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What is This?
The effect of a lane change on a car-following manoeuvre: anticipation and relaxation behaviour

Ali Ghaffari1, Alireza Khodayari2, Niloofar Hosseinkhani1 and Saeed Salehinia2

Abstract
Car-following and lane-changing manoeuvres are the most common driving behaviour on urban roads and highways. Although these two manoeuvres have been studied extensively, the effect of a lane change on a car-following manoeuvre remains elusive. Analysing these effects leads to integration of the car-following and the lane-changing manoeuvre which has been relatively neglected. A lane-changing manoeuvre causes the immediately following driver to deviate from common car-following models to accommodate the lane changer ahead; this is called anticipation and relaxation behaviour. These behaviours are transient states which occur between two car-following behaviours owing to the lane-changing manoeuvre. In this paper, a novel adaptive neurofuzzy model is proposed for simulating the behaviour of the follower vehicle during anticipation and relaxation behaviour. Comparison between the simulation results and the field data shows that errors in the proposed model are significantly smaller and the model can describe anticipation and relaxation behaviour properly. The anticipation and relaxation model can improve current car-following model applications to enhance the safety of vehicles such as driving assistant and collision avoidance systems.

Keywords
Anticipation and relaxation behaviour, car-following manoeuvre, lane-changing manoeuvre, adaptive neurofuzzy inference system

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Introduction
In recent years, microscopic traffic simulation models have received increasing attention owing to their applications in the areas of simulation-based dynamic traffic assignment. Car-following behaviour and lane-changing behaviour are the two most common applications of microscopic modelling. The car-following models aim to describe the longitudinal action of the follower vehicle (FV) when the driver tries to maintain a safe distance from the leading vehicle. Although single-lane car-following models have been successfully applied to describe traffic dynamics, a realistic description of a traffic stream is possible within a multi-lane modelling framework. Hence, lane-changing models have received considerable attention and many studies have been done in this field (see, for example, the papers by Laval and Daganzo4 and Ghaffari et al.5). A lane-changing manoeuvre consists of different levels of driving. On the strategic level, the driver knows about his or her route in a network, which influences the lane choice. In the tactical stage, a lane change is initiated by the accelerating or decelerating of the driver or the cooperation of drivers in the target lane. Finally, the driver determines whether an immediate lane change is both safe and desirable in the operational stage. This choice is typically modelled by gap acceptance models in which drivers compare the available gaps with the smallest acceptable gap or the critical gap. The critical gap generally depends on the relative speed of the lane changer (LC) with respect to

1 Mechanical Engineering Department, K.N. Toosi University of Technology, Tehran, Iran
2 Pardis Branch, Islamic Azad University, Tehran, Iran

Corresponding author:
Alireza Khodayari, Pardis Branch, Islamic Azad University, Tehran, Iran. Email: arkhodayari@dena.kntu.ac.ir
the lead vehicle and the lag vehicle in the adjacent lane. A principal drawback of common lane-changing models is that they do not address relaxation behaviour. This phenomenon occurs when the LC accepts a short spacing upon insertion but relaxes to a more appropriate spacing soon afterwards. To eliminate this drawback, some lane-changing models based on the relaxation behaviour of the LC have been developed (see, for example, the papers by Laval and Leclercq, Leclercq et al. and Duret et al.). As shown in Figure 1, relaxation behaviour occurs for the FV when the LC enters the target lane and becomes the new leader of the FV. Upon the entrance of the LC, the FV suddenly has a smaller spacing and it may take several seconds for the driver of the FV to adjust to his or her desired spacing for the given speed. During this accommodation time, the observed behaviour of the FV deviates from common car-following models and should be investigated separately.

In addition, before a lane-changing manoeuvre, the LC informs the FV about his or her intention in changing lanes by either signalling or beginning to enter the target lane without signalling. Hence, the FV responds to the LC by decelerating to open a gap. This behaviour, which occurs before a lane-changing manoeuvre, is called anticipation. Overall, anticipation and relaxation behaviour for an FV are transient states between two car-following manoeuvres which occur because of the lane change of the new leader, i.e. the LC. Despite their great importance, anticipation and relaxation behaviour have not been fully studied yet.

This paper aims to provide a more detailed understanding of anticipation behaviour and relaxation for an FV. Towards this end, an intelligent model based on real traffic data is designed. The rest of this paper is organized as follows. The second section summarizes the research literature on anticipation and relaxation behaviour. The design of a model for these behaviours based on the adaptive neurofuzzy inference system (ANFIS) is presented in the third section. The fourth section provides a discussion of the findings. Finally, conclusions are presented in the fifth section.

**Related studies on anticipation and relaxation behaviour**

Smith first reported that vehicles involved in a lane change manoeuvre accept short spacing during the first 20 s or 30 s, gradually attaining a more desirable spacing. Other reports corroborated the relaxation phenomenon with the average time of 15 s (see, for example, the papers by Leclercq et al., Duret et al. and Ma and Ahn). Laval and Leclercq proposed a microscopic framework (hereafter called the Laval–Leclercq (LL) model) based on the extension of the simplified Newell car-following theory which analyses the relaxation behaviour of the LC by using macroscopic theory of the lane-changing manoeuvre.

Afterwards, Leclercq et al. took a microscopic approach to corroborate the results of the LL model employing empirical data. Wang and Coifman used microscopic vehicle trajectory data to examine the impacts of a lane-changing manoeuvre on the spacing–speed relation and to investigate the linearity of this curve. According to this research, a lane-changing manoeuvre not only perturbs the spacing–speed relation of vehicles immediately following the manoeuvre but also affects the spacing–speed relation of the vehicle making the manoeuvre. Xuan and Coifman also employed an instrumented probe vehicle to provide validation of the findings reported by Wang and Coifman. Chevallier and Leclercq introduced a relaxation procedure within car-following rules in which a new insertion decision algorithm is proposed.

Since the parameters of the LL model were not easy to calibrate, Duret et al. reformulated the LL model by using the passing rate. This variable is the rate at which flow passes through the kinematic wave. The passing rate is continuous in time and space and can be easily measured from the trajectory data. This model was analysed for both the LC and the immediate follower after a lane-changing manoeuvre. Calibration results based on the vehicle trajectories indicated that the revised relaxation model is acceptably consistent with real traffic data. Subsequently, Zuduo et al. introduced anticipation behaviour which occurs before a...
lane-changing manoeuvre. During this period, the FV tries to accommodate the LC ahead. Then, the passing rate was used to study both anticipation and relaxation behaviour for the immediate follower in the target lane. This report concluded that the Duret et al. model of relaxation behaviour can be extended to represent both anticipation and relaxation behaviour with acceptable accuracy.

In general, all the proposed models can be classified into two distinct groups, i.e. equation-based models and input–output-based models. In equation-based models, the driving behaviour is expressed by a set of mathematical equations. These equations consist of different variables which describe the relationship between the states of the model. Moreover, there are some parameters which are chosen as the average values of the experimental data. Since these parameters highly depend on time, the resulting model is unique for each data set. In other words, equation-based models are not reliable for all case studies. In input–output-based models, experimental or real data are applied to form a model without simplifying the state. Therefore, a generic parameterized model is fitted to real measured values. For this reason, input–output-based models have great potential in describing non-linear and complex systems.2 According to the literature review, it is noteworthy that most of the past research studies focus on equation-based models, generating a wide range of scaling constants which in turn limit the applications of equation-based models. Unlike previous studies, where anticipation and relaxation behaviour are modelled on the basis of mathematical equations, in this paper an input–output-based model for describing the behaviour of the FV during anticipation and relaxation behaviour is proposed. This model can replicate the behaviours of real drivers without simplifying the real state and is modelled on the basis of real traffic data.

**Anticipation and relaxation model design**

*An innovative approach for determination of anticipation and relaxation behaviour*

The complexity and latent nature of anticipation and relaxation behaviour pose difficulties in analysing these behaviours. To design a comprehensive input–output model of anticipation and relaxation, these behaviours should be investigated thoroughly. In this section, a new approach for specifying the start point of anticipation and the end point of relaxation is proposed.

Zuduo et al.10 used the Newell12 simplified car-following theory to specify the start point of anticipation and the end point of relaxation. Based on the Newell theory, in congested traffic on a homogeneous highway, the time–space trajectory of the FV is similar to that of the preceding trajectory vehicle, except for shifts in time and space. Suppose that vehicle $i + 1$ is following vehicle $i$ in congested traffic on a homogeneous highway, as shown in Figure 2(a). First, vehicle $i$ travels at speed $v$ and then accelerates to $v'$. According to the Newell theory, the FV also travels at $v$ until the spacing between this vehicle and the leader becomes sufficiently large to accelerate10 to $v'$, which causes a time shift $\tau_{i+1}$ and a space shift $d_{i+1}$.

Zuduo et al. specified the start point of anticipation by intersecting the theoretical trajectory of the FV from the Newell theory with its actual trajectory before changing lanes. In the same way, the end point of relaxation behaviour is obtained by intersection of the theoretical and actual trajectories of the FV after the lane-changing manoeuvre. This specification is based on the hypothesis that the spacing–speed relation for a given vehicle is linear during a car-following manoeuvre, as shown in Figure 2(b), but that the anticipation and relaxation phenomena cause the FV to deviate from the theoretical trajectory of the Newell model. In this figure, $\mu_i$ is the slope of the linear curve and $\hat{V}_i$ is the speed at which the FV ceases car following. To
evaluate this hypothesis, the spacing–speed relations for two test vehicles of real data are depicted in Figure 3. According to this figure, the spacing–speed relation during a car-following manoeuvre is not exactly linear. Therefore, an innovative method for determination of the start point of anticipation behaviour and the end point of relaxation behaviour seems necessary, and this is proposed hereafter.

Generally, because of the latent nature of human driving decisions, determination of the exact time at which anticipation behaviour starts or relaxation behaviour ends is very complicated. In this paper, a novel idea for determination of the start point of anticipation and the end point of relaxation is proposed by considering the behaviours of real drivers during these phenomena.

For safe and successful anticipation and relaxation behaviours, some situations should occur which are obtained by analysing real traffic data. Before a lane-changing manoeuvre, the LC examines the lead gap and the lag gap in the target lane, as shown in Figure 4, to determine whether these gaps are desired or not. If both the lead gap and the lag gap are acceptable, the LC executes a lane change instantly. The procedure for evaluating the gaps in the adjacent lane is studied in gap acceptance models. Usually gap acceptance models propose a critical gap which is the minimum required gap for changing lanes (see, for example, the papers by Toledo et al.15 and Zhang and Kovvali16).

Zhang and Kovvali16 proposed a gap acceptance model for the Next Generation SIMulation (NGSIM) data set. This research classified lane changes as either a mandatory lane change (MLC) or a discretionary lane change (DLC). An MLC happens when a driver has an obligation to leave the current lane, for instance to use an off-ramp or to follow lane use regulations, while a DLC is conducted to improve driving conditions even though a lane change is not required.16 Zhang and Kovvali proposed a mathematical relation for the gap acceptance behaviours of an MLC and a DLC for different vehicle types. The critical gap (in metres) for automobiles in a DLC and the critical gap (in metres) for automobiles in an MLC can be simplified to the equations

\[
\text{Gap}_{\text{DLC}} = 0.3048 \exp \left(3.921 + 0.0626V_{\text{LC}} - 0.0164 R_{\text{Acc leading}} \right) \tag{1}
\]

\[
\text{Gap}_{\text{MLC}} = 0.3048 \exp \left(3.6760 + 0.085V_{\text{LC}} \right) \tag{2}
\]

respectively. In these equations, \( V_{\text{LC}} \) is the speed (m/s) of the LC and \( R_{\text{Acc leading}} \) is the relative acceleration (m/s²) between the leading vehicle and the FV. Based on the gap acceptance model proposed by Zhang and Kovvali, the LC compares this gap with the available gap, which is the summation of the lead gap, the lag gap and the length of the LC, to decide whether to perform the lane change or not. If the available gap is smaller than the critical gap, the FV decelerates to enlarge this

![Figure 3. Spacing–speed relation during a car-following manoeuvre: (a) first test FV; (b) second test FV.](image1)

![Figure 4. Lead gap and lag gap before a lane-changing manoeuvre.](image2)
gap or the LC continues to find another appropriate gap. Otherwise, if this gap is much larger than the accepted gap, the lane-changing manoeuvre does not have any effect on the FV’s behaviour. A comparative study of real traffic data for this behaviour leads to the assumption that the lag gap between the LC and the FV should not exceed 1.5 times the critical gap obtained by Zhang and Kovvali. This criterion guarantees the impact of a lane-changing manoeuvre on the FV’s behaviour caused by the anticipation phenomenon.

In addition, the LC tries to inform the FV about the intention to change lanes. To achieve this aim, the LC travels continuously towards the target lane and the lateral velocity for each time step is non-zero. When these situations occur, the time of maximum acceleration of the FV before conducting a lane change is denoted as the start of anticipation behaviour. That is because, after this time, the FV decelerates to extend the lead gap, i.e. the FV does not accelerate to provide sufficient spacing for the LC to conduct a lane change.

The end point of the relaxation behaviour is determined by using the Pipes\(^1^)\) law which indicates the standard safety distance \(S\) (m) between two vehicles as

\[
S = L \left(1 + \frac{V_{FV}}{4.47}\right) \tag{3}
\]

where \(L\) is the length (m) of the FV and \(V_{FV}\) is the velocity (m/s) of the FV. When the LC enters the target lane, the spacing between the LC and the FV is quite small. However, during the relaxation behaviour, this spacing changes until both vehicles reach their preferred spacings. This desired spacing highly depends on the age of the drivers, the degree of risk taking and the traffic conditions. Comparison of the Pipes law with real traffic data leads to three different situations.

1. When the spacing between the LC and the FV intersects with the Pipes law, this time is considered as the end point of the relaxation behaviour because the FV reaches the safety distance from the leading vehicle. Thus, the relaxation behaviour ends.
2. Aggressive drivers usually tend to require a smaller spacing than the standard safety distance. For these drivers, the time at which the behaviour of the FV has the least distance to the Pipes law is chosen for the end point of the relaxation behaviour.
3. For conservative drivers, when a lane-changing manoeuvre is completed (i.e. when lateral motion of the LC for each step time is less than 1 cm), if the spacing is 1.5 times less than the Pipes value, this moment is considered as the end point. Otherwise, because of the large spacing, the FV does not experience relaxation behaviour.

Determination of the start point of anticipation and the end point of relaxation for a test vehicle, based on the above-mentioned criteria, is shown in Figure 5. By repeating this procedure for all the vehicles in the data set, anticipation and relaxation behaviour can be excluded from other types of driving behaviour in real traffic data.

### Design of the ANFIS model for the anticipation and relaxation behaviours

These days, application of an intelligent algorithm is a common approach because of the highly non-linear nature of driving behaviour.\(^2\) ANFIS is an effective intelligent algorithm method for dealing with structural and uncertainties in driving. It can import the qualitative aspects of human knowledge and reasoning process by data sets without employing precise quantitative analysis.\(^18\) The combination of human expert knowledge with learning methods of neural networks enables ANFIS models to describe non-linear systems efficiently.

ANFIS is a multi-layer feedforward network where each node performs a particular node function on incoming signals. It is characterized by a set of parameters pertaining to that node. To reflect different adaptive capabilities, both square node and circle node symbols are used. A square node (adaptive node) has parameters, while a circle node (fixed node) has none. The parameter set of ANFIS is the union of the parameter sets associated with each adaptive node. To achieve a desired input–output mapping, these parameters are updated according to training data and a recursive least-squares-based learning procedure.\(^19\) Here, ANFIS is used to model the anticipation and relaxation behaviours, which are discussed in this section.

The ANFIS modelling procedure is initiated by obtaining a data set including pairs of input–output data which represent the main characteristics of the anticipation and relaxation behaviours. For designing the input–output model, the behaviours of real drivers are investigated thoroughly to derive the main features of their behaviours. The ideal inputs for the ANFIS model are attained by considering the real behaviours of drivers and a trial-and-error procedure. Four inputs of the distance between the LC and the FV, the relative velocities of these two vehicles, and the velocity and acceleration of FV in the previous time step are chosen for this model. The acceleration of the FV is the output of this model, as shown in Figure 6.

The distance input is calculated as the square root of the summation of the lateral spacing and the longitudinal spacing between the LC and the FV. When the anticipation state begins, the lateral spacing is mostly larger than the longitudinal spacing and dominates this input. As time passes, the longitudinal spacing becomes larger than the lateral spacing and the effect of the lateral spacing decreases.

As stated before, vehicles behave differently during an MLC manoeuvre and a DLC manoeuvre. To design a more homogeneous and accurate model, an anticipation and relaxation data set is divided into two distinct groups of MLC behaviour and DLC behaviour. A hybrid algorithm is applied to train these models, and
three triangular-shaped membership functions are used for each fuzzy set. In this paper, 75% of data are randomly chosen as training data, and the remaining data are set aside for model validation.

Design of the ANFIS model for the anticipation and relaxation behaviours based on elapsed time

In the previous section, the start time of anticipation and the end time of relaxation are determined on the basis of the behaviour of the FV. Then, an input–output model is designed to replicate the behaviour of the FV during anticipation and relaxation. The accuracy of the previous model can be improved by considering human factors. This parameter, which is the overall duration of the anticipation and relaxation behaviours, is called the elapsed time. The elapsed time indicates the degree of cautiousness and environmental conditions for drivers. The longer the elapsed time is, the more cautious the drivers are, i.e. the vehicles respond earlier to the entering vehicle and gradually relax to more spacing.

Figure 5. Determination of the start point of the anticipation behaviour and the end point of the relaxation behaviours (a) trajectories of the involved vehicles; (b) the Pipes law and the Zhang–Kovvali criterion in comparison with the longitudinal distance of the FV; (c) acceleration of the FV.

Figure 6. Structure of the ANFIS model for anticipation and relaxation behaviours.
FV: follower vehicle; ANFIS: adaptive neurofuzzy inference system.
To investigate the effects of this parameter on the anticipation and relaxation behaviours, a new input–output model is trained in which the elapsed time is added to the aforementioned inputs. Figure 7 shows the inputs and the output of the ANFIS model for this new model. Like the previous procedure, data are divided into MLC groups and DLC groups, and 75% of the total data are used for training.

Discussion and results
In the previous sections, an intelligent model for anticipation and relaxation behaviours is designed. For training this model, a data set of anticipation and relaxation behaviours is necessary. Thus, a real data set from the US Federal Highway Administrations Next Generation SIMulation (NGSIM) data set is applied.

However, this data set seem to be unfiltered and have some noise artefacts; thus, they were filtered as earlier studies (see, for example, the papers by Ghaffari et al. and Thiemann et al.). A moving-average filter is designed and applied to unfiltered data before any further data analysis. Comparison of the filtered data and the unfiltered data for the acceleration of a vehicle is demonstrated in Figure 9.

To obtain a homogeneous model, all trucks and motorcycles are excluded from the data set. In addition, multiple successive lane changes are ignored because it is possible that the observed behaviour for one lane change is unknowingly influenced by another lane change.

According to the above-mentioned criteria explained in the second section, the start point of the anticipation behaviour and the end point of the relaxation behaviour for each vehicle in the data set are specified, and the excluded data are used to train the ANFIS modelling. The DLC group contains 62.5% of the total data and the rest are for the MLC group. For the NGSIM data set, the elapsed time lies between 3.9 s and 16 s with a median of 12.25 s.
To evaluate the competence of the ANFIS models, the validation data set is used to compare the result of the models with real traffic data. Figure 10(a) shows the performance of both ANFIS models for a test vehicle with respect to the acceleration of a real driver during the anticipation and relaxation behaviours for a DLC. Figure 10(b) depicts the errors of these models regarding the behaviour of a real driver. As shown in this figure, the trajectories of the real driver and the ANFIS model are nearly the same. Furthermore, insertion of the elapsed time considerably modifies the performance of the ANFIS model and results in a better model which mimics the behaviour of the real driver more accurately.

Figure 11(a) shows the performance of the ANFIS models during anticipation and relaxation behaviour for an MLC and the error between the two proposed models is shown in Figure 11(b). According to these figures, adding elapsed time as an input improves the accuracy of the ANFIS model in replicating the behaviour of a real driver and reducing the errors.

To examine the performance of the DLC model and the MLC model, various criteria are used to calculate the errors.\(^2\) The mean absolute percentage error (MAPE) according to

\[
\text{MAPE} = \frac{1}{N} \sum_{i=1}^{N} \frac{|x_i - \hat{x}_i|}{x_i}
\]  

shows the mean absolute error that can be considered as a criterion for model risk when using it in real-world conditions. The r.m.s. error (RMSE) according to

\[
\text{RMSE} = \sqrt{ \frac{1}{N} \sum_{i=1}^{N} (x_i - \hat{x}_i)^2 }
\]

is a criterion for comparing the error dimensions in various models. The correlation coefficient \(R^2\) according to

\[
R^2 = \frac{\sum_{i=1}^{N} (\hat{x}_i - \bar{x})(x_i - \bar{x})^2}{\sum_{i=1}^{N} (\hat{x}_i - \bar{x})^2 \sum_{i=1}^{N} (x_i - \bar{x})^2}
\]

is another criterion that provides a measure of how well the real data are replicated by the model. In these

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Table 1. Results of error for anticipation and relaxation models.

<table>
<thead>
<tr>
<th>Test vehicle</th>
<th>MAPE</th>
<th>RMSE</th>
<th>(R^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Without elapsed time</td>
<td>With elapsed time</td>
<td>Without elapsed time</td>
</tr>
<tr>
<td>DLC model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test vehicle 1</td>
<td>0.4508</td>
<td>0.3513</td>
<td>0.1324</td>
</tr>
<tr>
<td>Test vehicle 2</td>
<td>0.5169</td>
<td>0.2290</td>
<td>0.1928</td>
</tr>
<tr>
<td>Test vehicle 3</td>
<td>0.5585</td>
<td>0.3245</td>
<td>0.1786</td>
</tr>
<tr>
<td>MLC model</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Test vehicle 1</td>
<td>0.4603</td>
<td>0.0925</td>
<td>0.1543</td>
</tr>
<tr>
<td>Test vehicle 2</td>
<td>1.1547</td>
<td>0.2280</td>
<td>0.1775</td>
</tr>
<tr>
<td>Test vehicle 3</td>
<td>0.4032</td>
<td>0.2139</td>
<td>0.1182</td>
</tr>
</tbody>
</table>

MAPE: mean absolute percentage error; RMSE: r.m.s. error; DLC: discretionary lane change; MLC: mandatory lane change.
equations, $x_i$ is the real value of the variable (observed data), $\hat{x}_i$ is the value of the variable modelled by the anticipation and relaxation model, $\tilde{x}$ is the mean value of the variable and $N$ is the number of test observations.

Errors in modelling, taking into account the MAPE, the RMSE and $R^2$ for the MLC model and the DLC model, are summarized in Table 1. For each model, the errors of three test vehicles are shown. According to this table, the MAPE and the RMSE decrease for the ANFIS model with an elapsed time and $R^2$ approaches one. Hence, the insertion of an elapsed time as an input modifies the behaviour of the anticipation and relaxation model.

Conclusion

Anticipation and relaxation are two transient states which occur before and after the lane-changing manoeuvre. Because of the complexity and hidden nature of these driving behaviours, anticipation and relaxation have been relatively neglected. This paper aims to provide a more detailed understanding of anticipation and relaxation behaviours. Towards this end, unlike previous studies which mostly focus on equation-based models, in this paper a novel ANFIS model based on real traffic data is proposed. This model can be applied as a modified model to describe car-following behaviour considering the effects of a lane-changing manoeuvre. The anticipation and relaxation model is developed on the basis of a novel idea for determination of the start point and the end point of these behaviours. The proposed notion is used to selecting appropriate inputs and an output of the ANFIS model. Then, two models, with and without considering the duration of the anticipation and relaxation behaviours as an input, is proposed. The elapsed time is the overall duration of the anticipation and relaxation behaviours which takes into account human and environmental factors. Comparison of the simulation results with real traffic data shows the satisfactory performance of the proposed model. Furthermore, insertion of the elapsed time significantly modifies the performance of the ANFIS model and reduces its error. The proposed model can be used in driver assistant devices, safe-distance-keeping observers, collision avoidance systems and other intelligent transportation systems applications.

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Declaration of conflict of interest

The authors declare that there is no conflict of interest.

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