Gliding on Simulated Ice: Effect of Low-μ Emulation on Drift Training

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Figure 1: Drifting under low-μ (low-friction) emulation that mimics vehicle behavior on slippery surfaces using the vehicle's rear steering capability.

ABSTRACT

Drifting, a skillful driving technique involving intentional traction loss and counter-steering, traditionally demands high-speed maneuvers under high-friction conditions, posing significant risks and fear for novices. Our study explores low-μ (low friction) emulation, simulating icy conditions to facilitate drift training at safer, lower speeds. This approach not only enhances safety and mitigates fear by reducing the required speed for drifting, but also extends the time for them to react. A between-group design was employed, comparing drift training outcomes between participants trained exclusively in higher-μ conditions (control group) and those who trained initially in lower-μ conditions before transitioning to higher-μ conditions (target group). The performance was assessed through the average distance of continuous sliding, along with subjective measures of motivation and workload. The results showed that the target group achieved greater slide distances in the retention session and reported higher scores on the positive intrinsic motivation factors, suggesting enhanced performance and engagement.

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CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**; • **Applied computing** → **Interactive learning**

environments; • **Computing methodologies** → *Control methods*; **Interactive simulation**; • **Software and its engineering** → Virtual worlds training simulations.

KEYWORDS

Drift training, performance driving, low-μ emulation, dynamic emulation, driving on ice, skill acquisition, motor learning.

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1 INTRODUCTION

Performance driving, particularly drift driving, is an area where drivers can test and expand their limits within a controlled setting. Such driving demands exceptional vehicle control, rapid decision-making, and a nuanced understanding of dynamic environments [19]. While autonomous technologies have advanced to enable vehicles to drift without human intervention [10–12], the application of these technologies to actively improve human driving skills, especially under extreme conditions, remains unexplored. This research introduces the novel application of dynamic emulation [26] of low-μ (low-friction) surface for drift training. We hypothesize that this technique not only facilitates skill acquisition by offering a safer training environment but also enhances the overall engagement and learning experience for drivers.

Traditional methods of High-Performance Driver Education (HPDE) led by professional instructors, vary from classroom lectures to practical demonstrations and real-time feedback during driving sessions. Although effective, these traditional methods have limitations, such as scalability, accessibility, and time efficiency. Recognizing these challenges, our study explores the machine's potential to provide quality training that is broadly accessible and uniquely tailored to individual learning needs. The principles of HPDE [3] —ensuring safety, fun, and learning— are core to our approach, albeit achieved through technology. Drift training's inherent difficulties are twofold: 1) technical challenge requiring precise control over multiple inputs within tight time frames, and 2) mental challenge, where the initiation of a drift poses a significant psychological barrier due to perceived risks. The low-μ emulation addresses these challenges by simulating conditions where the vehicle slides at reduced speeds, thereby allowing drivers more time to react and reducing the intimidation factor associated with high-speed maneuvers.

This paper investigated whether simulated lower-μ conditions can indeed improve the quality of drift training. Through a comparative user study, we examined if training under these conditions leads to better retention of performance skills and motivation. The study was set at low friction ranges to ensure participant safety, and results were compared between a group that only experienced constant higher-μ conditions and the other group that experienced both lower-μ and higher-μ conditions.

2 RELATED WORKS

One of the known challenges of assistance in motor learning is the dependency problem, more formally known as the guidance hypothesis [29]. That is, when too much assistance is provided, the student will depend on the assistance and cannot improve their skills. This effect is known to be stronger in physical guidance [30]. A good example is training wheels for bicycle training. If a kid keeps depending on the support wheels, the kid will not learn how to ride a bicycle without them. The known mitigation of the dependency problem is to reduce the amount of assistance. The reduction strategy can vary, including faded feedback and bandwidth feedback, which reduce the frequency of feedback as the skill progresses, and delayed feedback and summary feedback, which provide more room for self-reflection [2, 30, 35]. In the driving domain, it is natural to think of shared control as a potential approach for training drivers that can mitigate the dependency problem since it can adjust the assistance level dynamically. Shared control is a common approach to assist driving at the operational level of driving task [1, 7, 18, 21]. In particular, haptic shared control is widely used for lateral control assistance in advanced driver assistance systems (ADAS) [28]. When the vehicle deviates from its safe path, the system applies torque to the steering wheel to control the vehicle and communicate the system's intention to the driver intuitively. The torque is dynamically adjusted depending on the amount of correction needed. Marchal-Crespo et al. investigated the effect of haptic guidance in low-speed driving (2 m/s) using a driving simulator [22]. The results showed that haptic guidance was helpful to young drivers and non-skilled elderly drivers. Whether it is effective in more realistic driving conditions is still debatable [7] and awaits the results of future studies. Our approach in this paper was that instead of adjusting the assistance level, we adjusted the task difficulty, especially by allowing drift training under simulated low-μ surfaces. We investigate if such an approach of training in artificial lower-μ conditions positively affects drift training.

Dynamic difficulty adjustment (DDA) is a widely used strategy in video games to maintain user engagement [5, 15, 17, 23, 37]. Csikszentmihalyi's flow theory [24] supports this approach, which suggests that aligning the challenge of a task with a user's skill level fosters complete engagement in the activity. Keeping joy and engagement is one of the key ingredients of successful motor learning. Naturally, DDA has shown its effectiveness in rehabilitation applications [6, 16, 20], yet no prior study exists in the driving training domain. In this paper, we focused on the initial investigation of the effect of low-μ emulation in drift training rather than attempting to optimize it to each driver's skill level dynamically. We controlled that all participants were novices and that everyone in the target group experienced the same difficulty adjustment schedule.

High-speed driving training carries inherent risks, which are traditionally mitigated through the use of simulators. However, the challenge of accurately simulating vehicle physics and motion raises concerns about the fidelity of such training tools. While virtual and mixed reality technologies have been employed to enhance realism in safer driving scenarios [4, 9, 33, 34], they fall short in high-speed or performance driving contexts due to the elevated risks involved. Our approach, leveraging a real vehicle equipped with dynamic emulation capabilities, aims to maintain high physical fidelity while ensuring safety by controlling the environment's difficulty, specifically through low-μ emulation.

3 CURRENT PRACTICES IN DRIFT TRAINING

3.1 CPR Training

CPR (Correct, Pause, Recover) training is a foundational method in drift training, designed to train drivers with the skills necessary to regain control of a car during a slide. This technique is crucial for safely navigating conditions like ice patches on roads. The first step of CPR training is to bring the vehicle close to the friction limit while driving in a circle, then initiate sliding by applying the gas pedal. Once the vehicle starts sliding, the driver needs to "Correct" it by applying counter-steering and reducing the gas pedal application. After some moments of "Pause" where the counter-steer and reduced acceleration are maintained until the vehicle stabilizes, rewind the steering wheel and "Recover" their grip on the road.

CPR training poses both mental and technical challenges, which overlap with drift training. The mental challenge is the fear of losing control in high-speed driving. It can prevent drivers from applying enough acceleration to initiate the sliding. Our approach aims to mitigate the mental barriers associated with high-speed sliding, providing a safer training environment at reduced speed. Through our pilot studies, we found that letting drivers experience spinning out at an early stage of training is effective in demonstrating enhanced safety by low-μ emulation and removing their fears. The technical challenge is the timing and magnitude of the counter-steer and deceleration. The driver needs to apply a large amount of adjustment to the steering and the gas pedal in a very short period. Most non-professional drivers do not have a correct mental model of counter-steer[36], which introduces additional challenges to the task as well. Our low-μ emulation gives a driver a longer time to react correctly because of its ability to slide in a lower speed range.

3.2 Drift Training

After CPR training, students learn how to drift, maintaining sliding along a circle in a controlled manner. The first steps are common with CPR training: bring the vehicle to its friction limit, initiate the slide, and "Correct" by applying counter-steer and reducing the acceleration. After the correction, instead of "Pause" and "Recover", drifting requires the driver to "Maintain" the slide, which requires continuous adjustment of steering and acceleration to sustain the slide without full traction recovery. The mental and technical challenges shared with CPR training often prevent students from progressing to the "Maintain" phase in conventional training scenarios. Our application of low-μ emulation seeks to lower the entry barriers to these critical initial phases, offering students more opportunities to develop their skills in steering and acceleration control while sliding.

4 LOW-μ EMULATION TECHNOLOGY

Our research vehicle is equipped with front steering, rear steering, independent electric motors, and independent brakes on each tire. We use the vehicle to explore a wide variety of new driving experiences made possible by a technology called dynamics emulation [26]. Essentially, dynamics emulation uses a vehicle with extra degrees of freedom, including rear steering and independent motors, to replicate the motion of a different vehicle or environment. Unlike traditional driving simulators, a driver feels exactly the same forces as the emulated vehicle. The emulated vehicle can be a sports car with a quick steering response, a bus that accelerates slowly and turns awkwardly, or either one of those vehicles driving on ice. Traditional vehicles allow drivers to control only longitudinal and rotation velocities, but our vehicle can also independently manage lateral speed due to its rear steering capability, allowing for precise emulation of vehicle dynamics. While some production vehicles on the market have rear steering capability, their range of steering is limited to a small angle. Our vehicle provides rear steering over 40 degrees, which allows it to replicate the motion of a wide variety of vehicles and road conditions.

We implemented the dynamics emulation based on Russell and Gerdes[26]. The model can change various parameters, including the friction coefficient of the tires, the understeer or oversteer tendencies, the steering ratio, and so on. In this paper, we change the friction coefficient μ to match slippery road surfaces and call it low-μ emulation. For more detailed information about the emulation technology, please refer to our web article[32].

5 METHODOLOGY

5.1 Study Design

We conducted a study with a between-group design, comparing drift training outcomes between participants trained exclusively in higher-μ conditions (control group) and those who trained initially in lower-μ conditions before transitioning to higher-μ conditions (target group).

The experiment comprised a total of five sessions per participant: four active training sessions and a final retention session conducted under higher-μ conditions for both groups. Participants were divided into two groups randomly. The control group underwent all training sessions under consistent, higher-μ conditions. In contrast, the target group was exposed to lower-μ conditions for their initial two training sessions, followed by higher-μ conditions for the subsequent sessions, including the retention session. Both higher-μ and lower-μ conditions were at low friction ranges to ensure participant safety.

5.2 Experimental Setup

Our experimental setup leveraged the research vehicle with low-μ emulation capabilities, as described in section 4. The vehicle was also equipped with safety measures, including hardware-based emergency stops and a software-enforced speed limit of 25 mph, to ensure the safety of all participants during the training sessions. The tests were conducted on a flat skidpad measuring 70 meters by 70 meters, providing a controlled environment for the training. Participants were guided to roughly follow a predefined circular path with a diameter of 24 meters to keep enough distance from the barriers.

We carefully selected the values of simulated road friction coefficient, μ, 0.3 and 0.4 based on our numerical analysis of stability and behavioral insights from pilot studies. The values were within the range that provides relatively stable control around the constant drifting equilibrium; see Appendix A for more details of the analysis. Our empirical evidence from pilot studies confirmed that drivers could control vehicle stability under these values, and the two levels were different enough for them to feel the difficulty changes. The upper limit of 0.4 was also determined from our observation of some drivers surpassing the 25 mph safety speed limit of the test site if μ value exceeds it. These values are approximately half of that for dry asphalt (0.8) when driving at 25 mph, and slightly lower than that for wet asphalt (0.45)[8]. While both values are low friction in a general context, for ease of reading, we refer to 0.3 as the "lower-μ" condition and 0.4 as the "higher-μ" condition in this paper.

We incorporated simulated environmental cues to enhance the realism of the drift training experience. Recognizing the importance of auditory and haptic feedback in drifting, we introduced simulated tire screeching sounds and steering wheel torque changes as indicators of vehicle slide intensity. By integrating these simulated cues, we aimed to closely mimic the sensory feedback drivers would encounter when drifting on dry surfaces, thereby minimizing the domain gap.

5.3 Procedure

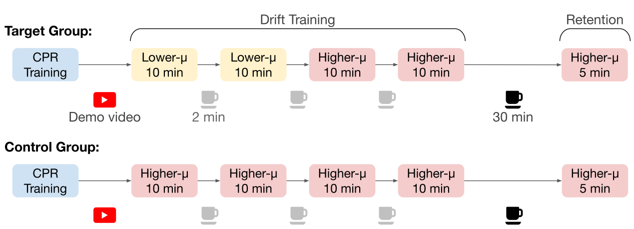


Figure 2: An overview of the study process.

The whole session took approximately 2 hours to complete. The participants were first given basic instructions on the vehicle operation and a comprehensive briefing on safety procedures, including the use of four-point seatbelts, helmets, eye protection, and emergency protocols. The participants were then asked to drive through a short slalom course constructed with traffic cones. This was done to familiarize themselves with the operation of the experimental vehicle without the low-μ emulation.

After the familiarization, the low-μ emulation was activated with higher-μ, and the participants went through CPR training by a human instructor in the passenger seat. Starting from letting the participants experience a spin-out, the instructor explained how to mitigate it by applying counter-steer and provided feedback as participants tried it out. The session continued until the participants successfully recovered from sliding a few times. This normally took 10 to 15 minutes.

Following the CPR session, the participants watched a short training video on drifting, covering topics such as throttle control and steering techniques. The video was followed by an explanation from the instructor relating to the CPR training earlier. The participants were notified about the training schedule, including the change of μ after the first two sessions for the target group. Each training session lasted for 10 minutes, and the instructor gave no feedback during the sessions except for encouragement and affirmative feedback. This was done to ensure the participants were not influenced by the instructor's feedback during the training sessions. Between these sessions, there were 2-minute breaks during which the instructor gave feedback on how to improve, depending on the mistakes the participants made during the sessions. To minimize the impact of the diversity of the feedback contents and styles, we did a prior analysis of typical failure patterns and prepared associated feedback.

After the four training sessions, the participants were given a 30-minute break before the retention session. During this break, they were asked to complete questionnaires. The retention session was 5 minutes long, and no feedback was given during the session, similar to the training sessions.

5.4 Metrics

We measured several metrics to evaluate the effectiveness of the training. For an objective performance metric, we measured the average distance of continuous sliding within each session. This metric allowed us to assess the participant's ability to maintain control of the vehicle during sliding. For a subjective engagement metric, we used Intrinsic Motivation Inventory (IMI) questionnaires [27]. Additionally, we used an unweighted NASA-TLX questionnaire [13, 14] to measure the workload difference between the two training conditions.

5.5 Participants

We collected data from 16 participants, with 8 participants in the target group and 8 in the control group. All participants were driver's license holders and employees of an automotive industry company. None of them had prior experience with performance driving, including race track driving and drift driving.

Since race driving experience in simulated environments may impact the training performance, we also measured the participants' experience with racing video games using a questionnaire adapted from Schrum [31]. There were no significant differences in the scores between the two groups.

Two participants in the control group identified themselves as women, while the rest of the participants, including the target group, identified themselves as men. The age of the control group (M = 39.43, SD = 14.32) and the target group (M = 30.83, SD = 2.64) did not differ significantly, $t(6.473) = 1.558$, $p = .167$, $Cohen's\ d = 0.802$.

Furthermore, we used the BFI-10 (Big Five Inventory - short form with ten items) scores [25] to assess the participants' personalities. The results showed no significant personality differences between the two groups for all five personality traits. See Appendix B for the detailed results.

6 RESULTS

6.1 Performance

In order to measure the performance progress, we compared the average continuous sliding distance for each session. The results revealed two outliers in the target group, whose learning patterns significantly differed from the rest of the participants. We employed the Interquartile Range (IQR) method to assess retention session

Table 1: A summary of 2-way mixed design ANOVA in the performance progress across sessions and groups.

Source	*SS*	*DF*1	*DF*2	*MS*	*F*	*p*	η_p^2
Group	33.07	1	11	33.07	1.77	0.21	0.13
Session	206.50	4	44	51.62	6.84	0.00	0.38
Interaction	234.01	4	44	58.50	7.75	0.00	0.41

performance and identified the two statistical outliers. The first quartile of the performance was 21.97 m, and the third quartile was 31.83 m. The two outliers had performances of 69.16 m and 175.70 m, which deviated significantly from the expected range based on the IQR criteria. We will discuss these outliers in more detail in section 7. To ensure the validity of our results, we removed these outliers from the results below.

Figure 3 illustrates the performance of both groups across the five sessions. The graph shows that both groups started with similar performance. The control group reached its peak performance on the third session and struggled afterward, indicating a plateau in the motor learning process. In contrast, the target group's performance dropped in the third session when the simulated road friction changed. A significant and sustained improvement followed this in the later sessions that surpassed the control group's performance.

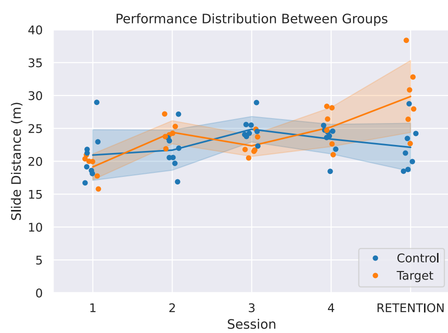


Figure 3: distribution of average slide distance over the sessions; including the four training sessions and the retention session.

Table 1 shows the results of a 2-way mixed design ANOVA to evaluate the effect of the session and group on performance. The results show a significant main effect of the session, $F(4, 44) = 6.841$, $p < .001$, with a large effect size $\eta_p^2 = 0.383$. This indicates that regardless of the group, performance changed as the session progressed. Additionally, we found a significant interaction between the session and group, $F(4, 44) = 7.752$, $p < .001$, with a large effect size $\eta_p^2 = 0.413$. This suggests that the changes in performance over the sessions were different for the two groups.

We conducted post hoc one-sided pairwise T-tests between sessions to investigate the performance progress independent of the group difference. The results show significant improvement from the first session to the third ($t(12) = -3.946$, $p < .05$, $Hedges'g = -1.231$), and the fourth ($t(12) = -3.144, p < .05$, $Hedges'g = -1.235$), both with Holm-Bonferroni method correction. All the other session progressions were not significant. This indicates that both groups improved performance over time in the training sessions compared to their first session. Note that the retention test was designed to observe performance degradation after an extended break period, so the difference from the first session was expected to be less significant than that of the third and fourth sessions.

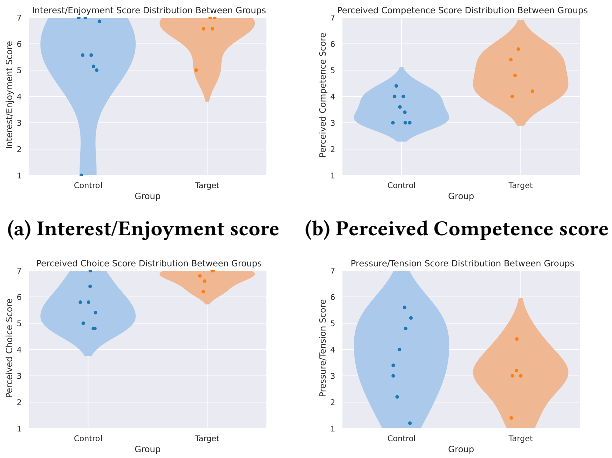
In order to test our hypothesis that the target group performs better, we conducted post hoc one-sided T-tests between the groups for each session. The results indicate that the target group's performance was significantly higher than the control group in the retention session, $t(8.523) = -2.942$, $p < .05$ with Holm-Bonferroni method correction, and with large effect size ($Hedges'g = -1.572$). The performance differences in the other sessions were not significant.

In summary, our results indicate that the target group, which experienced the lower-µ training, showed significantly better performance than the control group.

6.2 Motivation

We used a short form of the Intrinsic Motivation Inventory (IMI) [27] with 22 items to measure the participants' motivation after the training sessions. The IMI consists of four subscales: Interest/Enjoyment, Perceived Competence, Perceived Choice, and Pressure/Tension. The Interest/Enjoyment subscale directly measures intrinsic motivation, while Perceived Competence and Perceived Choice are positive factors that lead to motivation, and Pressure/Tension is a negative factor. Figure 4 shows the results comparing the distribution in the two groups. The Interest/Enjoyment score shows that the control group ($M = 5.39$, $SD = 1.96$) and the target group ($M = 6.43$, $SD = 0.83$) were both highly motivated, but there were no significant differences between them. The target group had significantly higher scores on the Perceived Competence score ($M = 4.84$, $SD = 0.77$) compared to the control group ($M = 3.55$, $SD = 0.54$), $t(6.529) = -3.283$, $p < .05$, with large effect size, $Cohen's\ d = 2.037$. Additionally, the target group had higher scores on the Perceived Choice ($M = 6.72$, $SD = 0.33$) compared to the control group ($M = 5.62$, $SD = 0.79$), $t(10.141) = -3.460$, $p < .01$, with large effect size, $Cohen's\ d = 1.657$. There was no significant difference in the Pressure/Tension scores. Note that due to a mistake during the experiment, the IMI score of one target group participant is missing. Overall, our results suggest that exposure to the lower-µ condition positively impacted intrinsic motivation among the participants.

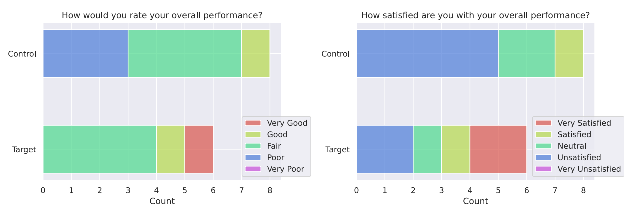
The participants were also asked to assess their performance and asked if they were satisfied with it. The actual performance was not disclosed to the participants. Figure 5 shows the results. Some control group participants rated their performance as Poor (3/8), with a single participant indicating Good (1/8). In contrast, there was no negative response from the target group participants. The difference is more significant in the satisfaction levels, with more than half of the participants in the control group being Unsatisfied (5/8). In contrast, the responses from the target group were diverse, yet half were positive, with Satisfied (1/6) or Very Satisfied (2/6). The results are consistent with the IMI score results.



(a) Interest/Enjoyment score **(b) Perceived Competence score**

(c) Perceived Choice score **(d) Pressure/Tension score**

Figure 4: Comparison of IMI (Intrinsic Motivation Inventory) scores between groups.



(a) Self-assessment of the performance **(b) Satisfaction to the performance**

Figure 5: Between group comparison of self-assessed performance and satisfaction levels.

6.3 Workload

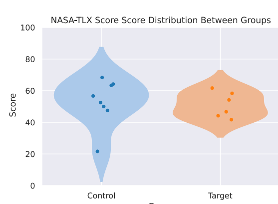


Figure 6: Comparison of NASA-TLX scores between groups.

We used the unweighted NASA-TLX scores [13, 14] to measure workload after the training sessions. The results show that there was no significant difference in workload between the control group ($M = 53.02$, $SD = 14.64$) and the target group ($M = 51.11$, $SD = 8.13$), $t(11.268) = 0.311$, $p = .768$. Additionally, none of the subscales showed significant differences, as detailed in Appendix C. This suggests that the exposure to the lower-μ condition did not have a significant impact on the participants' perceived workload.

6.4 Racing Game Experience

We measured the participants' experience with racing video games using a questionnaire adapted from Schrum [31]. The scale has two subscales: Familiarity and Confidence. We conducted a Pearson correlation analysis to examine the relationship between the participant's performance in the retention session and their Familiarity and Confidence scores. Similarly to the IMI score, one sample is missing from the target group for this analysis. The results showed that there was no significant correlation between the participants' Familiarity with racing video games and their retention performance, $r(12) = 0.415$, $p = .180$. Similarly, we found no significant correlation between the participants' Confidence in playing racing games and their retention performance, $r(12) = 0.462$, $p = .130$. These results suggest that the participants' experience with racing games did not have a significant impact on their performance in the retention session.

7 DISCUSSION

7.1 Effect of Condition Change

Our results show that the target group's performance progress was better than the control group's, indicating that exposure to lower-μ can improve skill acquisition. However, it is important to note that the positive impact may not be solely due to the lower-μ condition. It is possible that the condition change itself contributed to the improvement in performance. For instance, there might be the same positive impact if the participants were exposed to even higher-μ instead of lower-μ. Unfortunately, we could not test this hypothesis due to the safety speed limit that led us to eliminate conditions with higher friction as described in section 5.2. Despite this limitation, our results provide sufficient evidence that our novel approach of changing road friction for drift training can benefit skill acquisition.

7.2 Performance Shaped Motivation

We anticipated that the engagement of the target group would be higher due to the slower and less intense training in the lower-μ condition. The results revealed that the target group had stronger positive motivation factors, but the difference can be explained mostly by their performance gain. The difference in Perceived Competence could be due to the large performance improvement seen in the target group in the latter sessions, while the control group struggled in contrast. Perceived Choice measures if the participants felt they were forced to do the task. The results indicate that the control group felt strongly that they were forced to practice, which could be due to frustration from lack of progress. The differences in responses to the self-performance assessment and the satisfaction level with the performance support these interpretations. Contrary to our expectation, there was no significant difference between the groups in the Pressure/Tension factor, despite the lower-μ condition requiring less time pressure and less intense accelerations. One possible explanation is that the lower-μ condition was only the first half of the training and only weakly reflected in the participants' overall impression after all training. The performance difference, on the other hand, was larger in the later sessions, therefore having a larger impact on the impression. There may be observable differences in the Pressure/Tension factor when longer training is performed or when compared to intense training on a dry surface.

7.3 Outliers with Exceptional Performance

We removed two outliers from the analysis due to their exceptional quick skill development. Considering the total number of participants is 16, even two is not a small percentage. Their rapid skill development pattern may not be rare if we collect data from more participants. Therefore, we investigated whether we could find a commonality between them.

The two outliers were opposite extremes in racing game Familiarity scores, with one scoring 0.0 and the other scoring 5.0, supporting the finding in section 6.4 that racing game experience is not strongly correlated to their performance. Their Big Five characteristics were not significantly different from the rest of the participants, although they were relatively high on Neuroticism (3.5 and 4.0). Correlation analysis between the five traits and performance did not find any significance.

Both outliers were in the target group, and their performance was similar to the other participants during the first two sessions. In the third session, while other participants experienced a performance dip due to the friction change, the two outliers maintained continuous skill improvement. One of the outliers mentioned in an open-ended question, "During the first two sessions, I was unsure about pretty much any aspect of the driving." It may indicate that the participant gained some insights in the third session, which led to continuous improvement in subsequent sessions. More extensive data collection is needed to confirm whether the change in friction facilitated these insights.

7.4 Limitations

Several limitations to our study should be taken into account.

First, the retention test took place only after 30 minutes of training. While the duration before the retention test largely varies in the motor learning literature [30], it is relatively short compared to other studies investigating the long-term learning effect. The reason for the shorter retention test in our study was to reduce logistics and scheduling hardships for both researchers and participants. This limitation may have affected the results, as the long-term learning effect may not have been fully captured.

Second, the skill transfer from the low-μ emulation to real drifting under dry surface conditions still needs to be explored. While we observed a transition between the two conditions, both conditions are significantly lower than dry asphalt. Outside of this study, we observed that drivers who can drift real vehicles on dry surfaces could also drift in low-μ emulation easily. Additionally, we designed the system so that the required skills for successful drifting in both the low-μ emulation and real drifting are the same except for speed range and time budget, which should minimize the domain gap. Despite these backgrounds, we lack direct evidence of skill transfer from the low-μ emulation to real drifting. Future studies could investigate this further by comparing drivers' performance in dry conditions after training in the low-μ emulation.

Lastly, our approach requires vehicles equipped with steer-by-wire and rear steering capabilities, which are currently less available compared to traditional human instructor-based training. Due to this limitation, we cannot say that the scalability and accessibility of our method have any advantage over traditional training. However, this work demonstrated the future potential of intelligent vehicles to support driver training in a way that human instructors cannot provide and to complement them by offering more frequent training opportunities.

8 CONCLUSION

We investigated if exposure to lower-μ condition in drift training can facilitate the training outcome. The results showed that training in lower-μ conditions improved performance and positively impacted intrinsic motivation. Low-μ emulation can facilitate drift skill improvement and engagement at safer, lower speeds. When combined with training by human instructors, our approach has the potential to provide quality training that is broadly accessible and allows drivers to master drift techniques in safer conditions.

It is important to note that our experiment was conducted in a controlled environment and with a vehicle with multiple safety measures. We do not encourage people to practice drifting on actual icy surfaces, using regular vehicles, or on public roads. One of the significant differences between the real icy road and our simulated environment is the consistency of the road surface friction. On a real icy road, the μ value can change drastically within a short distance, making it challenging to maintain vehicle control and unsuitable for drift training.

As a potential next step, we plan to incorporate skill assessment and dynamic adjustment of the task difficulty. This personalization ensures the training is even more engaging to keep students motivated, promoting a sense of accomplishment and satisfaction that encourages continued training.

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A STABILITY ANALYSYS

In this section, we describe the process of stability analysis with regard to the vehicle parameter change. We chose to use a planar bike model, shown in equation 1, which demonstrated good performance in autonomous drifting tasks [12].

$$\begin{bmatrix}\dot{r}\\ \dot{V}\\ \dot{\beta}\end{bmatrix} = \begin{bmatrix} \frac{aF_{yf}cos(\delta)+aF_{xf}sin(\delta)-bF_{yr}}{I_z} \\ \frac{-F_{yr}sin(\delta-\beta)+F_{xf}cos(\delta-\beta)+F_{yr}sin(\beta)+F_{xr}cos(\beta)}{m} \\ \frac{F_{yf}cos(\delta-\beta)+F_{xf}sin(\delta-\beta)+F_{yr}cos\beta-F_{xr}sin\beta}{mV} - r \end{bmatrix} \tag{1}$$

Where r is the yaw rate of the vehicle, V is the magnitude of velocity, β is the sideslip, δ is the steering angle at the roadwheel, a is the distance from the center of mass to the front axle, b is the distance from the center of mass to the rear axle, and m is the mass of the vehicle. F_{xf}, F_{yf}, F_{xr}, and F_{yr} are the forces generated by the tires with a nonlinear brush tire model.

We first assume the vehicle is in a perfectly stable drift.

$$\begin{bmatrix} r\\ V\\ \beta\end{bmatrix} = \begin{bmatrix} r_{eq}\\ V_{eq}\\ \beta_{eq}\end{bmatrix} \quad \text{and} \quad \begin{bmatrix}\dot{r}\\ \dot{V}\\ \dot{\beta}\end{bmatrix} = \begin{bmatrix}0\\0\\0\end{bmatrix} \tag{2}$$

Then, we numerically linearize the planar bike model around the equilibrium point. This yields the following equation:

$$\begin{bmatrix}\dot{r}\\ \dot{\beta}\end{bmatrix} = A\begin{bmatrix} r - r_{eq}\\ \beta - \beta_{eq}\end{bmatrix} + Bu \quad \text{where} \quad A = \begin{bmatrix} \frac{\partial \dot{r}}{\partial r} & \frac{\partial \dot{r}}{\partial \beta} \\ \frac{\partial \dot{\beta}}{\partial r} & \frac{\partial \dot{\beta}}{\partial \beta} \end{bmatrix} \tag{3}$$

The numerical values of the A matrix are calculated using the central difference method and Equation 1.

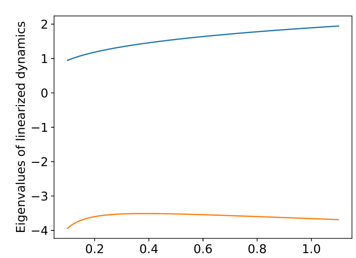


Figure 7: Eigenvalues of linearized vehicle dynamics as the road friction increases. The vehicle becomes more unstable as friction increases.

Finally, we can analyze the stability of the drift equilibrium by studying the eigenvalues of the matrix A. The eigenvalues provide information about the stability of the system:

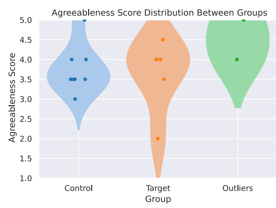
- If A has all negative eigenvalues, the system is stable

- If A has one or more positive eigenvalues, the system is unstable
- If A has complex eigenvalues, the real part defines stability, and the complex part describes the oscillation

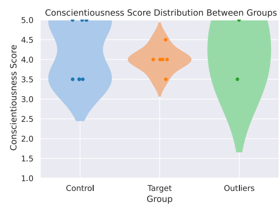
Figure 7 shows the eigenvalues of the linearized dynamics with different road friction values. The positive unstable eigenvalue, a blue line, becomes larger and, therefore, more unstable as friction increases.

B PERSONALITY DISTRIBUTION

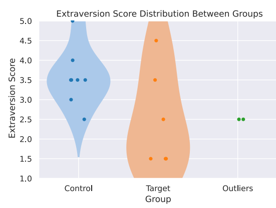
Figure 8 illustrates the distribution of the Big Five personal traits of the participants.



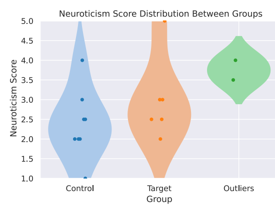
(a) Agreeableness



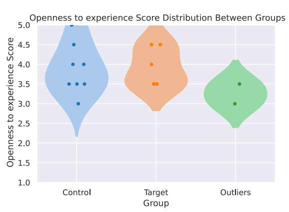
(b) Conscientiousness



(c) Extraversion



(d) Neuroticism

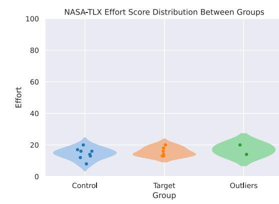


(e) Openness to experience

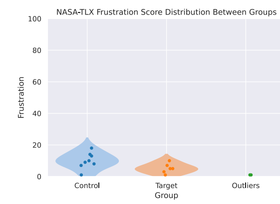
Figure 8: Comparision of Big Five personality traits between groups.

C NASA-TLX SUBSCALE DISTRIBUTION

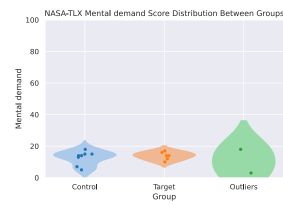
Figure 9 illustrates the distribution of the NASA-TLX subscales reported by the participants.



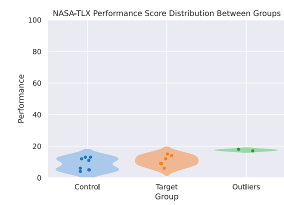
(a) Effort



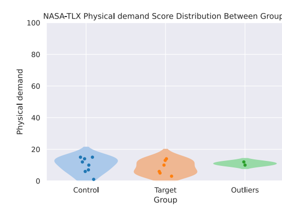
(b) Frustration



(c) Mental demand



(d) Performance



(e) Physical demand

Figure 9: Comparision of NASA-TLX subscales between groups.