Final Report

A Virtual Reality-Based Evaluation of Human-in-the-Loop Connected Cruise Control (hC3)

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16. Abstract

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Introduction

Most modern vehicles have adaptive cruise control (ACC) systems, which allow longitudinal control of the ego vehicle depending on the speed or distance to the preceding vehicle. The major disadvantage of ACC is that when the preceding vehicle switches lanes, the ego vehicle accelerates, which can be unsafe in certain contexts. Moreover, when the ego vehicle has a time headway of more than two seconds, it can trigger other vehicles to cut in front of the ego vehicle, disturbing the platoon. As a result, not all drivers use ACC when driving [1].

Humans' poor acceleration or deceleration when driving behind a leading vehicle is generally caused by the inability to perceive and respond optimally. In most cases, drivers can either over-compensate or under-compensate the throttle. Since over 50% of new vehicles have some form of connectivity (e.g., GM OnStar), it is becoming more likely that the ego vehicle will be in communication with a preceding connected vehicle. Thus, an algorithm that uses vehicle connectivity to help human drivers and enhance string stability is required [2].

To satisfy this requirement, the Human-in-the-Loop Cooperative Cruise Control (hC3) algorithm has been put forward to integrate vehicle connectivity with real-time human input, but this algorithm has not been tested in a full immersive simulation setting [3]. It is necessary to evaluate the advantages of the hC3 system using a realistic VR simulation before creating a prototype and testing it in real-life conditions. A high-fidelity environment is a critical framework that can be used to explore the capability of drivers to react to the semi-automatic functionality on heterogeneous vehicle platforms and drive in different driving contexts. This form of immersive simulation plays an important role in validating the impacts that hC3 can have on driver trust, control, and energy efficiency before real-world implementation.

Before on-road testing deployment, extensive simulation testing of hC3 is required due to safety and cost challenges. Field implementation requires instrumented vehicles, V2V hardware, and controlled road environments, making early testing expensive and impractical. High fidelity simulation provides a safe, repeatable, and cost-effective environment to understand human-automation interaction and test the performance of the system before testing it in the real world. The control strategies that will moderate the acceleration, ensure smooth time intervals, and minimize unnecessary braking can contribute to system stability and directly result in a reduction of fuel energy consumption.

This study develops a VR-based simulation framework to evaluate the performance of manual driving and hC3 systems. Using BeamNG and an HTC Vive Pro 2 headset, twenty participants went through controlled car-following scenarios that allowed for the detailed measurement of driving performance, levels of driver trust, and user readiness to adopt hC3. The immersive setup also allowed us to quantify driver energy-related actions. Combining high-fidelity vehicle dynamics with human-in-the-loop data collection, this study offers one of the first realistic and comprehensive assessments of hC3 in an immersive VR environment. The remainder of this paper includes background information VR-based driving research, simulation design and data collection methodology, the details of the hC3 system framework and evaluation metrics, a comparative analysis of driving performance and user perceptions during manual and hC3 control in the immersive environment, and implications for energy efficiency.

Literature Review

Virtual Reality in Driving Simulations

The use of VR in research has become popular in recent years as its potential is wide in many areas, such as product design, prototyping, and simulation-based training [4]. Within the scope of driving simulations, VR is expected to reproduce sensory stimuli that drivers encounter in real-life settings. Some research has been conducted to determine whether VR is more effective in simulating realistic driving dynamics than conventional simulators with 2D or stereoscopic 3D displays [5][6]. According to recent studies, the fact that VR offers a three-dimensional view with complete head tracking helps to enhance spatial awareness and scene comprehension during driving activities [7]. Research further indicates that Head-mounted displays (HMDs) have demonstrated a high potential in simulating peripheral and dynamic visual cues necessary to maneuver and detect hazards [6][8]. Although older VR systems had technical limitations, recent systems have shown equal or better performance and validity over multi-monitor systems [8]. Comparisons made in experiments show that VR simulations enhance perceived realism and enable more natural interaction by the user in dynamic tasks like overtaking or intersection navigation [5]. Such benefits are particularly noticeable when high-fidelity VR systems are integrated with realistic traffic conditions and movement limitations. However, most of the available studies focused on basic driving tasks or the validity of simulators in general and do not consider semi-automated or cooperative control systems. In particular, there is little work using VR to study human automation interaction and energy related outcomes in advanced driver assistance systems such as hC3.

Metrics for Comparing VR and Non-VR Simulations

Driving Performance

Driving performance in VR and non-VR environments has been examined in different studies. Lap times and path accuracy were investigated in one study [9], and lane-change precision was investigated in another [6]. The conclusion of these studies is usually that VR is more immersive, but the differences in performance vary. In car-following simulations in particular, relative distance, jerk, acceleration, and minimum time to collision have been used as measures of driving performance [10]. Recent evidence indicates that the type of task is a major factor that influences the effects of VR on driving performance, whether positive or negative [5]. Lane keeping and straight-line navigation are likely to be similar in VR and non-VR but performance differences appear in complex or high speed tasks where fast reaction is needed. VR systems based on HMDs have been demonstrated to be as accurate as screen-based systems in braking and turning situations when the frame rate and resolution are optimized [5]. Other users might be a little more cautious in VR because of the increased perceived speed and distance compression effects. In general, VR driving seems to better replicate real-life safety-critical behavioral tendencies of caution [7].

Simulation Sickness

VR environments are usually associated with higher levels of simulation sickness which is often quantified with the Simulator Sickness Questionnaire. Researchers have always reported more nausea, dizziness, and disorientation in VR than in non-VR simulators [6], [8]. These symptoms are commonly explained by the discrepancies between the visual motion signals and the vestibular input, particularly during sudden turns or accelerations without physical motion platforms [9]. The weight of the headset, field of view, and frame rate stability are some of the factors that greatly affect the level of simulation sickness [8]. The Full Motion Sickness (FMS) scale has also been found to be valid as an addition to the Simulation Sickness Questionnaire (SSQ) in measuring sickness levels during long VR sessions [7]. Recent research focuses on the need to have a slow acclimation process and adaptive rendering methods to minimize discomfort during the first use [6]. However, studies have shown that symptoms may reduce with repetition and improved hardware especially in well-designed experiments involving controlled motion stimuli [5].

Immersion in VR-Based Driving Simulations

Realism in simulations has been assessed through both biometric feedback (heart rate, blood pressure, and head movement) and immersion. Research indicates that VR causes greater head movement and provides stronger immersion than non-VR systems [5], [9]. Previous research has demonstrated that physiological measures of cognitive load and engagement (such as EDA, pupil dilation and gaze tracking) can be used to efficiently capture user engagement in VR-based driving research [8]. Increased heart rate variation and amplitude of head rotation are also correlated with increased sense of presence and perceived realism [6]. Additionally, postural instability and spontaneous body sway have been used as implicit indicators of simulator realism and immersion [9]. The combination of eye and head tracking in VR offers valuable insight into the distribution of attention drivers bring to their driving by navigating, detecting hazards, and changing lanes [5]. Although biometric data are not analyzed in this study, previous research using such measures allows a conclusion that VR environments are better in their immersion and realism than non-VR simulations. Yet, these immersion and engagement measures have hardly ever been related to detailed car following performance, safety measures, and energy use in a single framework. As a result, it is not clear yet how immersive VR can be used in order to systematically analyze cooperative control algorithms from a behavioral and energy efficiency point of view.

Human-in-the-Loop Connected Cruise Control (hC3)

Design Motivation and Limitations of ACC

Conventional ACC systems have limited capabilities for incorporating human preferences and often have difficulties in adapting to sudden changes in traffic, such as cut-in, lane changes, etc., while maintaining optimal headways. Many algorithms used in ACC are based on fixed car-following algorithms that do not mimic human-like responses, and this leads to a high rate of disengagement and lower driver satisfaction. To overcome these problems, the hC3 system that combines driver intention, vehicle-to-vehicle (V2V) communication, and adaptive control logic was proposed by Zheng et al. Their results show that hC3 provides better string stability, less acceleration variance and a higher driver confidence than traditional ACC [3].

Features of the hC3 Controller

The hC3 controller allows human machine collaboration, where drivers can stay engaged in longitudinal control while the system supplements their actions with other acceleration or deceleration. This controller is based on Cooperative Adaptive Cruise Control (CACC), but it differs in the interaction with the human driver in the control loop. CACC is a well-established connected automation framework that allows vehicles to exchange speed and acceleration data with their predecessors via V2V communication, thereby improving string stability and fuel efficiency while maintaining shorter headways [3]. However, since CACC requires the assumption of a fully automated control loop, the use of CACC is limited to connected and automated vehicles (CAVs), which are not practical in the current mixed traffic environment. The proposed hC3 is based on the feedback/feedforward structure and spacing policy of CACC but purposely keeps the driver in the control loop. By combining human and automation inputs through connected information, hC3 gives the cooperative benefits of CACC to human-driven vehicles to improve stability and comfort while not taking the driver out of the loop.

By taking into account information such as speed and acceleration from the previous vehicle V2V communication, hC3 improves the consistency and smoothness of headways. Evaluations done so far shows that hC3 can reduce fluctuations in acceleration, jerk, and time gap and improve energy efficiency as compared to human driving only [3]. However, these research efforts have been carried out in non-immersive simulation environments and have paid limited attention to driver trust and willingness to adopt hC3. Thus, there is a need to test hC3 in a high-fidelity VR environment that accounts for safety, comfort, energy efficiency, and user acceptance.

Building upon the reviewed literature, this study is an attempt to fill these gaps by using an immersive VR-based driving simulator to compare manual and hC3 car-following. We investigate how drivers drive this type of vehicle, measure improvements made by implementing hC3 in terms of safety, comfort, and energy-related aspects, and determine if the improvements are noticeable enough to influence the driver's trust in and willingness to adopt hC3 as a driver assistance system.

Methodology

Simulation Environment Setup

This research was conducted on a high-performance simulation workstation with a Core i9-13900K processor, 64GB DDR5 RAM, and a GeForce RTX 4090 GPU. This system configuration allowed for a smooth and high-resolution VR-based data collection using the BeamNG simulation platform since it offers an easier VR setup, and high-frequency real-time data make it far superior for studying detailed platoon behavior and string-instability effects. In addition, an HTC Vive Pro 2 VR headset, along with a Logitech steering wheel and pedal set was used to provide participants with full-field, high resolution visual and tactile feedback. BeamNG was the preferred platform to other simulation software due to its visual prowess and improved compatibility with VR. Figure 1 shows the VR-based system simulation setup overview.

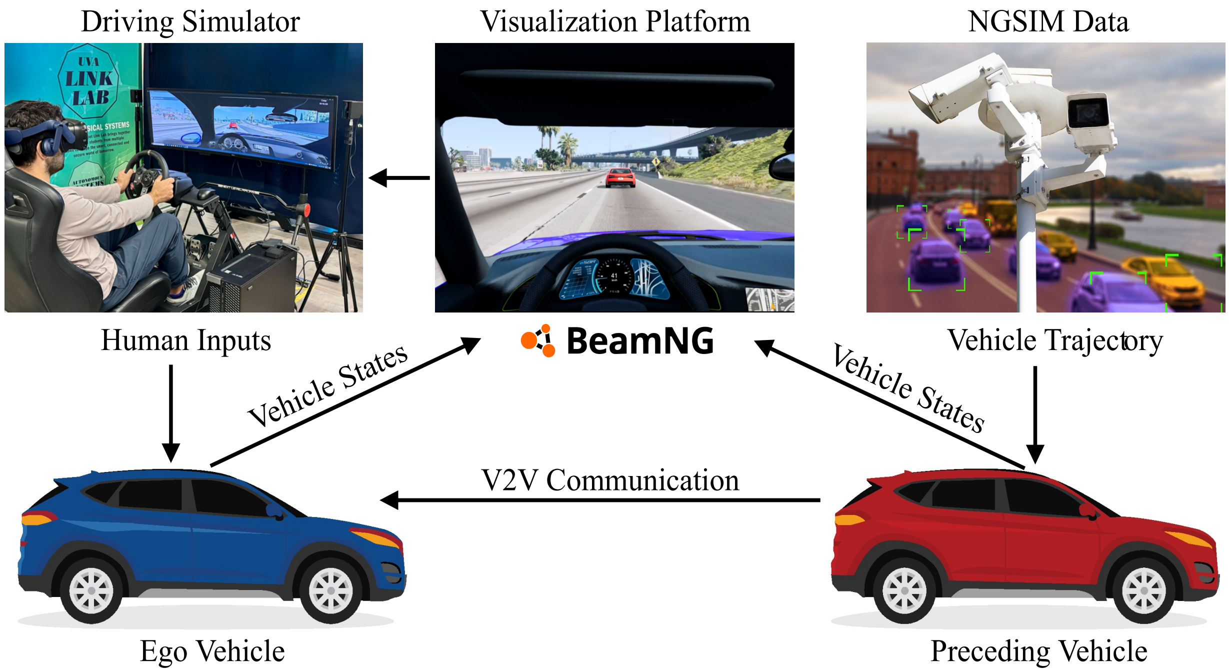

Figure 1. Overview of the VR-based hC3 system simulation

Experimental Design

This research included two different driving modes of manual and hC3 controls. Manual control is traditional driving (Level 0 automation) where the participants have complete and direct control over the acceleration and braking of the vehicle via physical applications of the pedals with no automation and system assistance. Conversely, hC3 integrates driver information in real-time with vehicle connectivity to enhance the car-following capability and longitudinal stability of the vehicle. The two driving modes were implemented within BeamNG for the purposes of comparing the control performance of the vehicle.

To increase simulation realism, the speed trajectory of the preceding vehicle was originated from real world vehicle trajectory data provided by the Next Generation Simulation (NGSIM) program [11], initiated by the U.S. Federal Highway Administration (FHWA). Data from US Highway 101 (US-101) segment was selected for its detailed representation of the highway traffic highlighting high resolution trajectories recorded at 10 Hz using overhead video cameras. It is important to note that the speed profile is not directly imposed on the preceding vehicle during evaluation and it is followed using a Proportional Integral Derivative (PID), which is a type of feedback control system. This approach helps reducing the presence of unrealistic velocity fluctuations and unnecessary jerks (i.e., rapid changes in acceleration) commonly observed in the original NGSIM dataset [12]. The PID controller and the dynamics model used together serve as a smoothing mechanism to ensure that the trajectory of the vehicle is acceptable. To ensure the same experimental conditions, the trajectory of the previous vehicle remains the same in all test situations.

Participant Demographics and Trial Procedure

At the beginning of the experiment, the participants were asked to give their demographic data and information about their driving history. The study recruited twenty participants (10 males and 10 females). The age structure was as follows 20% between the ages of 16-20 years, 30% 21-25 years, 40% between 26-30 years and 10% were above 30 years. Regarding the level of education, 30% of the respondents were undergraduate students and the rest (70%) were graduate students. All participants had driving experience. Figure 2 shows the VR-based driver view versus the non-VR-based view, looking at the desktop.

Figure 2. VR-based driver view (left) vs. non-VR-based driver view (right) in BeamNG

To ensure participants were acquainted with the simulation environment and the control mechanics, each of them received two trial simulations in a random order. These consisted of manual driving of (1) a vehicle without a VR headset, and (2) a vehicle with a VR headset. These sessions enabled participants to become familiar with the VR and the non-VR interfaces as well as the dynamics of the vehicle type and stabilize performance for the main experiments.

After the trial phase, participants were asked to compare the realism of the two control modes by responding whether the VR headset helped them feel the experiments were realistic to the real world compared to the non-VR simulation. Their preference determined the simulation condition (VR or non-VR) in which they would complete the main simulations. Each driver then drove two primary scenarios in his/her preferred condition: Manual and hC3. This study therefore has a mixed (between-within) design that included the variable, i.e. control mode (manual vs. hC3), as a factor in the within-subject conditions, and the display condition (VR vs. non-VR) as a factor in the between-subject conditions, decided by the preference of each participant's interface. Following the simulations, participants were asked the following questions about the hC3 mode: While driving this vehicle, how much do you trust the hC3 mode? If your vehicle had the hC3 mode, how often would you use it over manual driving? Would you be willing to buy a vehicle with hC3 mode? If so, how much would you spend on it?

This process allowed for participants to be exposed to a variety of test conditions such that meaningful comparisons in driving performance, user trust, and system usability between interface settings were possible. Though twenty participants were recruited, the data of three participants were excluded from the final analysis based on predefined performance criteria. Specifically, participants were disqualified if they (i) did not maintain continuous car following engagement (i.e., frequent stops or long time periods of standstill unrelated to traffic flow), or (ii) exhibited overly aggressive driving behavior that led to probable near-miss or minor collision events, Consequently, data from seventeen participants who not exhibited these characteristics were used for the final analysis. The analysis was conducted among ten results for reporting.

Framework of the hC3 System

The cooperative control behavior of hC3 can be represented by the following equations:

$$h(t) = x_2(t) - x_1(t) - l$$
$$\ddot{x}_1(t) = \alpha\left(\frac{1}{t_h}h(t-\varphi) - \dot{x}_1(t-\varphi)\right) + \beta\dot{h}(t-\varphi) + g(\beta'[\dot{x}_2(t-\theta) - \dot{x}_1(t)] + f(\ddot{x}_2)) \quad (1)$$

where $h(t)$ is headway distance between preceding (x_2) and following (x_1) vehicles, l is effective vehicle length, φ is driver reaction delay, α is driver sensitivity to headway error, β is headway rate gain, t_h is desired time headway, $g(.)$ represents the actual acceleration achieved by the longitudinal vehicle dynamics, β' is the automatic speed feedback gain feedback, θ is V2V communication delay, and $f(\ddot{x}_2)$ is a linear feedforward filter that generates commands based on the received acceleration of preceding vehicle. Detailed parameter values can be found in Zheng et al. [3].

Equation (1) captures the cooperative interaction between the human driver and automation. The first term is to model the delayed human reaction to headway errors and the feedforward and automatic speed feedback terms are for assistance to stabilize the spacing between vehicles and make driving smoother. By using a combination of human feedback and these automated control actions, the hC3 system allows safe, consistent and smooth car-following in even complex traffic scenarios. Figure 3 shows the framework of the hC3 system.

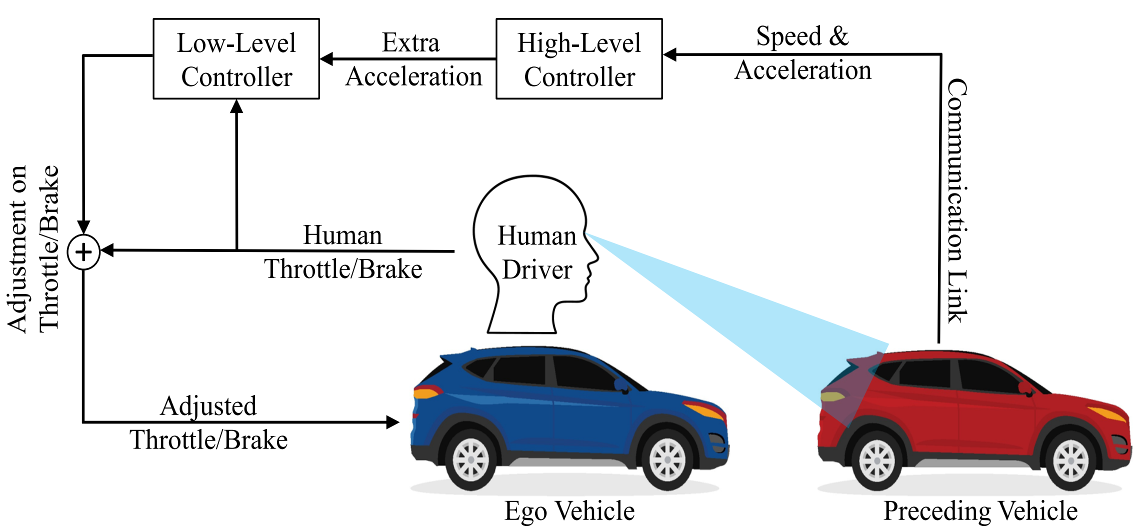

Figure 3. Framework of the hC3 system

Evaluation Metrics and Data Collection

The BeamNG simulator recorded detailed driving states of both vehicles in each scenario at every time step, including vehicle position, velocity, and throttle/brake inputs. Based on this data, a set of quantitative performance indicators was applied to evaluate the efficiency of the suggested control strategies, which are related to safety, energy efficiency, and driving stability:

- *Headway and Velocity:* Headway and velocity were used to evaluate the longitudinal motion characteristics of the ego vehicle relative to its surroundings. Headway was characterized as the spatial distance between the front bumper of the ego vehicle and the rear bumper of the vehicle ahead, while velocity was characterized as the instantaneous speed of the ego vehicle. The mean and standard deviation (STD) of both values were calculated over the simulation horizon. For headway, these metrics represent the average following distance and its fluctuations, indicating the stability and regularity of car-following behavior. For velocity, they represent the average traveling speed and its fluctuations, indicating the smoothness and consistency of the vehicle's motion. Together, these measures can give a comprehensive understanding of how well the vehicle interactions are managed, as well as how effectively the controller or human driver can maintain both a safe following distance and a desired pace under different conditions.

- *RMS Acceleration:* The smoothness of longitudinal motion was captured using the Root Mean Square (RMS) of the acceleration of the ego vehicle. Lower RMS value indicates less sudden variations of speed, and better control.

- *Time Gap:* Time gap was computed as the ratio of headway to the ego vehicle speed at each time step. It is the average and variability that reflects the consistency and safety of the following vehicle behavior.

- *Time Exposed Time-to-Collision (TET):* TET was chosen as a measure of safety, which is the total time that the ego vehicle was at a potentially dangerous Time-to-Collision (TTC) value. In particular, TET is provided by:

$$TET = \int \delta_i(t)\, dt$$
$$\delta_i t = \begin{cases} 1\text{ , if } TTC < TTC^* \\ 0\text{ , otherwise} \end{cases}$$
$$TTC = h(t) \,/\, \dot{h}(t) \qquad (2)$$

where *h(t)* is the headway distance between the ego and the preceding vehicles at time of *t*, and $\dot{h}(t)$ is the rate of change of headway, which is their relative velocity. The minimum safe time before a possible collision is called the critical time-to-collision threshold, *TTC**. According to the NHTSA recommendations, the *TTC* of less than 2 seconds is deemed dangerous and is enough to trigger the Forward Collision Warning (FCW) system [13]. Therefore, *TTC** will be 2 seconds in this study.

- *Fuel consumption of vehicle:* The fuel consumption was estimated according to the Virginia Tech Comprehensive Power-Based Fuel Consumption Model (VT-CPFM-1) [14].

- *String Stability:* String stability is an ability of a system to avoid the amplification of traffic disturbances as they travel upstream through a chain of vehicles and maintain traffic flow stable and smooth [15][16].

Results and Discussions

This experiment provides a comparative study between manual driving and driving with hC3, as well as VR and normal screen-based simulation environments. Quantitative measures of longitudinal control, such as headway stability, smoothness of acceleration, effort to operate the throttle and brakes, and fuel consumption are evaluated. Subjective measures of driver trust, perceived realism, and overall system acceptance are also quantified. These findings show how hC3 mode could potentially impact car following behavior, driving efficiency, safety, and driver perception and show its potential for wider application in vehicles.

Comparison of VR vs. Non-VR Simulations

In all simulation experiments, all the participants reported that the VR simulation created a more realistic experience compared to its non-VR version. This observation supports previous research that VR has the potential to improve immersion and situational awareness. Some of the participants reported that the non-VR simulations were more like playing video games, whereas the VR environment was much more realistic and immersive when driving.

Comparison of Manual vs. hC3 Performance

Figure 4 shows the speed profiles of one participant under the two experimental conditions of Manual and hC3. The visual patterns show that the speed trajectories of vehicles were more stable and smoother in the hC3 mode than in manual mode. To complement this, Table 1 gives the aggregated performance measures averaged over all participants in each scenario. The findings prove that hC3 decreased RMS acceleration and time gap variations, proving better longitudinal control and driving efficiency. Although drivers in the manual mode generally showed safe car-following behavior, there were moments of slightly unsafe car-following, which are reflected in low TET values. In contrast, the hC3 mode effectively prevented these occurrences from occurring, maintaining consistently safe headways. In addition, speed overshoots that occurred during manual tests were absent during hC3 tests, indicating improved string stability.

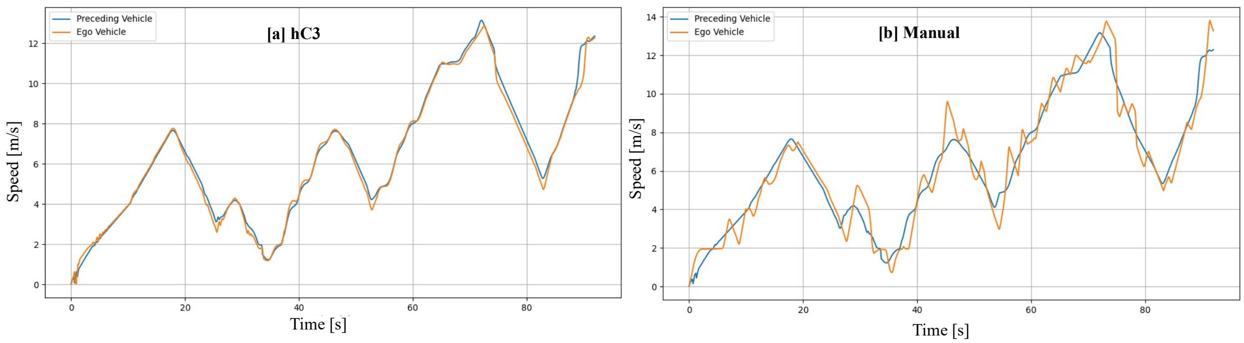

Figure 4. Speed profiles of a participant in each controller

TABLE 1. Summary of the evaluation metrics across all different control modes

Controller	Headway (mean+STD) (meters)	Ego Velocity (mean+STD) (meters/seconds)	RMS Acceleration (m/s^2)	Time Gap (mean+STD) (sec)	TET (sec)	Fuel Consumption (Liters)
hC3	5.74 ± 2.03	6.30 ± 3.11	0.85	1.55 ± 3.87	0.00	0.035
Manual	7.73 ± 3.26	6.26 ± 3.31	1.18	1.88 ± 4.35	0.22	0.046

RMS acceleration was reduced by 28%, showing smoother car following behavior. Both headway and time gap decreased when using hC3 (25.7% and 17.6%, respectively). There was also much less variability in headway and time gap during hC3 tests, showing more consistent spacing between vehicles. Fuel efficiency was also improved, with a 26.1% reduction in fuel consumption, a significant improvement in the overall driving efficiency. Overall, these results indicate that hC3 enhances comfort, control, and fuel efficiency compared to manually driven vehicles. All differences were statistically significant according to paired t-tests. Detailed comparisons are presented in Table 2.

TABLE 2. Comparison between the hC3 and the manual controller

Metric	Manual (Mean ± STD)	hC3 (Mean ± STD)	Difference
Headway (m)	7.73 ± 3.26	5.74 ± 2.03	−1.99 (−25.7%)
Ego Velocity (m/s)	6.26 ± 3.31	6.30 ± 3.11	+0.04 (0.0%)
RMS Acceleration (m/s^2)	1.18	0.85	−0.33 (−28.0%)
Time Gap (s)	1.88 ± 4.35	1.55 ± 3.87	−0.33 (−17.6%)
TET (s)	0.22	0.0	-0.22 (−100%)
Fuel Consumption (L)	0.046	0.034	−0.012 (−26.1%)

Implications for hC3 Adoption

This study proves that hC3 increases safety and efficiency in longitudinal control while promoting stable car-following. Besides smoother acceleration and more even spacing, hC3 also has a measurable energy saving effect: fuel consumption of vehicles was reduced by 26.1% on average during hC3 tests. These energy savings not only indicate that hC3 improves safety and comfort, but serves as a method for increasing operational efficiency. In addition, the VR immersive environment was also essential in allowing the participants to test the performance of hC3 in a realistic setting. This finding support the use of VR-based simulations in future studies of HMI as well as automated vehicle systems, both in terms of evaluation and development. Additionally, 80% of participants expressed interest in purchasing a vehicle with hC3.

Conclusions and Future Research

This study developed a VR-based simulation framework to evaluate the performance of the hC3 system by comparing manual driving with the hC3 driving mode. A mixed within-subject design in which each driver was able to experience each control mode in their preferred (VR or non-VR) display setting. Results show that hC3 can significantly improve longitudinal driving performance by reducing the variability and driving effort with a strong stabilizing effect in the case of manual driving.

Participants were open to adoption of hC3 in vehicles. All participants also rated VR as more realistic and immersive compared to non-VR interfaces, which supports the use of VR as an instrument for testing human–machine interaction and driver behavior under the hC3 system.

Quantitative efficiency benefits were recorded with a 26.1% reduction in fuel consumption in vehicles, showing that hC3 can be used for a better comfort and sustainability but also for a better stability of traffic strings.

These findings highlight the value of VR-based simulation for testing and refining semi-automated driver assistance systems such as hC3 before real-world deployment. Future research should include validating hC3 in real-world driving conditions, possible deployment driving through open-source platforms or an industry partnership and possible long-term adoption by a more diverse set of drivers and vehicles. While the present results are promising, the study included only participants who belong to a university community; including wider groups of participants will be important to generalize the findings. Overall, widespread integration of hC3 has the potential to improve driver experience, road safety, energy efficiency, and inform vehicle design, policy, and sustainable transportation strategies.

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