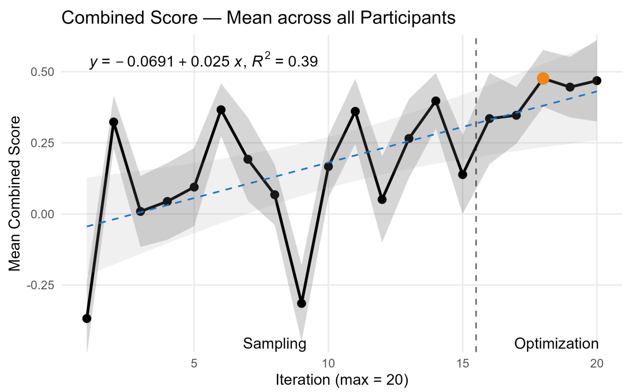

Figure 6: The combined score is the mean of the three objectives after normalization to [-1, 1], with perceived workload inverted; orange points mark non-dominated candidate configurations.

In contrast, Other traffic members (Module 5) (3/12) and Obstacles at exit (Module 2) (2/12) were rarely included.

6.3 Semi-Structured Interview

We conducted semi-structured interviews with all 12 participants after the study session. Interviews were recorded (with consent), locally transcribed (using [26]), and analysed using the analysis approach of Clarke and Braun [23] by two researchers.

Across all 12 interviews, participants reported that MoTUI is helpful, and that the final configurations felt appropriate for their individual needs, indicating that the 20 trials of the HITL-BO process successfully produced personalized setups over successive iterations. Thematic analysis reveals five main themes: (1) perceived usefulness and acceptance, (2) sufficiency and relevance of information, (3) speech rate and cognitive load, (4) layout and number of modules, and (5) interpretation of tactile movements, with a cross-cutting theme that several participants explicitly framed the final variants as "theirs,". Note that participants' reflections frequently reference intermediate configurations encountered during the optimization process; criticisms of specific parameter settings (e.g., speech speed) therefore describe the exploration phase rather than the final optimized result.

6.3.1 Perceived Usefulness and Acceptance. All 12 participants stated that they could imagine using a comparable system in everyday HAVs or public transport, typically on the condition that it worked as reliably as in the study. For example, P1 noted: "Yes, and it will probably become even more important as my vision deteriorates. Especially when travelling alone, you need such a system," while P10 summarized: "I was excited and thought it was awesome how it was set up. I found it great! … Yes, I could imagine using such a system in an autonomous vehicle; that would be really helpful, better than just getting in without anything." Several participants directly tied this acceptance to increased independence, with P11 explaining: "for me it is about becoming independent if I can really use such a car. Better than public transport."

6.3.2 Sufficiency and Relevance of Information. Ten of the 12 participants (P2–P7, P9–P12) described the available seven information types as sufficient for understanding the ride and feeling safe, but their views on which items were *useful* versus *unnecessary* diverged sharply. This was particularly pronounced for curve information: some participants (e.g., P3, P4, P8) explicitly valued advance announcements of curves to orient their body and avoid collision with interior elements, whereas others (e.g., P2, P7) stated that curves were not important for them personally and that they could "do without" this type of information.

A similar polarity appeared for other traffic members. Several participants downplayed the importance of knowing about other vehicles while driving and instead prioritized exit-related hazards and remaining time, while others requested richer situational context, such as the direction of approaching pedestrians, tunnels, or nearby landmarks. In effect, each participant articulated a slightly different ideal subset of the seven information types. The HITL-BO process accommodated these heterogeneous preferences by iteratively adding, removing, and reweighting information sources per participant, converging on curve-rich configurations for those who valued them and curve-light configurations for those who did not.

6.3.3 Speech Rate and Cognitive Load. Seven participants (P1, P2, P7, P9, P10, P11, P12) explicitly criticized fast speech rates encountered during intermediate optimization trials as stressful or hard to understand. P1 reported that "the speech output was sometimes too fast, especially when there were additional sounds in the car," and P9 described that fast speech "really annoyed" them, creating "inner unrest and a sense of hecticness." Similarly, P7 and P12 both framed speech rate as a source of frustration, and P10 stated that the speed "sometimes stressed" them.

Several of these participants directly requested a user-controlled speech-speed setting analogous to smartphone screen readers. P2 suggested: "When you get in, you should be able to set the speech speed yourself, like on the phone where you can choose the percentage," and P7 made the same comparison to VoiceOver on the iPhone, emphasizing that they need a slower setting than many other users.

6.3.4 Layout and Number of Modules. Eleven of the 12 participants (all except P7) articulated concrete preferences for the spatial layout and module grouping, often advocating one-handed reachability and thematic grouping of related information. P1 explicitly wanted "thematically related modules placed next to each other" and a design that can be operated with one hand, while P6 proposed "three buttons under one hand" arranged like arrow keys. P3 and P8 independently argued for hand-shaped or slightly curved arrangements that allow the fingers and palm to rest comfortably while still covering multiple buttons.

Participants also discussed the density and number of active modules, revealing a clear trade-off between information richness and cognitive load. Seven participants (P1, P2, P5, P6, P7, P8, P11) cautioned that too many active buttons can be confusing or stressful—P5 worried that "too much information is not good" and P8 described frustration when "too many buttons have to be felt and you are just waiting to see what pops up or rotates." In contrast, three participants (P3, P4, P10) explicitly preferred richer boards with more active modules; P4 confirmed that they "favored it when there was simply more on the board," and P10 stated that "a bit more information is better, then I can press where I want."

6.3.5 Interpretation of Tactile Movements. Nearly all participants (11 of 12; all except P5) found the basic tactile behaviors, especially modules moving up out of the surface, to be understandable and helpful cues for information availability. P1 reported that tactile information was "easy to understand," and several others (P2, P4, P8–P10) described the upward movement as a clear signal that a module is active and can be pressed for more information. P9 valued that movement and vibration made it obvious when "something has changed" even without constantly pressing buttons.

At the same time, six participants (P2, P4, P5, P7, P10, P11) viewed horizontal movements and rotation as unnecessary or confusing outside of very specific mappings, such as an arrow for the exit direction. P2 stated that linear movement "is not needed, it is enough if it comes up," while P11 contrasted their understanding of the "cool" raising behavior with confusion about whether rotation or clicking was supposed to convey additional meaning.

6.3.6 Feedback on the HITL-MOBO Process. Four participants (P3, P4, P9, P12) explicitly referred to the progression across multiple variants and described the later or final configurations as matching their expectations or feeling like "their" setup. These reflections suggest the process arrived at configurations participants found well-suited to them, though we read the sense of ownership as suggestive rather than conclusive. P3 stated that "the last variants were now exactly as I had imagined; MoTUI announced everything outside that is really important: curves, pedestrians, goal, goal direction," and P4 contrasted earlier variants containing many "unnecessary" elements with the final state, judging this outcome as "actually not bad and well done."

Most strikingly, P9 explicitly framed the final configuration after all 21 runs as their personal optimum: "The last presentation of the 21 runs, that last demonstration, that was mine: the speech rate was right, the elements were perfectly tangible, and the cues like 'stop because of pedestrian' or 'oncoming car' and the mention of obstacles at the exit all fit. With that setup I could imagine getting into such a car and driving off alone."

Taken together with the finding that all 12 participants stated they could imagine using such a system and their consistent articulation of fine-grained personal preferences (e.g., number of modules, speech rate, and exact layout), these comments indicate that the HITL-BO effectively captured subjective trade-offs.

7 Discussion

Configuring multimodal tactile interfaces for VIPs involves numerous interdependent parameters and conflicting objectives, making manual exploration extensive. To address this, we presented MoTUI, a reconfigurable modular tactile interface paired with HITL-MOBO, and compared optimized configurations against a static baseline and an LLM-generated design in a within-subject study (N = 12 VIPs) across 20 iterative trials.

Prior HITL-MOBO work has optimized *visual* parameters for *sighted* users, including font readability [40], vehicle visualizations [38], and urban air taxi interfaces [50]. We extend this paradigm to *multimodal tactile* interfaces for *VIPs*. TPE's tree-structured nature handled MoTUI's heterogeneous parameter space without workarounds required by Gaussian-process-based approaches [4]. For every participant, a non-dominated Pareto-optimal configuration was found, with a significant improvement from exploration to exploitation (β_{phase}=0.21, p=.004).

MoTUI covers seven information needs that were derived from extensive prior workshop findings [14, 28, 51, 53]. Importantly, MoTUI does not replace participatory workshops but builds on them. Workshops are well-suited to identifying *what* information to convey and *which* modalities are broadly acceptable, yet they typically converge on a single consensus design because group dynamics favor compromise over individual optima [8]. HITL-MOBO complements this by allowing each user to arrive at their own set of Pareto-optimal (non-dominated) configurations rather than a shared compromise. For the final comparison we selected one non-dominated configuration per participant

7.1 Optimized Configurations Outperform Static and LLM Baselines (RQ1)

HITL-optimized configurations yielded significantly higher situation awareness than the LLM baseline, with the static design (OnBoard [51]) scoring in between but not differing significantly from either condition. This suggests that a carefully crafted one-size-fits-all approach is a reasonable starting point but still leaves room for individualized improvement. The finding parallels Jansen et al. [38], who showed that HITL-MOBO outperformed both expert-designed and user-customized *visual* AV interfaces. Our work extends their result to tactile and auditory modalities and VIPs, indicating that the advantage of feedback-driven personalization generalizes across modality and user population.

Overall workload was significantly lower for optimized configurations than for the LLM baseline, driven by the effort and frustration subscales. LLM-generated designs included poorly calibrated parameters, most notably speech speeds that participants found stressful. The static baseline performed comparably to optimization on workload, likely because its conservative, workshop-derived layout avoided such misconfigurations, suggesting that a well-designed default is a strong foundation upon which personalization can build.

Optimization also scored significantly higher on perceived satisfaction and psychological ownership than our baselines. Participants described their optimized configurations as "mine" and expressed willingness to continue using them, suggesting that the iterative HITL process itself fosters co-creation, aligning with core principles of participatory design [24]. Several participants emphasized that they are not "professionals" yet felt empowered to shape the interface to their needs. This raises the question of when the algorithm should lead and when it should defer. Our data suggest a division of labor: participants held confident, often unprompted opinions about layout, module grouping, and the information subset they wanted, whereas fine-grained temporal and feedback settings (e.g., vibration timing, speech rate) were preference-driven but hard to articulate. This points to a hybrid in which users specify hard constraints (such as a one-handed layout zone or must-include information) while HITL-MOBO explores the remaining space, reducing dimensionality and session length. We did not evaluate this hybrid, nor a comparison against direct user customization, and leave both to future work. MoTUI can therefore be understood as a *democratization tool*, enabling non-expert VIPs to meaningfully shape their own assistive technology during analysis, testing, and prototyping [42]. While the design phase itself is covered by the workshops, MoTUI builds upon. This aligns with Ladner [42]: "Self-determination means that those with disabilities have control of, and are not just passive recipients of, technology designs intended for them." [42, p. 28].

Although the LLM received structured vision-test data and full parameter descriptions, its single-shot recommendations could not capture person-specific perceptual and cognitive trade-offs. Nevertheless, an LLM-generated configuration could serve as an informed warm-start seed for HITL-MOBO after performing workshops, analogous to the expert-derived initializations that accelerated convergence in Jansen et al. [38]. Group-level MOBO approaches warm-start individual optimization from group-level priors [45], suggesting that population-level defaults derived from converged parameters could similarly initialize and shorten per-user optimization. This could speed up the process and reduce the required trials.

7.2 Individual Differences Confirm the Necessity of Personalization (RQ2)

The qualitative and quantitative results jointly confirm that interface preferences among VIPs cannot be reduced to a single clinical variable (visual acuity). While information needs like exit direction and reason for stopping were prioritized by most participants, other needs split the sample sharply, with each participant articulating a different ideal subset of the seven information needs. Critically, these individuals did not map onto visual acuity in a predictable way. Participants with comparable acuity sometimes held opposing opinions on the same information need, such as curve announcements, which some valued for bodily preparation while others dismissed as unnecessary clutter. This extends the observation by Meinhardt et al. [51, 53] that visual acuity positively correlates with engagement, and that preferences differ even within blind and low-vision subgroups. Our results indicate that the relevant differentiators are not primarily clinical but *personal traits*, shaped by factors such as whether impairment was congenital or acquired, familiarity with tactile media, personal risk tolerance, and habitual coping strategies. Personalization must therefore operate at the level of individual profiles, not predefined group classifications [66].

The layout and the number of models on the board exhibited a similar split. Half the sample preferred minimal boards to reduce cognitive load, while the other half preferred information-rich configurations. This trade-off did not align with a single clinical variable, further motivating runtime personalization over one-size-fits-all defaults. Regarding the model movement, it was universally understood as an attention cue; rotation was valued only when mapped to clear directional semantics, and horizontal slide was rated low-value by most. These patterns suggest that some design choices can be fixed as heuristics, while others require per-user tuning. The convergence and divergence of global parameters (e.g., the model's color) offer a complementary, quantitative perspective. Domain knowledge from prior work helped constrain the design space: vibration timing limits [44], speech speed ranges [9], and design heuristics for excluding infeasible configurations [55] jointly reduced dimensionality and enabled convergence within 20 trials. Among the remaining free parameters, vibration intensity ($CV = 0.14$) and speech speed ($CV = 0.25$) converged across participants and can serve as sensible population-level defaults. Parameters that remained individualized, notably vibration timing ($CV > 0.48$), module density, and spatial positioning, must be personalized at runtime. We therefore argue that future designs could set these converging features as fixed parameters to reduce the number of trials, as proposed by Mo et al. [55].

Interpreting parameter divergence requires caution, however. High variability does not necessarily indicate genuinely individual preferences. A parameter may vary freely because it is perceptually irrelevant to the participant rather than because preferences truly differ. Color hue illustrates this: we observed high dispersion ($CV = 0.42$), yet all participants had severe color vision deficiency, meaning hue drifted during optimization without affecting objective scores. It seems that parameters diverge because they are preference-driven and require personalization, whereas parameters that diverge because they are perceptually irrelevant can be fixed without loss. Disentangling these two sources of variability, through larger samples, controlled ablations, or perceptual pre-screening, remains an important direction for future work.

7.3 Limitations and Future Work

Our sample of $N = 12$, while consistent with prior work [51, 53], limits generalizability, and the simulated 40-second ride may not reflect real-world conditions with longer durations, richer sensory input, and genuine safety stakes. The 20 HITL trials (15 sampling, 5 exploitation) may not have sufficed for full convergence in the high-dimensional parameter space. All objectives relied on single-item self-reports without objective validation, and participants' awareness of the adaptive process may have positively biased later ratings (this effect is modelled in our GLM). While counterbalancing was applied, the baseline comparison is asymmetric, as it received no iterative feedback, unlike the 20-round HITL condition. Reconfiguring modules between trials required researcher intervention, limiting practical scalability. The current board dimensions (47 × 30 cm) and wooden chassis may also pose integration challenges in real vehicle cabins, where space is constrained, and form factors must comply with automotive safety and ergonomic standards. Our scripted 40-second ride with sparse, non-overlapping events leaves three questions open. Urgency is currently encoded via vibration and vertical pop-out (both reliably understood) but was not stress-tested under real time pressure; how to prioritize simultaneous events (e.g., an obstacle during an announced turn) is an open design question; and the personalization we studied yields a fixed per-user configuration from an offline session, whereas context-adaptive personalization remains future work that MoTUI's reconfigurability is well-suited to support. Finally, vision loss is often progressive, and while MoTUI retains optimization histories for re-personalization, validating this longitudinally remains future work.

8 Conclusion

MoTUI demonstrates that personalized tactile interfaces for VIPs are not only desirable but achievable. By pairing reconfigurable hardware with HITL multi-objective Bayesian optimization, we enabled 12 participants to iteratively converge on configurations that were measurably better (regarding situation awareness, mental workload, and perceived satisfaction) and felt made for them, within just 20 trials. The divergent outcomes across participants confirm what prior work has long suggested: there is no single interface that serves all VIPs well. MoTUI offers a practical path forward — one where the person with the disability is not a passive recipient of design decisions but an active co-creator of the technology they depend on, with the optimization loop translating their subjective feedback into concrete design improvements. As autonomous mobility becomes reality, tools like MoTUI can help ensure that this future is built with VIPs, not merely for them.

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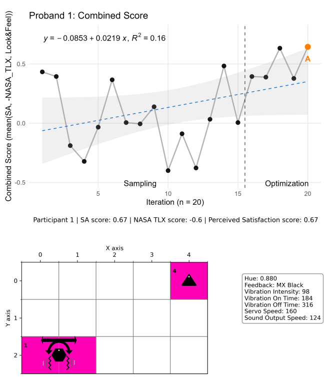
A Optimization Trials and Results



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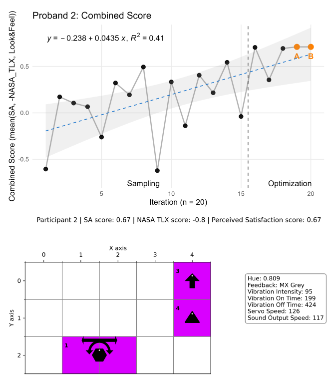

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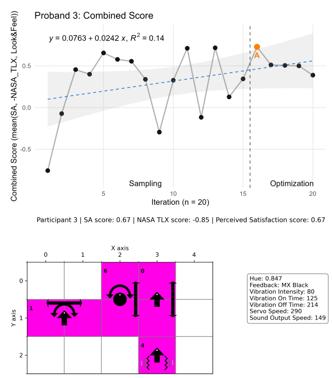

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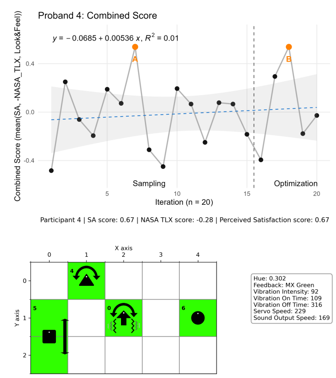

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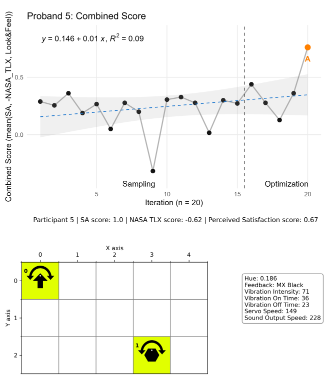

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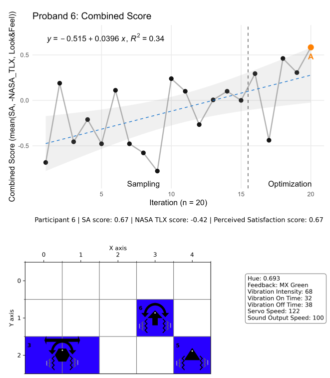

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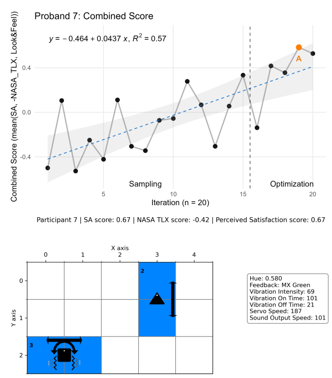

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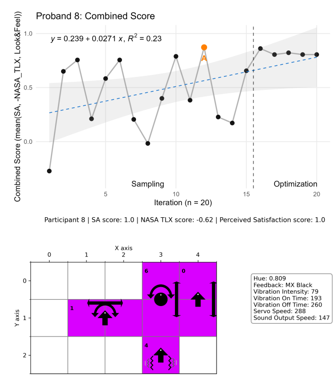

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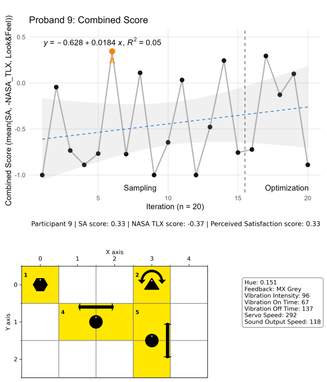

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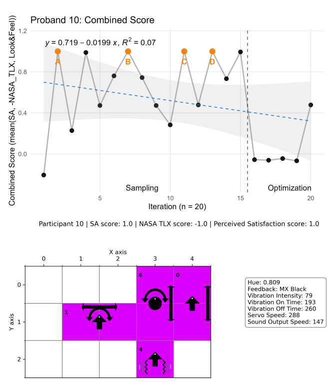

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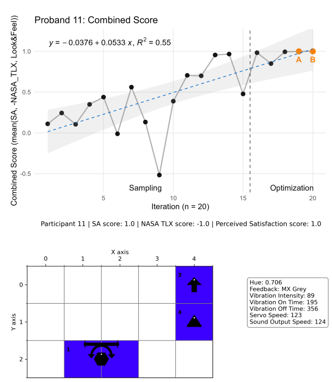

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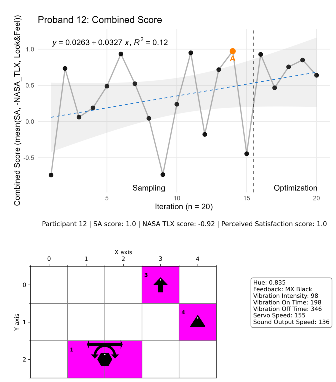

(l) Participant 12

Figure 7: Grid overview of the Combined Score visualizations (top) and the corresponding board representations (bottom) for all subjects. If multiple non-dominant occurrences version A is selected here for illustration

B Design Implications

Drawing on the convergent and divergent patterns observed, we derive the following implications for the design of personalized tactile in-vehicle interfaces for VIPs:

(1) **Adjustable speech rate at onboarding.** Provide a speech-speed slider (cf. VoiceOver model) during first use rather than relying on a fixed default. A population-level safe default of ≈138 WPM can serve as an initial value.
(2) **User-configurable information profile.** Offer a verbosity setting that lets users choose between a minimal set (exit direction, obstacles, time) and a comprehensive set (all seven information types). Individual differences likely correlate with, but are not fully predicted by, impairment severity.
(3) **Fix converged parameters, personalize the rest.** Parameters that converged across participants, such as vibration intensity (CV = 0.14) and speech speed (CV = 0.25), can be treated as sensible population-level defaults and fixed early on. Similarly, parameters that diverge due to perceptual irrelevance rather than genuine preference, such as hue for users with severe color vision deficiency, can be identified through pre-screening and removed from the optimization space. Reducing the number of free parameters shortens the optimization process and allows HITL-MOBO to reach a user's optimal configuration in fewer trials, lowering both session time and cognitive burden.
(4) **Exit-phase as primary use case.** Exit direction and obstacle detection emerged as the highest-priority information needs. System design should treat the exit phase as the core scenario and make in-ride traffic context (other road users, future turns) optional add-ons.
(5) **Prioritize vertical movement; use rotation selectively.** The upward pop-out was universally understood and should remain the primary attention cue. Rotation should be reserved for information with clear directional semantics (e.g., arrows). Lateral slide added little value and can be deprioritized or removed.
(6) **Design for one-handed, clustered operation.** Compact, ergonomically grouped layouts were strongly preferred. Future hardware iterations should explore curved or hand-shaped form factors that support single-hand operation without requiring visual search.
(7) **Longitudinal re-personalization.** Vision loss is often progressive. Personalized configurations should be stored and periodically re-optimized (e.g., at annual check-ups or when the user reports changed comfort). MoTUI's software architecture already supports this by retaining the optimization history per user.

C LMM Condition Prompt

```
This study is about a tactile user interface designed to help blind and visually impaired users achieve better situational awareness in an autonomous vehicle.
The tactile user interface can consist of up to seven modules. Each module is responsible for representing exactly one piece of information. Below is a list matching each module number to the specific information it represents:
0 = Orientation at destination
1 = Exit direction & Ground condition at Exit
2 = Obstacles at Exit
3 = distance/time and relationship to the destination
4 = reason for the vehicle stopping
5 = other traffic members
6 = future turn & Upcoming manuevers
These modules can be mounted on a board measuring 5 by 3 squares (x/y format). Information about the current situation is conveyed through linear, vertical, or rotational movements. Users can perceive this information by feeling the three-dimensional elements with different shapes attached to each module.
Each module can also vibrate when the corresponding situation changes. In addition, every module features a button that provides auditory feedback with additional information about the specific situation. The modules themselves are black, while the elements on the modules are colored.
Below is a list showing which information is represented by each module, along with the corresponding functions:

Number  Module  Rotation        Vibration       Vertical Extension      Linear Extension
0       Orientation at Destination      Top element points into the direction of the final destination in regards to the AV and follows it      Module vibrates for 4 seconds when new information gets presented       Module extends when AV reaches the destination  Vertical Orientation:
Linear position reflects the position of the final destination (the middle of linear extension is the position of the AV)"
1       Exit direction & Ground condition at Exit       Top element points into the direction of the Exit direction     Module vibrates for 4 seconds when new information gets presented       Module extends when AV reaches the destination  Horizontal Orientation:
Element moves left or right depending on the exit direction
2       Obstacles at Exit       Top element points at the obstacle      Module vibrates for 4 seconds when new information gets presented       Module extends when AV reaches the destination
& there is a obstacle at the destination        Vertical Orientation:
Linear position reflects the position of the Obstacle (the middle of linear extension is the position of the AV)
3       distance/time and relationship to the destination       Top element points into the direction of the final destination in regards to the AV and follows it      Module vibrates for 4 seconds when destination is reached       Module drives in when destination is reached    Horizontal Orientation:
Linear movement acts as a progress bar for the estimated time until reaching the destination
```

4 reason for the vehicle stopping 1. Top element points into the direction of the the reason for the stop and follows him (e.g. for pedesstrian crossing) else it does nothing

2. Top element functions as a clock and gives estimated time for the stop Module vibrates for 4 seconds when new information gets presented Module extends when AV stops Horizontal Orientation:
Linear movement acts as a progress bar for the estimated stopping time
5 other traffic members Top element points into the direction of the traffic member and follows him Module vibrates for 4 seconds when new information gets presented Module extends when there are other traffic members close to the AV Vertical Orientation:
Postion reflects the position of the other traffic member (the middle of linear extension is the position of the AV)
6 future turn & Upcoming manuevers Top element points into the direction of the upcomming curve Module vibrates for 4 seconds when new information gets presented Module extends when there is an upcomming curve Vertical Orientation:
Distance between element and top boundary signals the distance to the upcomming curve

The parameters that can be modified are:
(local) Position of the modules on the board:
Tuple (x, y) [x: int 0-4 y: int 0-2]
(local) Used traffic information:
Boolean value [0, 1] [Orientation at destination, Exit direction & Ground condition at exit, Obstacles at exit, Distance/time and relation to the destination, Reason for the vehicle stopping, Other traffic participants, Future turns & Upcoming maneuvers]
(global) Color of the module elements:
Triple tuple (R, G, B) [RGB: int 0-255]
(local) Shape of the module elements:
Categorical object type SHAPES = ["Circle", "Triangle", "Square", "Hexagon", "Arrow"]
(global) Tactile feedback:
Type of tactile feedback for the button used on the elements -> Discrete object type [int 0-2]
0 = No tactile feedback [MX Black Clear Top]
1 = Tactile feedback [MX Grey]
2 = Tactile and clicky feedback [MX Green]
(global) Servo speed:
Speed at which the elements on the modules move [int: 100 deg/s - 300 deg/s]
(global) Vibration intensity:
Intensity with which a module vibrates when conveying information [int: 65% - 100%]
(global) Vibration pattern:
Pattern used for module vibration:
- On-Time (PD): [int: 5 ms - 200 ms]
- Off-Time (IPI): [int: 10 ms - 500 ms]
(local) Functions used per module:
- use_rotation: [bool]
- use_vibration: [bool]
- use_horizontal_movement: [bool]
(global) Sound output speed:
Speed at which verbal information is delivered [int: 100 - 250 wpm]

Now, based on this description, decide on a configuration of these parameters that will provide the highest situational awareness, the lowest mental workload, and the best look and feel for the test subject described below.
Keep in mind that you will likely not be able to use all modules, since only one module can be placed on each field, and modules that use linear movement (use_horizontal_movement = large) require two adjacent fields.
You can also find below a list indicating whether a module (identified by its module number) requires one additional space in the x or y direction: (0 = y, 1 = x, 2 = y, 3 = x, 4 = x, 5 = y, 6 = y).
Test Subject (Description based on results from vision tests):
- Amsler Test:
  o The central dot is not visible
  o Presence of "holes" or gray veils
  o Dark or blurry areas
  o Squares appear in different sizes
  o Bent or distorted lines
- Ishihara Color Test:
  o Red-green color deficiency (Deuteranomaly/Protanomaly)
  o Color blindness (stronger form, Dichromasy)
- Snellen Chart Test:
  o 20/40 visual acuity
- Pelli-Robson Chart:
  o logCS = 1.65
- Completely blind.

Provide me with an assignment of these parameters in the following JSON format within their respective defined value ranges (only for the parameters that are also included in the example JSON file). Maintain the JSON format exactly ("extension_length": 8.5 is a fixed value)!

```
Note that the global parameters are the same for all modules. This means that the RGB colors, tactile feedback, servo speed, vibration
      intensity, vibration pattern, and sound output speed have the same values for all modules.
Provide all additional parameters that are not included in the JSON file as a separate list (not in JSON format): [Used Traffic Information |
      Position of the modules on the board | Shape of the module elements | Tactile feedback].

JSON Format:
{
    "extension_length": 8.5,
    "servo_speed": 200,
    "sound_output_speed": 125,
    "use_module_0": true,
    "large_0": false,
    "r_0": 208,
    "g_0": 249,
    "b_0": 118,
    "use_vibration_0": false,
    "vibration_intensity_0": 0,
    "vibration_on_time_0": 0,
    "vibration_off_time_0": 0,
    "use_rotation_0": true,
    "use_module_1": true,
    "large_1": false,
    "r_1": 236,
    "g_1": 138,
    "b_1": 210,
    "use_vibration_1": true,
    "vibration_intensity_1": 71,
    "vibration_on_time_1": 110,
    "vibration_off_time_1": 396,
    "use_rotation_1": false,
    "use_module_2": true,
    "large_2": false,
    "r_2": 30,
    "g_2": 32,
    "b_2": 211,
    "use_vibration_2": false,
    "vibration_intensity_2": 0,
    "vibration_on_time_2": 0,
    "vibration_off_time_2": 0,
    "use_rotation_2": true,
    "use_module_3": true,
    "large_3": true,
    "r_3": 147,
    "g_3": 103,
    "b_3": 104,
    "use_vibration_3": false,
    "vibration_intensity_3": 0,
    "vibration_on_time_3": 0,
    "vibration_off_time_3": 0,
    "use_rotation_3": false,
    "use_module_4": true,
    "large_4": false,
    "r_4": 37,
    "g_4": 188,
    "b_4": 82,
    "use_vibration_4": false,
    "vibration_intensity_4": 0,
    "vibration_on_time_4": 0,
    "vibration_off_time_4": 0,
    "use_rotation_4": true,
    "use_module_5": true,
    "large_5": true,
    "r_5": 160,
    "g_5": 96,
    "b_5": 121,
    "use_vibration_5": false,
    "vibration_intensity_5": 0,
    "vibration_on_time_5": 0,
    "vibration_off_time_5": 0,
```

```
    "use_rotation_5": true,
    "use_module_6": false,
    "large_6": false,
    "r_6": 0,
    "g_6": 0,
    "b_6": 0,
    "use_vibration_6": false,
    "vibration_intensity_6": 0,
    "vibration_on_time_6": 0,
    "vibration_off_time_6": 0,
    "use_rotation_6": false
}
```