(Eco-)Logical to Compare? - Utilizing Peer Comparison to Encourage Ecological Driving in Manual and Automated Driving

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The highest CO_2 quota per person is personal transport. An ecological driving style (eco-driving) could drastically reduce it's emissions. Current interventions focus mainly on training, which benefits are mostly short-term, and individual feedback, which needs commitment by setting (individual) goals. We present the concept of displaying not only the eco-friendly behavior of the driver but peers around them. As perceivable competition has been shown to lead to higher task performance and a more eco-friendly behavior, adding a competitive aspect and social enforcement to ecological driving shortcuts the goal-setting. In a virtual reality within-subjects study (N=19), we explored this possibility in manual and automated driving. We found that adding a comparative factor to ecological feedback did not lead to significantly more ecological driving in manual or automated driving.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**; *Haptic devices*; User studies.

Additional Key Words and Phrases: eco-driving; virtual reality; peer comparison

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1 INTRODUCTION

Climate change is expected to drastically alter the world and make various places inhabitable, if not stopped [30]. One contributing factor to climate change is greenhouse gas [38]. The individual and household sectors are large emitters of greenhouse gas [62]. A large part of the individual pollution can be attributed to personal transport, especially automobile mobility [63]. By estimation, on-road transportation could have a contribution of 10 to 20% to worldwide climate change by the year 2050 [50]. While the choice of the vehicle plays a major role in energy consumption, the driving style also has an immediate influence on the on-road fuel economy [49].

Eco-driving, the term describing beneficial adjustments in driving style to reduce greenhouse emissions, has been shown to significantly reduce fuel consumption by at least 9% [1, 5, 17, 33, 35, 54]. Previous research showed that ecological driving could be achieved in two ways. Firstly, by undergoing eco-driving training [1, 6, 17] or by receiving feedback on current driving [4, 8, 36, 54, 56, 59, 60]. It was shown that training had a high initial impact but vanished over time [1, 17], with participants falling back into their old driving behaviors. Regular (direct) feedback, in turn, has shown to be more promising in having an impact over a more extended period of time [36]. Drivers, however, need to set goals to have a metric by which they can judge the otherwise non-normative feedback information [54]. This means that drivers need to be willing to be more proactive in dealing with their driving behaviour.

Prior work added elements of gamification [45] and comparison [44]. While only comparing completed journeys to other similar vehicles (in terms of size and other characteristics) in a potentially distant location, Magana and Munoz-Organero [44] showed that these elements helped drivers to drive more ecologically and not lose interest over a more extended time. In turn, direct comparison to others on the same task [46] and in the same context has shown to have a substantial effect on general energy consumption when compared to colleagues [48] and neighbors [2].

Windshield Head-Up Displays are currently evaluated in numerous scenarios, including manual [40, 41, 53] and automated driving [11, 12, 14, 39, 65, 69]. These allow to display information in the respective location, for example, attached to other objects such as pedestrians [11, 12, 14] or vehicles [12, 14]. With the advancement of this technology, the possibility arises to display not only the own current eco-driving evaluation and feedback but also organically integrate those of direct peers visible in the current driving situation. These scores can be obtained either via communication standards but also with already integrated sensors such as cameras and radars.

While most work on ecological driving focuses on a manual driver, also, in automated driving, the current research examines the potential to adjust the vehicle's driving style to reflect personal preferences better [31]. Therefore, even in automated vehicles (AVs), being able to adapt, for example, maximum speed, is possible and seems appropriate to be a factor for more ecological behavior.

Based on this previous work, we propose to combine the comparison and gamification approaches using Windshield Head-Up Displays both in manual and automated driving. This allows the evolution of Magana and Munoz-Organero's [44] concept to enable permanent imminent comparison with peers. However, it is possible that only vehicles with different characteristics are present (e.g., bigger, heavier, older). Therefore, we are interested in whether the findings of Magana and Munoz-Organero [44] also hold in this imminent and potentially considered "unfair"comparison.

Contribution Statement: This work provides insights into the effects of peer comparison of ecological driving both in manual and automated driving. The results of a Virtual Reality (VR) within-subjects study (*N*=19) show that automated driving was perceived significantly less demanding, that having visualized one's ecological score improved ecological driving best and that, while not improving the driving style, visualizing the ecological score of other's did not result in significantly worse performance or subjective assessments.

2 RELATED WORK

This work builds on work on the general usefulness of feedback and in a more specific ecological context as well as the benefits of general and ecological comparison.

2.1 Feedback Effects

Previous work has shown that while a person might have the intention to drive eco-friendly, it can be difficult to overcome behavior patterns. Lauper et al. [37] conducted a longitudinal study over the cause of four months and only found a weak link between behavioral intention and actual behavior. They conclude that a person no matter their intention needs repeated reminders in the form of behavioral feedback. This is supported by multiple authors stating that ecological training, while successful on the short term, did not lead to lasting changes in their behavior [1]. While research by Beusen et al. [7] first showed that a majority of participants showed lower levels of fuel consumption even ten months after a training session, Degraeuwe and Beusen [17] showed that the longitudinal ecological benefits vanished when controlling for the season's influence on fuel consumption.

In a one-year lasting longitudinal study on household gas consumption, Van Houwelingen and Van Raaij [61] showed that the most intermediate feedback condition (daily) produced the greatest outcome in gas saving. They also stated that many participants in subsequent interviews wished for even more instantaneous feedback. In the context of eco-driving, Kurani et al. [36] report results from a study with 118 drivers. The drivers were provided with a fuel recording system for their cars. Receiving direct feedback for ecological driving led to a significantly decreased fuel consumption compared to the control group. Tulusan et al. [56] showed that ecological feedback also had an impact when neither driver nor passenger had monetary stakes in their journey but were driving a corporate car. Like those, multiple studies utilized instantaneous feedback to foster eco-logical driving.

One factor that makes this feedback effective is the newly raised ability to compare one's eco-driving against a baseline. Stillwater and Kurani [54] report that participants in their study used instantaneous feedback as a tool for "experimentation and learning" [54] of new eco-driving behaviors as they had no possibility to directly compare the rather abstract feedback values. Comparison and concomitant evaluation of their ecological driving happened by setting personal goals and comparing after finishing their journey. Three-fourths of the participants used this goal-setting as motivation to participate in ecological driving. In a gamification approach, Massoud et al. [45] proposed expanding the idea of goal setting by being able to reach different fuel-saving levels ('Careless','Typical' and 'Saver') simplifying the goal-setting process. Magana and Munoz-Organero [44] in turn proposed the possibility of altering a self-focused goal-setting process to not compare against one-self in a self-chosen baseline but to others driving similar cars and contexts by having their journeys ranked on a scoreboard in hindsight. This approach led to better eco-driving results which held up over time.

We take a similar approach to simplify goal setting and motivate by allowing comparison to others and using this comparison as a baseline. Notwithstanding we propose an ad-hoc comparison to cars that are not only in a similar but the same context. Additionally to sharing the same context, allowing an instantaneous comparison with peer cars, the driver can compare to visible others and not abstract names on a scoreboard.

2.2 Effect of (Direct) Comparison

Comparison between individuals, groups, or even the past self can be a motivating factor to improve one's performance, especially when combined with feedback. However, the results of social comparisons can be described as mixed. Siero et al. [48] compared two groups of workers in a metallurgical company and found that the group with comparative feedback performed better in terms of energy-saving. Therefore, the authors conclude that "comparative feedback appears to promote competitive feelings, increased attention to feedback information, and a striving to perform better than the other group" [48, p. 236]. In line with this, Mitchell et al. [46] found that presenting the performance of others on a wall chart raised one's own task performance. Regarding the household, Allcott [2], by comparing 80000 treatment and control households in Minnesota, estimated that the comparative feedback reduced energy consumption by 1.9 to 2.0%. Ayres et al. [3] also argued in this line. However, Egan [20] and Haakana et al. [25] showed that comparisons do not necessarily lead to a behavior change. One aspect that has to be considered is that there is a performance plateau. When this is reached, additional feedback may not be effective.

3 COMPARATIVE ECO-DRIVING

In the following, we describe our concept which consists of the capabilities to deduce the eco-score based on a given equation, current technology capabilities, and the proposed visual design.

3.1 Concept

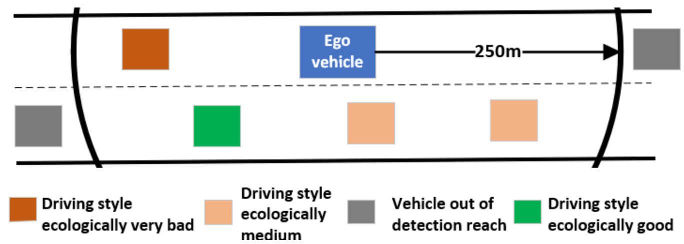

Fig. 1. Schematic representation of the visualization concept with peer comparison. The visualization is based on a snapshot. Four vehicles surrounding the ego vehicle (blue) are in a range of the radius of 250m, thus, their eco-score can be determined.

To allow instantaneous ad-hoc comparison to surrounding cars, two prerequisites have to be fulfilled. First, the driver's current driving status and those of the surrounding cars has to be observable. Second, both have to display the same data in a way that allows comparison. We, therefore, propose a concept that displays their current eco-driving score to the driver/user of an (automated) vehicle as well as the eco-driving score of nearby vehicles. To allow comparison to the whole surrounding while avoiding visual clutter, only vehicles up to up to a distance of 250m (see Figure 1; Waymo even claims to "identify [...] stop signs greater than 500 meters away" [29]), should be augmented.

To allow comparison in this context, we identified relevant metrics of eco-friendly driving. Wang et al. [67] already discussed five eco-driving related behaviors: Driving Maneuver, Travel Planning and Trip Chaining, Trade-off between Travel Time and Energy Saving, Route Choice Preference when using a Navigation System, and In-Vehicle-Display (IVD)/On-Board-System (OBS) Technologies.

For the peer comparison during the journey, only the driving maneuvers are relevant. Regarding the driving maneuver, Wang et al. [67] name velocity, acceleration, and deceleration as relevant factors for eco-driving. Tulusan et al. [56] also included these three factors into their calculation. As we were only interested in the concept of ad-hoc comparison could influence *driving behavior* in an eco-friendly way, we excluded vehicle characteristics. These factors defined by the vehicle type (e.g., air resistance, weight, motorization) are not influenceable by the driver/user once in a driving situation and, therefore, not influenceable through comparison. Utilizing velocity, acceleration, as well as deceleration relevant factors, an eco-score can be calculated (see below) for each vehicle. This eco-score, combined with the velocity and acceleration/deceleration values and the combined score were shown both for the own vehicle in a Head-Up Display located directly behind the steering wheel and above the other vehicles in the field of view (see Figure 3).

This visualization is independent of the automation of the vehicle (manually driven or automated). For an AV, the passenger was able to set the desired speed value (called "target speed) via a SpaceMouse Wireless (see Figure 4 on the table). We opted not to enable an acceleration value. While this would be possible, we assumed an AV that enables an adequate acceleration.

In the following, we will describe how we calculated the singular values for the study presented in this paper. We begin with the **velocity score** which was calculated with the square increase of air resistance in mind. As the scenario of our study is based on a highway, the score of 100 is given up to the velocity of 100km/h:

$$v_{current} = \begin{cases} 100, & \text{if } v \leq 100 \\ (-(v-100)^2/2500+1)*100, & \text{if } 100 < v \leq 150 \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

With acceleration and deceleration being opposites of the same dichotomous factor *velocity change*, we combined both into one score. The **acceleration and deceleration score** is based on the assumption that a velocity change of 100 km/h in 10s should result in a value of 0 as is calculated as follows:

$$a_{Current} = \begin{cases} 100, & \text{if } -0.01 < a < 0.01 \\ 100 - (|a| - 0.01) * 333, & \textit{otherwise} \\ 0, & \text{if } |a| > 0.3 \\ \hline 100, & \text{if } -0.01 < a < 0.01 \\ 100 - (|a| - 0.01) * 33.9, & \textit{otherwise, if calculating with } m/s^2 \\ 0, & \text{if } |a| > 2.95 \end{cases} \tag{2}$$

We opted for a linear model of acceleration as Galvin [23] showed that, with an electric NissanSV, the relationship between positive acceleration and the total energy consumption with an equal distance was almost linear. This is a simplification and should be adjusted if more accurate information for the various vehicles is available.

The total eco-driving score was calculated as follows:

$$EcoScore = \frac{\alpha * v_{current} + \beta * a_{Current}}{\alpha + \beta} \tag{3}$$

where: α = weighting factor of velocity; here 1; β = weighting factor of acceleration, here 1 ; $V_{current}$ = current velocity value (0-100); $a_{current}$ = current acceleration value (0-100)

We only present an abstract eco-score and **not** the savings of ecologically improved driving behavior, as "environmental savings are considered more worthwhile than commensurate financial savings" [19, p. 1] and "ecodriving behaviours were mainly sensitive to the presence of feedback per se, rather than the content of feedback" [19, p. 1]. It was also shown that abstract feedback "is more effective in reducing fuel consumption than concrete feedback" [16, p. 7]. While "presenting the information in strategically advantageous locations that are not demanding for the driver" [32, p. 27] was discussed to be beneficial, we opted for a continuous display of the eco-score as determining advantageous locations is not trivial and the use case of a highway is mentally less demanding.

3.2 Interface Design

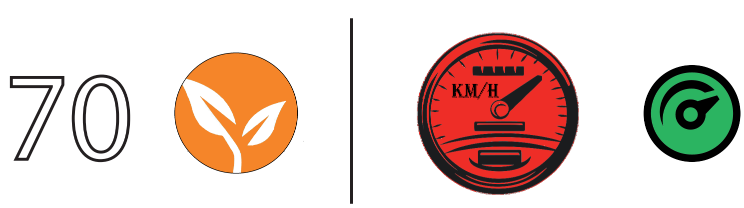

Fig. 2. Interface concept with the total eco-score on the left. The red symbol represents speed, the green symbol acceleration.

Regarding the interface design, the concept relies mostly on three dimensions: color, size (change), and icons (see Figure 2). We suggest to use the color green if the driving style is eco-friendly. In the Western context, green is perceived as positive [51]. Depending on the eco-friendliness, the color should transition towards red, indicating the negative aspect of the driving style. It was shown that negative stimuli evoke high attention allocation, thus, directing the attention to the eco-score [28, 52].

Color perceptions is different across the visual field [26]. Color perception is best in the fovea and deteriorates toward the periphery [26]. This is also true for red-green color variations [26]. Therefore, we additionally added a size change for the alteration of the eco-score from small (good eco-score) to large (bad eco-score). This size change is attention grabbing even in the periphery.

The interface for the other vehicles contained the same mechanisms and icons as well as the score, however, they were arranged in two rows to better utilize space and reduce visual clutter (see Figure 3 in the middle).

4 STUDY

The study was guided by the research question: *What impact does the visualization of a competitive eco-driving score have on (1) the own driving behavior, (2) usability, (3) acceptance, and (4) mental workload? Does the availability of comparative feedback in an automotive context raise attention on own driving information?*

4.1 Study Design

The study was designed as 2×3 within-subjects, repeated measures experiment. The independent variables were *eco-score visualization* (no/only own eco-score/own eco-score and other vehicles close-by) and *driving mode* (manual/automated), resulting in six conditions. We omitted the visualization of the eco-score only for the other vehicles (i.e., not displaying our own eco-score in this condition) as prior work already showed the positive effects of displaying one's own eco-score and reducing the time required for the study. We included the automated driving conditions to study the effects adjustable speed limits have on performance. This approach is in line with work on ethically-customizable AVs [15].

As AVs and full-screen windshield displays are not yet commercially available, we implemented our scenario in VR. This is a common approach both in research relating to manual [66] as well as automated driving [11, 13, 14].

4.2 Materials

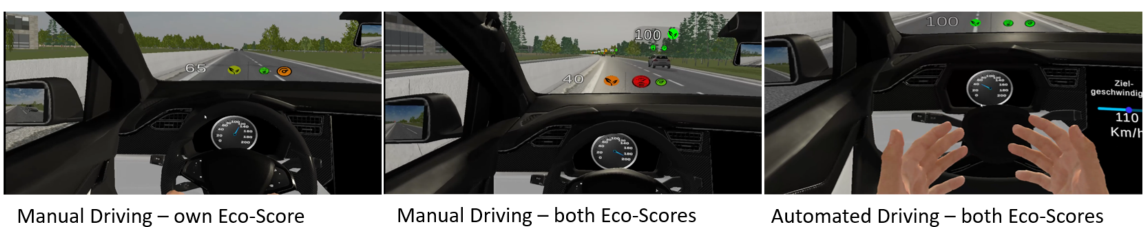

Fig. 3. Overview of two manual and one automated driving implementation.

To answer the research question, we designed a highway scenario using Unity version 2021.2.5f1 [58]. The highway represents the A7 from Illertissen, Germany to Senden, Germany, and was created using the OSM data and the Unity asset CityGen3D [10]. The suggested speed on highways in Germany is 130 km/h. To analyze if participants took notice, used the augmented scores, and whether they would be distracting, eye-tracking was implemented. For this, we used the Tobii eye tracker of the HTC Vive Pro Eye with the Tobii Eye Tracking SDK version 1.3.3.0 [55]. To allow a more realistic feeling while being in the virtual environment, we tracked the participants' hands and displayed virtual versions of them. For this purpose, hand recognition with a Leap Motion Controller utilizing Leap Motion Unity SDK version 5.0.0 was used. The surrounding cars were generated using the Simple Traffic System [57] in version 1.0.56 and adapted to our needs.

4.3 Procedure

Fig. 4. Setup of the study.

After giving informed consent, participants were introduced to the setting and could adjust the seat. Participants drove on a highway to get used to the setting (see Figure 4). Then, they were introduced to the setting as follows:

"You are driving on a highway. The vehicle detects how ecologically you and the other vehicles in your immediate vicinity are driving. Depending on the passage, you will drive manually or automated.
Your goal should be to drive in a reasonable time and be as environmentally friendly as possible. At the end of the trial, if the total time is reasonable, the reward will be increased by 2€.
Depending on the run, the vehicle will show you its own eco-score and that of the other vehicles via a head-up display. The total eco-score will be displayed on a scale from 1 (very bad) to 100 (perfect). The eco-score is calculated using acceleration and speed. Therefore, these two values are also displayed graphically."

Participants were then randomly assigned to conditions based on a balanced Latin Square. Each ride took approximately 6 min. After each condition, participants filled out the questionnaires described in Section 4.4.

Participants were told that their compensation was dependent on their performance. This reflects on the real-world aspect of having to constantly weigh arriving more quickly or saving fuel. However, all participants were compensated with 15 Euro. A session lasted approximately 75 min. Quotes were given in German and were then translated. The hygiene concept for studies regarding COVID-19 (ventilation, disinfection, wearing masks) involving human subjects of the university was applied.

4.4 Measurements

4.4.1 Objective Measurements. We logged velocity, acceleration, and eco-driving scores with 20 Hz. For the conditions with an AV, the target speed value for eco-driving was also logged. Additionally, we logged eye-tracking data with 20 Hz. We logged the eye gaze for 10 areas: the speed indicator, the setting for the target speed in the automated mode, the eco-score, and the three symbols for the eco-score. We also logged the eco-score and the symbols for the other vehicles as an eye-tracking area.

4.4.2 Subjective Measurements. After each drive, participants rated task load using the raw NASA-TLX [27] on 20-point scales. Additionally, we employed the System Usability Score (SUS) [9]. Finally, we measured the constructs of perceived ease of use, perceived usefulness, subjective norm, and behavioral intention to use that were adopted from TAM2 [64]. We employed the German translation by Olbrecht (see page 101; [47]).

Participants were also asked to indicate their perceived performance in terms of eco-friendliness (1=not at all - 7=totally eco-friendly) and their assessments of the driving style in terms of safety, fun, and distracted by the visualization. For the automated mode, we also asked participants how well the AV drove.

After all conditions, participants filled out questions regarding the necessity and reasonability of the visualizations, how far they estimated the vehicle could perceive others' eco-scores their ranking of the visualization conditions (no, only own eco-score, own and other's), and their demographic data and their immersion in the simulation by using the Immersion subscale of the Technology Usage Inventory (TUI) [34].

5 RESULTS

5.1 Data Analysis

Prior to statistical tests, we checked the required assumptions (normality distribution and homogeneity of variance assumption). For non-parametric data, we used the non-parametric ANOVA (NPAV) [43]. For post-hoc tests, we used Dunn's test with Bonferroni correction. We employed R in version 4.1.3 and RStudio in version 2022.02.0. All packages were up to date in April 2022.

5.2 Participants

We determined the required sample size via an a-priori power analysis using G*Power in version 3.1.9.7 [21]. To achieve a power of .8 with an alpha level of .05, 15 participants should result in an anticipated medium effect size (0.28 [22]) in a within-factors repeated-measures ANOVA with one group and six measurements.

We recruited N=19 participants (13 male, 6 female, 0 non-binary) with an average age of M=24.16 (SD=3.29). Eleven participants are students, seven are employees, and one is in training. Nine participants finished a college degree, seven high school, two finished secondary school, and one finished their training. Regarding their driving license, nine obtained their license between 5-10 years ago, three 10-20 years ago, three 3-5 years ago, three less than a year ago, and one 1-3 years ago. Seven participants drive between 7000-15000km in the last year, five between 15000-25000, five less than 7000km, and two more than 33000km.

5.3 NASA TLX and Usability

5.3.1 Usability. The NPAV found no significant effects on the SUS score. Usability was rated between M=78.03, SD=19.94 (manual with both visualizations) over M=82.11, SD=17.76 (Manual without visualization) to M=86.71, SD=11.09 (automated with own visualization).

5.3.2 NASA TLX. The NPAV found a significant main effect of *Driving Mode* on TLX score ($F(1, 18) = 28.44$, p<0.001). Manual driving was rated significantly more difficult (M=7.31, SD=4.32) than automated driving (M=4.39, SD=2.82).

Mental Workload: The NPAV found a significant main effect of *Driving Mode* on mental workload ($F(1, 18) = 66.84$, p<0.001). Manual driving was significantly more mentally demanding (M=9.00, SD=5.53) than automated driving (M=3.63, SD=2.86).

The NPAV found a significant main effect of *Visualization* on mental workload ($F(2, 36) = 7.38$, p=0.002). A post-hoc test, however, found no significant differences. Mental workload was lowest without a visualization (M=5.42, SD=4.71) and highest with the own and the visualization for the other vehicles (M=7.29, SD=5.88).

Physical Demand: The NPAV found a significant main effect of *Driving Mode* on physical demand ($F(1, 18) = 65.99$, p<0.001). Manual driving was significantly more physically demanding (M=7.11, SD=4.96) than automated driving (M=3.00, SD=3.12).

Temporal Demand: The NPAV found a significant main effect of *Driving Mode* on temporal demand ($F(1, 18) = 9.67$, p=0.006). Manual driving was significantly more temporally demanding (M=6.54, SD=4.80) than automated driving (M=4.35, SD=3.69).

Performance: The NPAV found no significant effects on performance. The values for performance ranged from $M = 5.21$ (automated driving with own visualization) to $M = 7.47$ (automated driving with both visualizations).

Effort: The NPAV found a significant main effect of *Driving Mode* on effort ($F(1, 18) = 25.81$, p<0.001). Manual driving required significantly more effort (M=7.96, SD=5.32) than automated driving (M=3.63, SD=3.36).

Frustration: The NPAV found no significant effects on frustration. The values for frustration ranged from $M = 5.05$ (automated driving with both visualizations) to $M = 8.32$ (manual driving without visualizations).

5.4 Technology Acceptance Model 2

Perceived Ease of Use: The NPAV found a significant main effect of *Visualization* on Perceived Ease of Use ($F(2, 36) = 3.56$, p=0.039). However, post-hoc tests did not show significant differences.

Perceived Usefulness: The NPAV found a significant main effect of *Visualization* on Perceived Usefulness ($F(2, 36) = 11.05$, p<0.001). A post-hoc test found that no visualization (M=4.43, SD=1.45) was rated significantly worse (p=0.005) than visualizing only the own eco-score (M=5.36, SD=1.16).

Subjective Norm: The NPAV found no significant effects on subjective norm. The values for subjective norm ranged from $M = 3.97$ (manual without visualizations) to $M = 4.55$ (automated with own visualization).

Behavioral Intention to Use: The NPAV found no significant effects on intention to use. The values for intention to use ranged from $M = 5.50$ (manual with both visualizations) to $M = 6.00$ (manual with own visualization).

5.5 Perceived Driving Style

Fun: The NPAV found a significant main effect of *Driving Mode* on Driving Style - Fun ($F(1, 18) = 8.28$, p=0.010). Manual driving was perceived as significantly more fun (M=5.75, SD=1.33) than automated driving (M=4.77, SD=1.65).

The NPAV found a significant main effect of *Visualization* on Driving Style - Fun ($F(2, 36) = 4.24$, p=0.022). A post-hoc test found no significant differences.

Ecological: The NPAV found a significant main effect of *Driving Mode* on Driving Style - Ecological ($F(1, 18) = 8.28$, p=0.010). Automated driving was perceived as being significantly more ecological (M=5.56, SD=1.34) than manual driving (M=5.47, SD=1.42).

The NPAV found a significant main effect of *Visualization* on Driving Style - Ecological ($F(2, 36) = 4.24$, p=0.022). The driving style was subjectively more found to be ecological with the own visualization (M=6.00, SD=0.99) compared to no visualization (M=4.79, SD=1.71; p=0.001).

Safe: The NPAV found a significant main effect of *Driving Mode* on Driving Style - Safe ($F(1, 18) = 8.28$, p=0.010). Automated driving was perceived as being significantly safer (M=5.91, SD=1.37) than manual driving (M=5.53, SD=1.60).

The NPAV found a significant main effect of *Visualization* on Driving Style - Safe ($F(2, 36) = 4.24$, p=0.022). A post-hoc test found no significant differences.

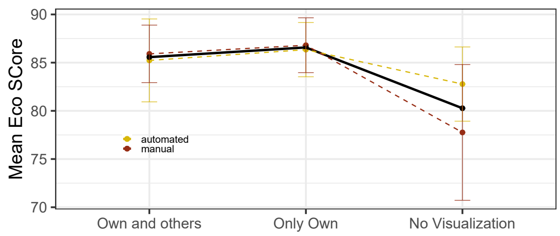

Fig. 5. Mean eco-score.

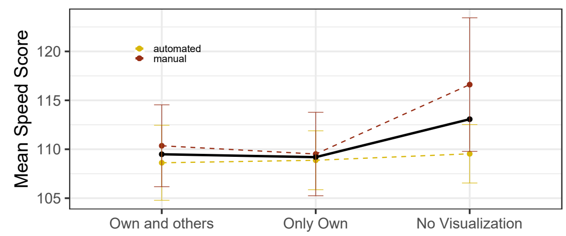

Fig. 6. Mean speed-score.

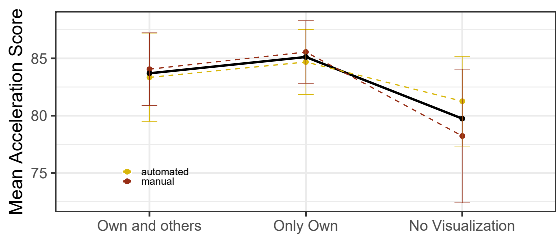

Fig. 7. Mean acceleration-score.

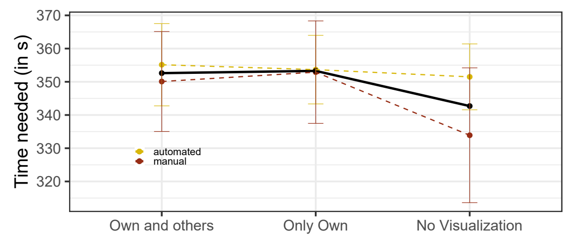

Fig. 8. Time needed.

Distracting: The NPAV found a significant main effect of *Driving Mode* on Driving Style - Distracting ($F(1, 18) = 8.28$, p=0.010). Manual driving was perceived as significantly more distracting (M=2.70, SD=1.94) than automated driving (M=2.04, SD=1.44).

The NPAV found a significant main effect of *Visualization* on Driving Style - Distracting ($F(2, 36) = 4.24$, p=0.022). Visualizing only the own eco-score was perceived as significantly less distracting (M=1.97, SD=1.52) than visualizing the own and the eco-score of the others (M=2.97, SD=1.95).

Driving Style Automated Vehicle: For the evaluation of the driving style as performed by the automation, a Friedman's test found no significant difference (p=0.42). It was rated medium between automated with both visualizations (M=4.74, SD=1.73) and automated with only visualizing the own eco-score (M=5.21, SD=1.84).

5.6 Driving Data

5.6.1 Mean Eco-Score. The NPAV found a significant main effect of *Visualization* on the mean eco-score ($F(2, 36) = 12.54$, p<0.001; see Figure 5). A post-hoc test showed that the score for no visualization (M=80.27, SD=11.89) was significantly worse than with only displaying the own eco-score (M=86.58, SD=5.79).

5.6.2 Mean Speed-Score. The NPAV found a significant main effect of *Visualization* on mean speed score ($F(2, 36) = 5.66$, p=0.007; see Figure 6). A post-hoc test found no significant differences. The NPAV found a significant main effect of *Driving Mode* on mean speed-score ($F(1, 18) = 8.00$, p=0.011). The speed-score was significantly lower when driving automated (M=109.01 km/h, SD=6.74) compared to manual (M=112.16 km/h, SD=11.14).

5.6.3 Mean Acceleration-Score. The NPAV found a significant main effect of *Visualization* on mean acceleration-score ($F(2, 36) = 5.38$, p=0.009; see Figure 7). A post-hoc test found that in the no visualization conditions, the mean acceleration-score (*M*=79.74, *SD*=10.28) was significantly lower than when visualizing the own eco-score (*M*=83.70, *SD*=7.25).

5.6.4 Duration. The NPAV found a significant main effect of *Visualization* on duration ($F(2, 36) = 5.66$, p=0.007; see Figure 8). A post-hoc test found no significant differences. The NPAV found a significant main effect of *Driving Mode* on duration ($F(1, 18) = 7.67$, p=0.013). The automated driving (*M*=353.43s, *SD*=22.32) took significantly longer than the manual driving (*M*=345.63s, *SD*=35.82).

5.6.5 Collisions. We found that there were in total 27 crashes. Of these, 13 occurred in automated driving and were, therefore, discarded. The reason for the crashes in automated driving can be traced back to our implementation. The automation was implemented to determine whether it should drive left or right based on the target speed and not on the basis of the actual speed. Therefore, at the beginning of the start, when the participant set the target speed to, for example, 120 km/h, the car changed directly to the left while still only driving 30-40 Km/h. This means that the other vehicles, which are already driving fast, have not always managed to brake in time. We explained this to the respective participants afterward.

In the manual driving conditions, two crashes occurred in the conditions with both visualizations, two in the conditions with only visualizing the own eco-score, and ten occurred without any visualizations. Two participants stepped on the gas and brakes at the same time. Most of the time, however, because the participants did not keep a safe distance and could no longer brake in a sudden traffic jam, leading to the accident. This happened less often with a visualization because the participants usually drove a little slower.

5.7 Eye Tracking Data

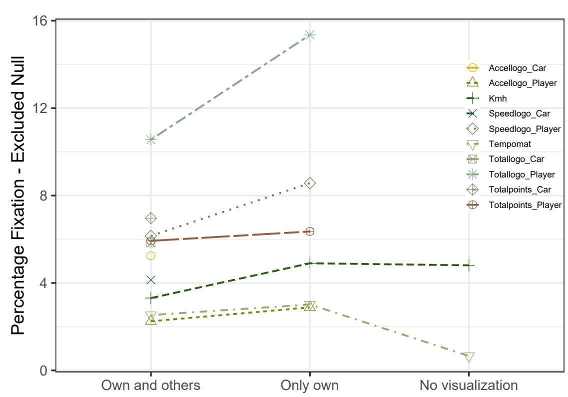

Fig. 9. Fixations of relevant areas of interest in percent.

We logged the eye-tracking data with 20 Hz. We calculated the percentage of tracked fixations on the ten different areas of interest (see Figure 9). Several observations can be made. The fixation of the the total **own** eco-score **logo** ("Totallogo_Player") was always highest, if present.

With direct comparison, the fixation of the total **eco-score** of the **others** was second most fixated, followed by the **own** speed logo and the own total eco-score and the total eco-score logo of the others.

Overall, all other ego vehicle-related visualizations were always more fixated when the visualizations of the other vehicles were not present. Interestingly, the speedometer ("Kmh") was equally fixated with no visualization and when only the own eco-score was displayed.

5.8 Open Feedback

Twelve participants provided open feedback. The eco-scores of the other vehicles were described as invasive (P2) and distracting (P19). However, participants argued that this could be reduced by not displaying all the scores and symbols but by providing only the aggregated score via color. In general, participants highlighted that visualizing the own eco-score was very useful.

6 DISCUSSION

We compared visualizing one's own eco score consisting of scores for speed and acceleration with additional peer comparison and a baseline. Additionally, we varied the *Driving Mode*: Manual or Automated. Our results are in line with prior work showing that constantly visualizing the own eco score leads to improved ecological driving [36, 54, 56]. However, our concept neither significantly improved nor impaired driving or any subjective assessment. We discuss these findings regarding the general validity of peer comparison and the actual implementation. Additionally, we discuss the implications of our results for AVs.

6.1 Peer Comparison for Ecological Driving

Previous work indicated that peer comparison could lead to improved performance [46, 48]. However, with our concept, we could not significantly improve the driving style with regards to ecological driving (e.g., see Figure 5). However, driving data shows that the driving style, while already being good without visualization (mean score of around 80 of 100), was increased (mean score around 85) and is approximately equal to only visualizing one's own score. Potentially, this already high value indicates that a plateau was reached, from which further improvements are difficult to achieve. Based on this, we are not able to definitely support or reject our proposed concept. With our limited duration per ride ($\approx$ 6 min), the long-term effects could not be studied. Potentially, the effect of comparison is larger when motivation starts to fall off after a longer duration of driving.

6.2 Visual Design

As described in Section 5.8, participants mentioned that the design for the visualization of the other vehicles' scores could be improved. While we opted for a very close visualization for the own and the visualization of the other's eco score to avoid confounding factors, for other vehicles, we would support only displaying the eco score and not the speed and acceleration scores to avoid visual clutter. While this reduces information content, the gaze analysis supports that participants looked primarily at the total score or the logo for the total score (see Figure 9). While not highlighted by participants, we argue that our attention-grabbing mechanisms and color design were helpful to direct gaze toward the relevant scores as indicated by the eye-tracking data.

6.3 Ecological Driving in AVs

We showed that automated driving results in lower workload, which we interpret as an indication of a valid study design. Currently, the driving style of AVs is not yet clear. While there is much hype about the potential for reduced fuel consumption, for example, via optimized driving behavior or novel maneuvers such as platooning [68], the demands of the user are less investigated. Most work goes in a direction of either investigating driving styles [18] or looking into the necessity to adjust the driving style to one's own style [24]. We found that, in the automated mode, participants drove significantly slower than in the manual mode and, therefore, the journey took longer. In general, we found less variance between the conditions when driving automated (e.g., see Figure 5 or Figure 6). This is a first indication that in automated driving, the effect of eco score visualization, even when the user has the ability to adjust the driving style, is less relevant. Nonetheless, visualizing one's own eco score is easily implementable and, we argue, should remain incorporated if the driving style is adjustable.

6.4 Practical Implications

With our data, we can state that, in line with previous work, the visualization of the own eco score is useful and reasonable. Our data does not support the necessity for a full windshield display to enable peer comparison. While this could become feasible in the near future [42], visualizing the own eco score in the HUD or the console seems appropriate. Therefore, no advanced visualization capabilities are required and manufacturers can leverage these effects already in current models.

6.5 Limitations

While we implemented an immersive scenario, the vehicle's vection could not be realistically simulated. This could be enhanced by using a simulator with higher degrees of freedom (e.g., [13]). Nonetheless, the Immersion subscale of the TUI showed that participants felt immersed (M=20.32, SD=3.79 on a scale from 4 (lowest) to 28 (highest immersion).

Additionally, our journey per condition was relatively short: five to six minutes. Future work could include this concept in longitudinal studies.

Our concept of direct peer comparison with other driving styles in the vicinity also heavily depends on other drivers' behavior. However, as displaying the own eco score was shown to be beneficial to the driving style, we believe that this would offset the potential negative effects of having others drive environmentally negative.

7 CONCLUSION

Overall, we present a concept to leverage the effects of direct (peer) comparison to improve ecological driving by visualizing one's own and others' eco scores. In a VR study (N=19), we compared the concept to no visualization and only visualizing one's own eco score. In the study, we compared these visualizations both for manual and automated driving. In automated driving, the participant was able to manipulate the driving style by setting the desired speed. We found that visualizing the eco score improves ecological driving both for manual and automated driving. However, peer comparison, while also improving ecological driving compared to no visualization, actually lead to a little worse mean eco score. We propose updated designs of the visualizations and discuss practical implications. This work helps to further unveil relevant factors in persuading manual drivers and users of AVs to drive ecologically.

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