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Car following with an inertia-oriented driving technique: A driving simulator experiment

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A R T I C L E I N F O

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A B S T R A C T

Background: For many decades, car-following (CF) and congestion models have assumed a basic invariance: drivers' default driving strategy is to keep the safety distance. The present study questions that Driving to keep Distance (DD) is a traffic invariance and, therefore, that the difference between the time required to accelerate versus decelerate must necessarily determine the observed patterns of traffic oscillations. Previous studies have shown that drivers can adopt alternative CF strategies like Driving to keep Inertia (DI) by following basic instructions. The present work aims to test the effectiveness of a DI course that integrates 4 tutorials and 4 practice sessions in a standard PC computer designed to learn more adaptive driving behaviors in dense traffic. **Methods**. Sixty-eight drivers were invited to follow a leading car that varied its speed on a driving simulator, then they took a DI course on a PC computer, and finally they followed a fluctuating leader again on the driving simulator. The study adopted a pretest-intervention-posttest design with a control group. The experimental group took the full DI course (tutorials and then simulator practice). The control group had access to the DI simulator but not to the tutorials. **Results**. All participating drivers adopted DD as the default CF mode on the pre-test, yielding very similar results. But after taking the full DI course, the experimental group showed significantly less accelerations, decelerations, and speed variability than the control group, and required greater CF distance, that was dynamically adjusted, spending less fuel in the post-test. A group of 8 virtual cars adopting DD required less space on the road to follow the drivers that took the DI course.

1. Introduction

Traffic jams bring together most of the undesirable consequences of road traffic, ranging from economic costs such as increased prices of goods and time spent travelling (Goodwin, 2004; Sweet, 2014), to fuel waste (Tong et al., 2000) and health problems, since traffic pollution is estimated to cause more deaths than road crashes in some countries (Caiazzo et al., 2013; Dora and Phillips, 2000). Inadequate distance and speed between vehicles boost drivers' cognitive load (de Lewis-Evans et al., 2011), foster adverse affective and emotional states, such as anger (Mesken et al., 2007; Zhang and Chan, 2014), aggressive behavior (Shinar and Compton, 2004),

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risky driving (Ni et al, 2016; Song and Wang, 2010), and road crashes (Davis and Swenson, 2006). Various different methods have been attempted to relieve congestion, such as encouraging public rather than private transport, building new roads, and setting up road pricing schemes, to name a few (Kerner, 2009; Penchina, 1997; Staley and Moore, 2009; Vester, 1997). However, despite these attempts, congestion remains a widespread phenomenon in all motorized societies.

In recent years, increasing attention has been given to drivers' car-following (CF) behavior in dense traffic (Deng and Zhang, 2015; Laval, 2011; Laval and Leclercq, 2010; Saiffuzzaman et al., 2017; Wei and Liu, 2013). A series of studies carried out within the so-called Nagoya paradigm has been decisive in understanding how traffic congestion is formed (Sugiyama et al., 2008; Tadaki et al., 2013). In these studies, vehicles follow each other in a 230-m perimeter circle while drivers are instructed to *safely follow the vehicle ahead of them, trying to maintain cruising velocity*. Results indicate that participants drove and maintained free flow speed. But when the number of drivers rose to 22, backward fluctuations broke the free flow, and several vehicles stopped momentarily to avoid crashing. At a given point, even a single vehicle's braking was transmitted back through the column of cars, forming the typical shockwave that eventually brought some vehicles to a complete halt. Put simply, the adoption of the standard safety distance was the ultimate cause of the occurrence of the so-called phantom traffic jams (Gazis and Herman, 1992). Apparently, safety distance arranges vehicle platoons to favor the spread of disturbances in a waveform. These findings illustrate that Driving to keep Distance (DD) is a CF strategy that only works well when the speed of the vehicle ahead is constant, however this is a scenario that is more often the exception than the rule in contemporary road traffic (Wille, 2011; Wille and Debus, 2005).

Most CF models assume DD as a traffic invariance, that is, as a predictable and recurring factor that is part of the overall behavior of drivers in a given platoon (see Pariota et al., 2016; Sharma et al., 2019; Toledo, 2007; Saifuzzaman and Zheng, 2014;). However, as shown by recent research, both human (Blanch et al., 2018; Taniguchi et al., 2015) and automated vehicles (Stern et al., 2018; Stern et al., 2019) can adopt alternative car-following strategies to improve traffic flow. Focusing on the human driver, it is important to highlight that DD is not consubstantial or endogenous to the driver, it is a taught and learned CF strategy. For example, Article 13 *Speed and distance between drivers* of the 1968 Convention on road traffic (UNECE, 2006) recommends in point 5: "The driver of a vehicle moving behind another vehicle shall keep at a sufficient distance from that other vehicle to avoid collision if the vehicle in front should suddenly slow down or stop." (p. 40). But drivers can learn to avoid sudden variations in speed by not driving too close to a lead car that varies speed and maintaining a speed with minimal oscillations, i.e., Driving to keep Inertia (DI). When DD and DI are compared in heavy traffic, the DI strategy becomes more functional, resulting in less dispersion of speed and lower fuel consumption (Blanch et al., 2018; Lucas-Alba et al., 2020). If the concept of eco-driving implies fewer accelerations and decelerations while keeping stable speed (Boriboonsomsin et al., 2010; Haas and Bekhor, 2017), the DI strategy is a tool to understand why and how to drive in an ecological way to avoid causing traffic jams.

1.1. Goals of this study

This study proposes an adaptive driving learning technique to implement in congested traffic by using a driving simulator. The study aims to test whether the DI strategy (see Section 2.4.2) is a useful driving technique, capable of replacing the ingrained DD strategy typically used by drivers. Previous studies described how DD and DI differ and the benefits of DI driving, confirming that drivers can adopt either DD or DI to follow a speed fluctuating leader, and that these techniques show opposite speed and distance patterns: DD presents high speed variability and low distance variability, while DI presents low speed variability and high distance variability (Blanch et al., 2018; Lucas-Alba et al., 2020). However, the drivers in these studies simply followed the DD or DI instructions given by the experimenter, without knowing the context in which the congestion arose or the effects of the DD or DI strategies they adopted on a platoon of followers. This study confronts drivers with a set of experiences (tutorials and simulated practices) that are aimed at educating them on congestion, how it reproduces and what its implications are, as well as how it can be avoided.

We expect that drivers experiencing the full DI course (tutorials + practice) will be more inclined to adopt DI strategy. Overall, we put forward the following hypotheses:

We do not expect pre-test/post-test differences for average speed between control and experimental groups (H1). However, with regards to the comparison of the experimental and control groups in the post-test, the experimental group is expected to yield a significantly lower speed dispersion (H2), show less frequent accelerations and decelerations (H3), yield a greater average distance to the leading car (H4), yield a greater distance variability to the leading car (H5), and yield a lower fuel consumption (H6). Furthermore, we expect that a platoon of 8 virtual vehicles will require less space on the road following the drivers of the experimental group in the post-test (H7).

2. Methodology

Participants in this study completed a driving course, adapted from Melchor et al. (2018), teaching them the DI strategy principles. We recorded a Hebrew narration of the tutorials to be used in this experiment. One group of participants were asked to drive the driving simulator both before and after the DI course, thereby allowing us to examine, in a close to real driving setting, the change in their behavior. A second group of participants drove the same driving simulator scenarios, yet without exposure to the DI principles. Whereas the DI group was presented both with DI tutorials and practice, this second (control) group only completed the DI course practice, without viewing the tutorials corresponding to the key modules (B-D), yet having full access to the Module A (including tutorial) to know the proper way to handle the DI course.

2.1. Goals

The study aimed to check if A) the driver adopts a DD strategy in the pre-test as a default; B) drivers change their driving patterns after the full experience with DI course (tutorials + practice) in the post-test; C) experimental group participants adopt a DI strategy in the post-test in terms of speed, distance and fuel consumption.

2.2. Participants

The participants were recruited by (1) ads that were hanged on student message boards in several faculties at the Technion, (2) electronic messages distributed to undergraduate and graduate students through the academic advising office, and (3) ads posted in several Technion student groups on Facebook. Most of the participants (79.4%) were students. The ads indicated that participants had to hold a valid driving license to participate in the experiment. For compensation, the participants received a coupon for a lunch meal in a nearby on-campus Café. A total of 68 drivers with normal or corrected to normal vision took part in the experiment. The participants were naive as to the purpose of the study. Approximately 32% of the sample were female. The participants' age ranged from 18 to 60 years, with an average of 29.14 years (SD = 7.10). Regarding the driving experience, the possession of the driving license of the participants varied between 1 and 35 years, with an average of 10.30 years (SD = 6.39). Most of the participants (82.1%) had an available car. The majority drove every day (38.2%), or 1–2 days a week (36.8%), while some drove between 3 and 5 times a week (11.8%), and the rest drove rarely (13.2%). Most participants indicated that they were used to drive in urban congested roads (72.1%).

2.3. Design

The present study included a 2 * 2 experimental design (group * scenario) with an equal number of participants per condition (n = 17). One half of the participants (n = 34) were randomly assigned to the DI group, whereas the other half (n = 34) were assigned to the control group. Given that all participants drove the driving simulator twice, two similar scenarios (A and B) were developed. For counterbalancing purposes, one half of the participants in each group (n = 34) were randomly assigned to drive scenario A in their first drive and scenario B in their second drive (A-B condition), whereas the other half (n = 34) were assigned to drive scenario B first and scenario A second (B-A condition). The study received the Technion's ethics committee approval number 2020–055 (form number: 104028).

2.4. Materials

A laboratory experiment using a STISIM driving simulator (Rosenthal, 1999) was developed in order to collect data on drivers' CF behavior. The simulator is a fixed-base interactive driving simulator. Its setup at the Technion lab includes a panoramic view of the road, powered by three inter-connected monitors with a 135° horizontal and 40° vertical display, with a rate of 30 frames/sec (see Fig. 1). In the present study, the participants drove in an automatic mode (without a shifter).

2.4.1. Driving simulator scenarios

To examine the study's goals, we developed two equivalent scenarios, both designed to end after 2100 m (mean duration 4.25 min). The scenarios included a two-way urban road, with two lanes in each direction (see Fig. 2). Speed limit signage was spread throughout the road indicating a 70 km/h speed limit. No horizontal or vertical curves were incorporated within the design, nor any intersections.

At the beginning of the scenarios, the participant's car was placed in the right lane. In total, 19 vehicles occupied the right lane, and the participant's car was 11th in the platoon. All vehicles were initially positioned with some distance between them, varying between

Fig. 1. One of the participants driving the simulator during the experimental run.

Fig. 2. A screenshot of the simulator display shown to participants from one of the scenarios.

10 and 40 m. The scenarios simulated driving in congestion, where despite the 70 km/h speed limit, the dense traffic did not enable free flow. Specifically, the driving speed of the first car in line was set to vary throughout the scenarios, with six stop and go waves. Its speed was programed to vary between 2 and 3 m/s (7–11 km/h) in “stop” phases, and between 12 and 15 m/s (43–54 km/h) in “go” phases. The scenarios began with a “stop” phase, to ensure that all participants would successfully begin to follow the preceding car. The two scenarios were highly similar, with only minor differences that were intended to give the participants the impression of a different scenario: colors and types of surrounding vehicles, and vehicles’ initial positions and driving speeds.

The setup of the left lane vehicles followed a similar pattern, the only difference being a reduced distance between the starting positions of the vehicles (aimed to minimize the probability the participants would overtake). Opposing traffic, added as a décor, was relatively light.

A third and final scenario was developed as a test trial, intended to familiarize participants with the driving simulator, and getting them comfortable driving it. In this scenario, the participants drove in free flow in a two-way two-lane road, up to a point where they came across two cars driving side by side. The cars drove in a particularly low speed, forcing the participants to decelerate (in order to become familiar with the brake pedal). This scenario included two horizontal curves aimed to allow participants to practice with the wheel, and finally ended after 1800 m (approximately 2 min).

2.4.2. Learning an inertia-oriented driving technique: DI course

Computer simulations designed to teach driving principles normally focus on experiences that promote elementary driving knowledge such as accelerating, decelerating or steering: that is, the main actions and reactions of a driver in a driving environment (Pollatsek et al., 2011; Schiff et al., 1994). Simulation environments are also effective in showing new or unusual traffic environments or circumstances, and in learning and training new driving behaviors (Arslanyilmaz and Sullins, 2019; Beloufa et al., 2019; Blissing et al., 2019; Cavallo et al., 2019) some related to congested flows (Levy et al., 2018).

The DI course (Melchor et al., 2018) targets two main purposes. The first is to teach an alternative CF technique, which focuses not only on keeping the safety distance (DD) but also on preserving inertia when following an oscillating leader (DI). Drivers are typically taught to Driving to keep Distance (DD), which sums and enlarges disturbances throughout the CF platoon. The alternative to cope with a lead oscillatory vehicle (the shockwave origin), is the Driving to keep Inertia (DI) strategy, i.e., anticipating the stop-and-go pattern and becoming shockwave proof offsetting or damping waves and keeping a uniform speed (Blanch et al., 2018; Lucas-Alba et al., 2020). Accordingly, drivers in the DI course are encouraged to compare the differing effects of adopting DD versus DI through different tasks and scenarios. The second main purpose of the DI course is to help drivers understand the close connection between adopting DD (normative CF technique) or DI (the alternative CF technique) and the emergence of congestion in a platoon of followers. To achieve these goals, some ordinary elements and circumstances (e.g., rearview mirror, presence of traffic lights, passing road sections with different speed limits) have been implemented in the DI simulator, as well as some very unusual or impossible ones (e.g., adopting bird’s-eye views from different angles and positions over the whole platoon at will, displaying traffic lights on each single car, connecting cars with springs, activating radar-like displays). Like other recent attempts to model and understand complex

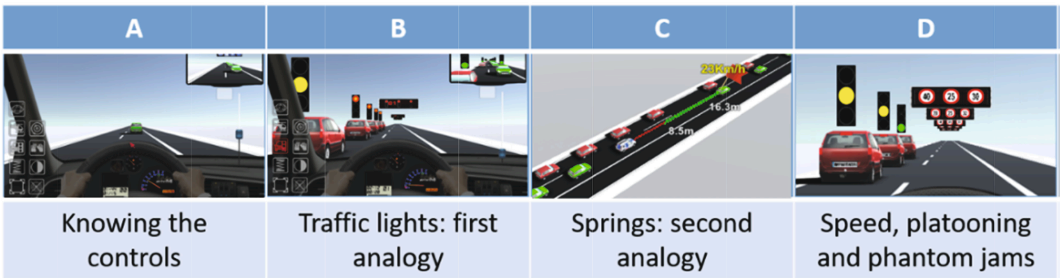

Fig. 3. The DI course learning modules.

systems (Levy et al., 2018), the DI simulator leverages uncommon paths or perspectives to frame participants' analysis and comprehension of CF at large. The DI course includes three modules (Fig. 3): Knowing the controls (Module A); Teaching DI (Modules B-D); and Evaluation (Module E). The sessions on the course are time-limited (around 2.5 min), and tutorials take no longer than this to address DI principles and what the learner should practice at each level. Thus, the time a learner would need to complete the DI course is roughly 25 min.

2.4.3. Questionnaires

Two questionnaires were used in this study: (a) participant details questionnaire, for collecting participants' socio-demographic data, (b) a questionnaire used as a filler task for participants in the control group. The former, a one-page paper and pencil questionnaire, began with a brief description of the experiment and the participant's task, including an informed consent. The questionnaire included personal detail questions (e.g., gender, age, years of holding a driving license), socio-demographic questions (e.g., income, number of cars in household) and driving habits questions (e.g., yearly km, driving frequency, typical travel modes). The second was an on-line questionnaire, used as a filler task for control participants. Whereas the DI group completed the entire DI course in the time frame between the two simulated drives on the simulator, the control group only practiced the DI course, without viewing the tutorials. This filler task, given after the DI course practice, ensured that the time frame between the two drives would be equivalent to that in the DI group. In this questionnaire, the participants were asked several rating questions about their experience with the DI course (unrelated to any of their tasks), e.g., how much they enjoyed it, estimating how effective such a simulation would be in real-world driving courses and its degree of resemblance to real-world driving.

2.5. Procedure

All participants began the experiment with filling in the participant details questionnaire. The experimenter then briefly described the different experimental stages. In the first stage, the experimenter introduced the driving simulator, providing an overview of the system's apparatus (e.g., pedals, steering wheel, rear and side mirrors), and invited her to drive the test trial. The experimenter asked the participant to imagine driving in a real car on a real road, avoiding collisions at all costs. During all simulated drives, the experimenter turned off the lights in the room.

After completing the test trial, the participant continued to the first simulated drive (i.e., the pre-test drive), which, she was told, included other cars driving in varying speeds. The participant was instructed to drive as she would normally do in the real world, yet she was asked not to overtake the car in front of her. In the next stage, the participant left the driving simulator station for the DI course station located in the same room. There, she completed the DI course on a PC, both tutorials and practice (in case she was assigned to the DI group), or merely the practice and the filler task (in case she was assigned to the control group). After completing this stage, the participant returned to the driving simulator station for driving the second and final scenario (i.e., the post-test drive). As in the pre-test, the experimenter asked her to drive as she sees fit. No other instructions were given at this stage, including no directions as to which driving technique to employ. Finally, the participant was debriefed and handed the compensation. The duration of the entire experiment was approximately 45 min for participants in both groups.

3. Results

In what follows, we present the results for the effects of the DI course on participants' driving behavior in terms of speed dynamics, distance between vehicles and energy consumption. Data were subjected to a two-way mixed-model ANOVA having two levels of group (DI vs. control) and two levels of drive test (pre-test vs. post-test). No traffic accidents were documented during the experimental runs in all conditions.

3.1. Speed analysis

3.1.1. Speed variance and means

The examination of mean SD of speed revealed a main effect for drive test, $F_{(1,66)} = 197.59$, $p < 0.001$, $\eta_p^2 = 0.750$, participants showed lower speed variance in the post-test compared to the pre-test. However, a significant interaction revealed that this effect differed between the groups, $F_{(1,66)} = 47.44$, $p < 0.001$, $\eta_p^2 = 0.418$. As seen in the right hand side of Table 1, despite an equivalent speed variance between participants of both groups in the pre-test ($F < 1$), DI participants showed significantly lower speed variance than control participants in the post-test, $F_{(1,66)} = 31.38$, $p < 0.001$, $\eta_p^2 = 0.322$.

Table 1
Mean speed (m/s) and mean SD of speed. SDs appear in parentheses.

	Mean speed		Mean SD of speed	
	pre-test	post-test	pre-test	post-test
DI group	8.24 (0.07)	8.11 (0.21)	3.38 (0.30)	2.21 (0.50)
Control group	8.22 (0.06)	8.24 (0.17)	3.32 (0.28)	2.92 (0.54)

An examination of mean driving speed revealed a main effect for drive test, suggesting participants drove slower in the post-test than in the pre-test, $F_{(1,66)} = 5.56, p < 0.05, \eta_p^2 = 0.078$. However, a significant interaction revealed that this effect differed between the drive tests, $F_{(1,66)} = 9.99, p < 0.005, \eta_p^2 = 0.132$, such that although DI and control participants' mean speed did not differ in the pre-test ($F < 1$), DI participants drove significantly slower than control participants in the post-test, $F_{(1,66)} = 10.80, p < 0.005, \eta_p^2 = 0.141$ (see left hand side of Table 1). Fig. 4 summarizes mean speeds along the CF task, demonstrating a lower speed variance for participants who completed the DI course, compared to their own speed variance in the pre-test, and also to the control participants in both pre-test and post-test.

3.1.2. Accelerations and decelerations

Examining participants' mean acceleration revealed a main effect for group, $F_{(1,66)} = 11.36$, $p < 0.001$, $\eta_p^2 = 0.147$, and a significant interaction, $F_{(1,66)} = 26.94$, $p < 0.001$, $\eta_p^2 = 0.290$, suggesting a differential effect for the two drive tests. As can be seen in Table 2, participants of both groups showed equivalent acceleration in the pre-test, $F_{(1,66)} = 1.65$, *ns*, $\eta_p^2 = 0.024$, yet in the post-test DI participants showed significantly lower acceleration than control participants, $F_{(1,66)} = 29.27$, $p = 0.001$, $\eta_p^2 = 0.307$. Mean acceleration values were found positive and relatively small, which can be expected given that participants started driving from a full stop and then accelerated to a certain speed(s), towards the end point. Further examination on acceleration variance revealed a main effect for drive test, $F_{(1,66)} = 181.94$, $p = 0.001$, $\eta_p^2 = 0.734$, and a significant interaction, $F_{(1,66)} = 56.06$, $p < 0.001$, $\eta_p{}^2 = 0.459$. Whereas both group participants showed equivalent acceleration variance in the pre-test, $F_{(1,66)} = 0.47$, *ns*, $\eta_p^2 = 0.007$, DI participants showed significantly lower acceleration variance compared to control participants in the post-test, $F_{(1,66)} = 25.88$, $p < 0.001$, $\eta_p^2 = 0.282$.

Fig. 5 shows mean frequency of accelerations, assembled in categories of 0.5 m/s^2. We regarded observations within the middlemost category (i.e., −0.25–0.25) as cases wherein the participants kept a relatively constant speed, only slightly deviating from 0. As seen in the figure, DI participants more frequently maintained a relatively constant speed in the post-test, compared to the pre-test, and also to control participants' post-test. Respectively, the pre-test data, as well as that of control participants' post-test, showed higher acceleration frequencies in the categories above $\pm$ 0.25 m/s^2, consistent with the stop and go waves observed in Fig. 4. This pattern of results suggests that the DI course affected the extent to which participants accelerated/decelerated, i.e., pressed the gas and brake pedals.

3.2. Referential measures: Distance between vehicles in the platoon

3.2.1. Distance between driver and the preceding vehicle

An examination of mean space headway between the participant's vehicle and the preceding vehicle showed a main effect for drive test, $F_{(1,66)} = 112.28$, $p < 0.001$, $\eta_p{}^2 = 0.630$, such that participants kept a larger distance from the preceding vehicle in post-test,

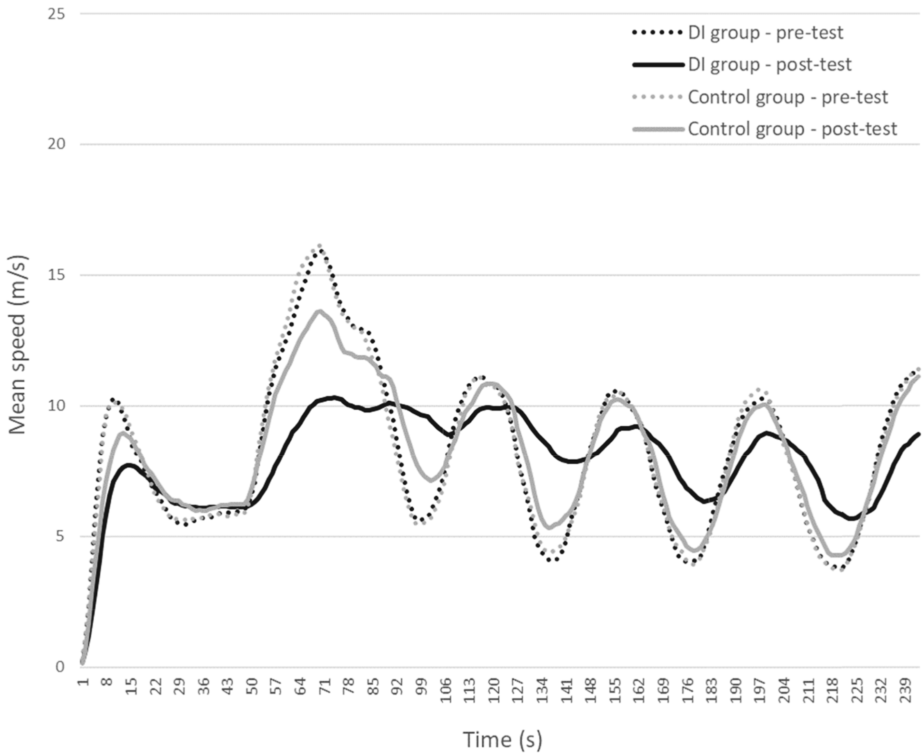

Fig. 4. Mean speed throughout the task for DI and control participants, in both pre-test and post-test.

Table 2
Mean acceleration (m/s^2) and Mean SD of acceleration. SDs appear in parentheses.

	Mean acceleration		Mean SD of acceleration	
	pre-test	post-test	pre-test	post-test
DI group	0.05 (0.01)	0.04 (0.01)	0.67 (0.13)	0.36 (0.13)
Control group	0.04 (0.01)	0.04 (0.01)	0.64 (0.14)	0.56 (0.19)

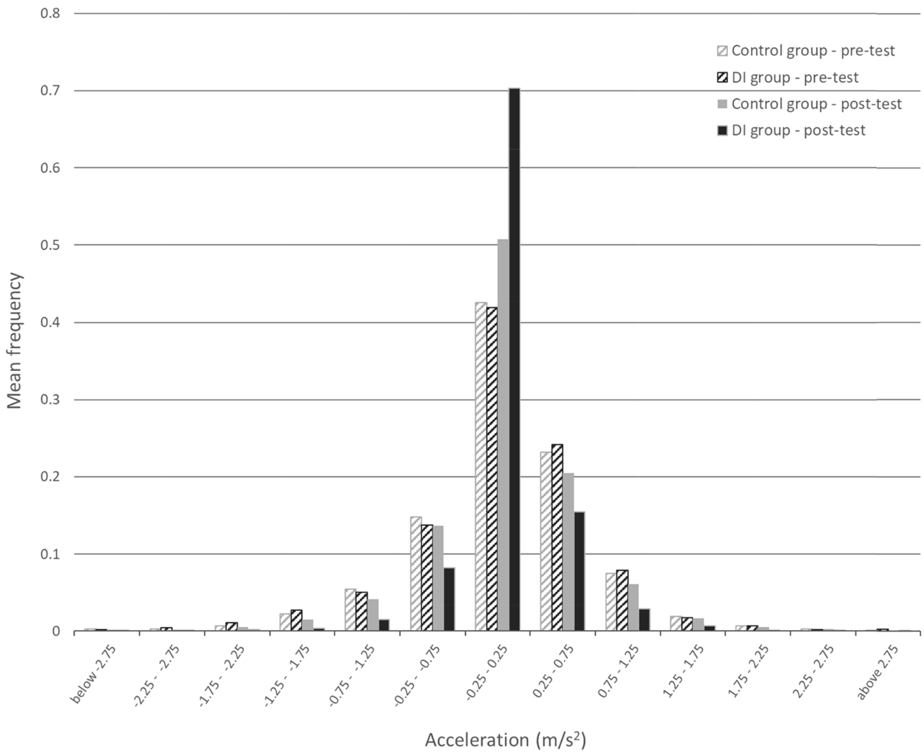

Fig. 5. Frequency distribution of acceleration for DI and control groups in pre-test and post-test.

compared to the pre-test (Table 3). A significant interaction showed that this effect differed between the two drive tests, $F_{(1,66)} = 38.75$, p < 0.001, $\eta_p{}^2 = 0.370$. Whereas both groups showed a comparable baseline in the pre-test ($F < 1$), DI participants kept a larger headway difference in the post-test compared to control participants, $F_{(1,66)} = 27.74$, $p < 0.001$, $\eta_p^2 = 0.296$.

An examination of mean SD of headway from the preceding vehicle revealed a main effect for drive test, demonstrating that overall headway variance was higher in the post-test compared to the pre-test, $F_{(1,66)} = 152.75$, $p < 0.001$, $\eta_p^2 = 0.698$ (Table 3). A significant interaction confirmed that this effect differed between the two drive tests, $F_{(1,66)} = 35.59$, $p < 0.001$, $\eta_p^2 = 0.350$, such that although both groups showed equivalent headway variance in the pre-test ($F < 1$), DI participants showed larger headway variance in the post-test, $F_{(1,66)} = 30.39$, $p < 0.001$, $\eta_p^2 = 0.315$. This pattern of results is also apparent in Fig. 6, as participants who completed the DI course both kept a larger distance from the preceding vehicle and showed greater headway variance.

Table 3
Mean headway (m) and Mean SD of headway of the participant's vehicle from the preceding vehicle. SDs appear in parentheses.

	Mean headway		Mean SD of headway	
	pre-test	post-test	pre-test	post-test
DI group	38.39 (13.96)	108.95 (50.43)	18.84 (7.87)	53.86 (22.10)
Control group	40.39 (10.48)	58.73 (23.40)	18.05 (5.02)	30.26 (11.60)

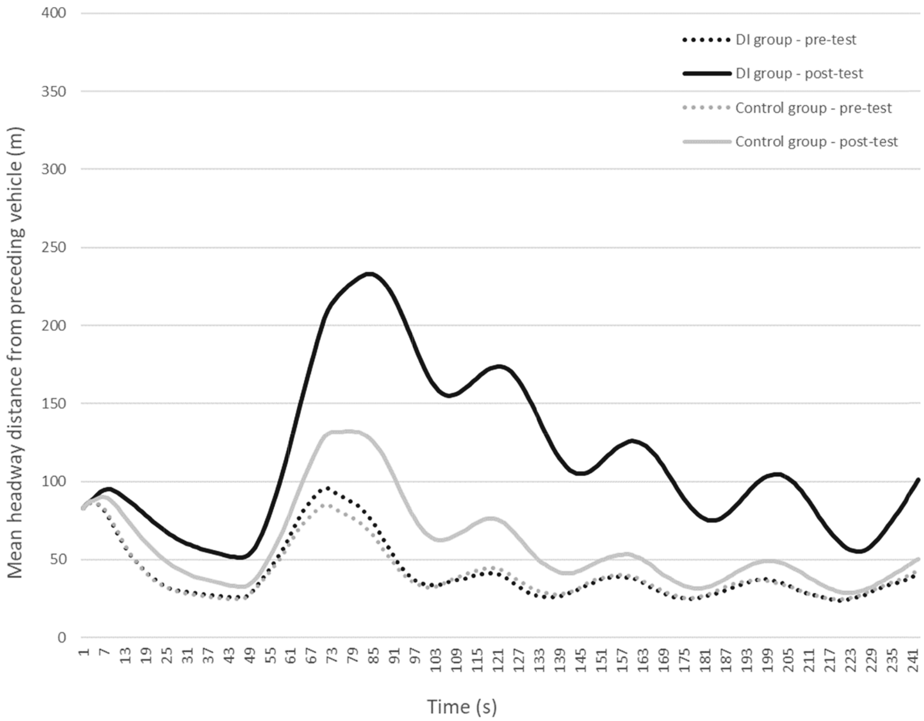

Fig. 6. Mean headway distance throughout the task between the participants' vehicle and the preceding vehicle, as a function of group and drive test.

3.2.2. Queue length

The distance between the participant's car and the last vehicle in line (eight vehicles followed the participant's car in both scenarios; henceforth, queue length) was examined. According to STISIM manual, vehicles added to the scenarios are programed to slow down when approaching other vehicles from behind (Rosenthal, 1999), reflecting the standard DD technique. ANOVA showed a main effect for drive test, $F_{(1,63)} = 40.92$, $p < 0.001$, $\eta_p^2 = 0.394$, such that queue length was shorter in the post-test compared to the pre-test (Table 4). A significant interaction, $F_{(1,63)} = 13.24$, $p < 0.001$, $\eta_p^2 = 0.174$ confirmed that this effect differed between drive tests. Whereas both groups showed equivalent queue lengths in the pre-test ($F < 1$), in the post-test the queue length of the DI group was shorter on average than that of the control group, $F_{(1,63)} = 18.84$, $p < 0.001$, $\eta_p^2 = 0.230$.

3.3. Overall energy consumption

To assess the effects of the DI technique on overall energy (e.g., fuel) consumption, we adopted vehicles' tractive energy consumption calculation (Et, in kWh/100 km) from He et al. (2020), integrating the power requirements (Pt, in kW) at the wheels over time (not considering negative power components from the regenerative braking):

$$P_t = \begin{cases} \left(F_0 + F_1\nu_p + F_2\nu_p^2 + 1.03ma_p + mg\cdot\sin\theta\right)\nu_p\cdot 10^{-3}, & P_t \geq 0 \\ 0, & P_t < 0 \end{cases} \quad (1)$$

Table 4
Mean distance (m) between participant's car and the last vehicle in line. SDs appear in parentheses.

	Mean queue length	
	pre-test	post-test
DI group	371.46 (11.70)	335.48 (26.81)
Control group	371.13 (12.99)	361.24 (20.90)

$$E_t = \frac{\int_0^T P_t dt}{0.036 \cdot \int_0^T \nu_p dt} \tag{2}$$

where F_0, F_1 and F_2 are road load coefficients; m is the vehicle mass (kg); v_p and a_p are the participant's vehicle speed (m/s) and acceleration (m/s^2), respectively; θ is the road gradient (rad); g is the gravitational acceleration (9.81 m/s^2); dt is the time interval(s) between consecutive measurement points; and T denotes the total duration(s) of the travel period. For this calculation, we assigned road load and mass coefficients of a Toyota Corolla, because of its similar attributes to the simulated vehicle.

An examination of energy consumption showed a main effect for group, $F_{(1,63)} = 11.52$, $p < 0.001$, $\eta_p^2 = 0.155$, a main effect for pre-test/post-test, $F_{(1,63)} = 213.95$, $p < 0.001$, $\eta_p^2 = 0.773$, and a significant interaction, $F_{(1,63)} = 62.57$, $p < 0.001$, $\eta_p^2 = 0.498$. As can be seen in Fig. 7, participants in the two groups showed equivalent levels of energy consumption in the pre-test ($F < 1$). Despite this, in the post-test DI participants consumed significantly less energy than control participants, $F_{(1,63)} = 36.26$, $p < 0.001$, $\eta_p^2 = 0.365$ (fuel consumption was 42.1 % lower after taking the full DI course).

Focusing on the intervention as indicated by the η_p^2scores, the effect size for the performance factors was wide-ranging. The effect size of the mean SD of speed was large for pre-test/post-test (0.750), and medium-to-large for the DI/control groups (0.418), but the mean speed scores were low, both for pre-test/post-test (0.078) and for experimental/control groups on the post-test (0.141). The effect size for the acceleration variance for pre-test/post-test was large (0.734), and also the interaction with the group condition (0.459). The effect size for mean acceleration was medium, the most remarkable one being the DI group mean acceleration in the post-test (0.307). Mean headway distance size effect was large for pre-test/post-test (0.630), and middle-sized for the DI/control groups (0.370). Mean SD of headway distance also presented large differences between pre-test/post-test (0.698) and medium size for experimental/control groups in the post-test (0.350). Pre-test/post-test differences were large in energy consumption (0.773) also when comparing experimental/control groups in the post-test (0.498). Finally, the effect-size in the differences in queue length were medium sized for pre-test/post-test (0.394), and relatively small for the experimental/control group in the post-test (0.230). Overall, pre-test/post-test effect sizes were large, and DI/control group effect sizes in the post-test were medium.

4. Discussion

Overall, the results indicate that the drivers who completed the DI course exhibited more efficient CF performance in the post-test than the control group. The experimental group exhibited less speed variation (Fig. 4), and fewer (and smoother) accelerations and decelerations (Fig. 5). Keeping inertia required anticipatory behavior with respect to the oscillatory behavior of the cars ahead, and drivers learning DI maintained, on average, a larger distance from the preceding vehicle compared to control participants (Fig. 6). However, this distance to the fluctuating leader varied: the DI technique involved converting the speed variations (ups and downs) of the leader into the distance variations (zooming in and out) of the follower along a stretch in which the DI CF operations (small speed adjustments, approaching until the safety distance limit, then moving away) were carried out. The logical consequence of these findings is that the DI group consumed less fuel in the post-test (Fig. 7). Furthermore, the drivers who completed the DI course stabilized the platoon, as the eight DD virtual-followers behind required less road space in the post-test compared to the pre-test and control group. Based on these results, we can conclude that in about 25 min, the DI course has been able to introduce significant and

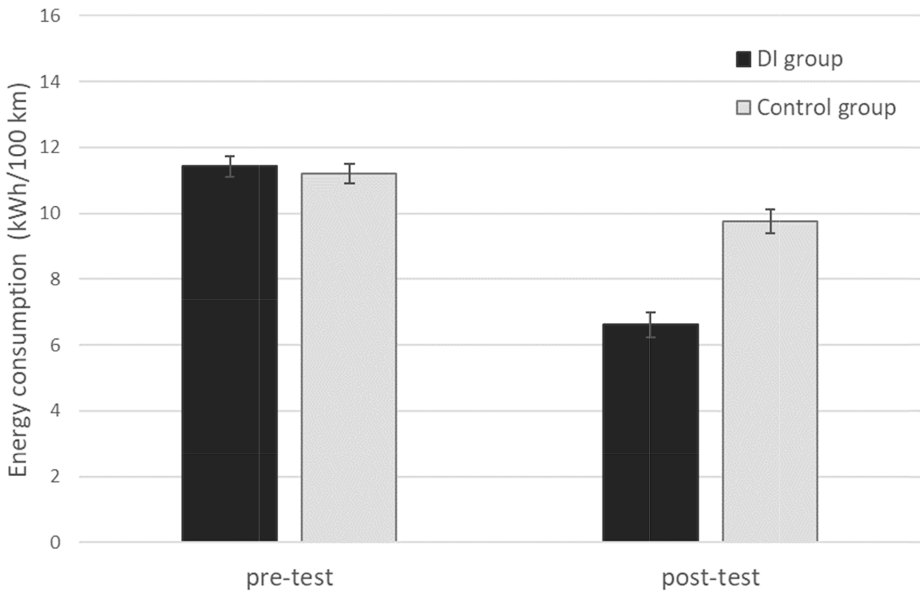

Fig. 7. Energy consumption (kWh/100 km) for DI and control groups as a function of drive test. Error bars indicate ± 1 SEM.

functional changes in the way drivers approach CF in congested traffic.

However, not all results are in line with our expectations. After following the DI course, participants adopted a mean speed that is slightly (but significantly) lower than expected and this should not be the case. Similar results were observed by Blanch et al. (2018), Lucas-Alba et al. (2020), Huang et al. (2018). This slightly lower average speed (0.13 m/s) has a connection with the average distance observed after the DI course in the post-test: it was certainly somewhat longer than needed. This is evident in Fig. 6, as these participants seem to reduce their CF distance progressively, reflecting a sort of learning curve of the DI technique. According to this notion, participants may begin to implement the technique by saving a considerable headway distance to ensure constant speed, yet with practice they refine it. Only in the last section of the run (after the second 181–187, see Fig. 6) the average distance looks as expected (approximately double the distance taken by a DD driver). The degree to which the differences in the mean speed of the leader in previous studies (mean speed around 3 m/s; Blanch et al., 2018; Lucas-Alba et al., 2020) compared to the present study (mean around 8 m/s), may induce differences in the mean speed decrease observed in the post-test. Therefore, the content included in the tutorials may be improved in this sense (especially in the second tutorial, which deals with distance management and car-following).

Another unexpected result concerns the performance of the control group in the post-test. While it is clear that completing the full DI course (tutorials and simulator practice) yielded significantly better results, the control group (DI course practice only) had some interesting variations that went in the same direction as the post-test: SD of speed decreased (Table 1; Fig. 4), also the mean SD of the accelerations (Table 2) fell somewhat (Table 2, Fig. 5), while mean headway distance and mean SD of headway distance went up (Table 3; Fig. 6). This resulted in the expected gains: lower energy consumption (Fig. 7), and more reduced queue length of virtual-followers were observed (Table 4). Clearly, watching the tutorials before practicing the simulator was decisive. But overall, it seems that experiencing the different modules of the course (i.e., looking at the virtual-cars speeding up only to stop at the red light in Module B; looking at the virtual-cars in the adjoining lane rapidly moving forward, only to stop at the vehicle halted in front in Module C; or realizing that cars moving in the adjacent-lane in the middle of mandatory speeds, higher on the average than those followed by participants, do not progress much in Module D) may have given drivers in the control group clues or ideas about the meaning of the task (Orne, 1962). Although beyond the scope of the present study, these results point to alternative ways to incorporate DI into drivers' behavioral repertoire (e.g., adopting discovery learning schemes, Kapur, 2016).

The main objective of this research was investigating whether the DI course could reliably introduce significant changes in the drivers' behavioral repertoire so that their CF behavior would change, from DD (the default) to DI, yielding benefits in terms of speed, acceleration, distance, energy consumption (pollution) and road occupancy. The results have confirmed our expectations, although more research is needed to determine whether these effects show long-term consolidation (e.g., 6–12 months) in drivers' behavior. In this study, some limitations of previous studies have been addressed (e.g., including older participant drivers, complementing the use of a PC simulator with a driving simulator, implementing higher speed ranges; Blanch et al. 2018; Lucas-Alba et al., 2020). Importantly, learning with a standard PC keyboard (DI course) quickly extrapolated to a driving simulator and essential learning transfer was achieved (Mayer, 2014; 2017). However, some other aspects will require further attention. Although the sample was, on average, 7 years older than in previous studies, a sample with even older and more experienced drivers should also be examined. In addition, the measures of emotions (Blanch et al., 2018) and eye-tracking (Lucas-Alba et al., 2020), not included in the present study, can shed light on the perceptual and cognitive-emotional processes during pre- and post-test with a standard driving simulator, but also during the actual learning phases of the DI course. It is also a pending improvement to incorporate more complex scenarios into the DI course, including overtaking, lane changes or exits and entries (see Levy et al., 2018) from the driver's perspective. Finally, analyzing the slight decrease for average speed and possibly improving the second tutorial also seems like an important future goal.

5. Conclusions

For many decades, CF and congestion models have assumed a basic invariance in dense traffic: the default for drivers is DD. This assumption underpins theoretical and empirical developments (see Toledo, 2007; Saifuzzaman and Zheng, 2014, for reviews) aimed at ameliorating the undesired yet pervasive consequences of traffic congestion: crashes, loss of life, poor health, noise, pollution, time and economic losses. It is important to note that many theoretical attempts that aim to improve our understanding of congestion and establish solutions, make use of large and complex databases, made of records of drivers who drove according to this default DD. Many statistical forecasts take full advantage of these databases. We should also note that statistical models elaborate predictions based on complex sets of previous data, but not on the current and exact knowledge of the variations of the ongoing physical system itself. The departure point of statistical models is past events, but the past has been shaped according to a DD traffic invariance that is untenable.

Previous studies (Blanch et al., 2018; Lucas-Alba et al., 2020) have shown that DD is but half of the coin. Drivers may also drive DI by following a simple set of instructions. Assuming the fundamental oscillatory nature of dense traffic (Ni, 2016; Sugiyama et al., 2008; Tadaki et al., 2013; Wille and Debus, 2005; Wille, 2011), but also that drivers can be proactive, changing their operative mode from automatic to controlled, if desired (Charlton and Starkey, 2011). DI reshapes traffic flow, adopting a fundamental equation of traffic for this type of CF engineering we have termed *WaveDriving* (Lucas-Alba et al., 2020, p. 421):

$$W_n = W_1 + \Sigma_d W_i \tag{3}$$

that may be defined as "The motion wave of the last vehicle W_n is the wave of the movement of the first vehicle W_1 plus the management of the space made by each of the following drivers $\Sigma_d W_i$.". Note that it is not a fundamental statistical equation, but an exact one, without loss of variables when taking average values. Shifting from DD to DI must form part of the equation modelling CF in spite of former traffic invariances, models, databases and statistical predictions.

In the present work, a group of normal drivers took to learn and implement DI CF strategy approximately 25 min. According to a recent Canadian study, on average, the mean daily time urban Canadians expend on moderate to heavy traffic ranged from 28.1 to 45.2 min (Matz et al., 2018). Going back to the classical triple E of the road traffic system - Enforcement, Engineering and Education (Evans, 1990; 2004), this time we just need to confirm (with the proper technology) that Education has lasting effects to unravel the phantom of traffic jams (Gazis and Herman, 1992) promoting changes that favour smoother and healthier traffic flows.

CRediT authorship contribution statement

Einat Tenenboim: Methodology, Formal analysis, Data curation. **Antonio Lucas-Alba:** Conceptualization, Methodology, Formal analysis, Writing – review & editing. **Óscar M. Melchor:** Conceptualization, Software, Writing – original draft, Visualization. **Tomer Toledo:** Writing – review & editing, Supervision. **Shlomo Bekhor:** Methodology, Investigation, Funding acquisition, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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