Predicting Individual Discomfort in Autonomous Driving

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Abstract

Given considerable advancements in automated driving systems, the day when autonomous vehicles will be regularly present in our everyday life is impending. It is, therefore, very significant to put emphasis on the effect that giving up autonomy might have on an individual. We take into consideration an experimental data set regarding participants' reported discomfort levels to tackle the following questions: How can we represent a discomfort measurement in a meaningful way? Using this representation, can future discomfort reactions be predicted? We identify key features, identify baseline models, and develop a new approach based on the *k*-nearest neighbor model to considerably improve the prediction of individual user's discomfort measurements. A discussion of limits and potentials concludes the paper.

Keywords: discomfort; autonomous driving; *k*-nearest neighbors; human-machine interaction;

Introduction

The rapid increase in the automation level of vehicles and the development of autonomous cars will soon lead to personal experiences and interactions with this technology in our everyday lives (ERTRAC, 2019). As a consequence, driving becomes a cooperative task between a human and a technical system that perceives, interacts, and decides. Technical challenges of the steering process have progressively been solved within the last years (Guo et al., 2018).

Whenever humans are involved, however, there is more than the technical level that needs to be taken into account for a smooth interaction. Human drivers are not technical systems. The cognitive, emotional, and affectionate state of the human is of high importance when aiming for successful cooperation and enhancing the driver's enjoyment, pleasure and most important – feeling of safety, while they transfer autonomy to the car. If the system has a general understanding of how specific actions affect the user, then it has the opportunity to perform an appropriate action towards achieving a goal while minimizing feelings of discomfort within the user.

Discomfort is hereby understood as any unpleasant experience during (automated) driving and is conceptualized as opposite part of comfort. Comfort is defined as a subjective, pleasant state of relaxation resulting from confidence in safe vehicle operation, which is achieved by the removal or absence of uneasiness and distress (Beggiato, Hartwich, & Krems, 2019). Traditional comfort aspects like noise, vibration, and harshness have been identified as main variables affecting driving comfort. However, in automated driving additional psychological determinants are discussed such as trust in the system, apparent safety or familiarity of driving manoeuvres (Elbanhawi, Simic, & Jazar, 2015).

These new comfort aspects do also differ from being a co-driver of a manually driven vehicle, mainly because 1) a human driver shares the same life-threatening risk in case of an accident (vs. a technical system) and 2) the social interaction with a human driver makes it easier to mention and reduce discomfort by changing the driving style. Even though, a starting point for identifying potentially uncomfortable automated driving scenarios is to categorize situations and parameters that affect comfort as manual driver and co-driver (for an overview see Beggiato et al. (2019)).

One of the most often mentioned uncomfortable situations as co-driver relate to distance keeping, i.e. driving too close behind a vehicle ahead. Thus, this potentially uncomfortable scenario (close approach) was selected and implemented in the driving simulator study from which these data originate (Beggiato, Hartwich, et al., 2020). As a consequence, the presented results are limited to such distance-related driving situations and not e.g. discomfort due to lateral deviations from the expected trajectory, driving too fast in curves, unpredictable behaviour of others etc. However, distance keeping is already an issue in currently available driving assistance system like Adaptive Cruise Control and thus, these assistance systems could also benefit from detecting discomfort due to subjectively perceived short distances.

In this paper, we focus specifically on individual differences in the extent of discomfort, which are important to adapt the behaviour of an autonomous vehicle (AV) to its respective user. So, once discomfort is detected the AV can make a more informed decision on how to react in a certain situation to reduce the user's discomfort.

Previous predictive approaches have focused on the detection of discomfort in a classification manner (Dommel, Pichler, & Beggiato, 2021). However, we are interested in more than solely predicting whether discomfort is present or not. How intense was the experienced discomfort? When did it start? We aim to find an appropriate representation for discomfort such that similar questions are answered, while also providing the basis for a predictive modeling task of an individual's experienced discomfort? This leads to the research questions that are approached in the following:

RQ 1: Given an individual's measurement of discomfort in

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the range 0-100, how can we represent it through meaningful features that can capture individuals?

RQ 2.1: How can a predictive modeling task based on the features in RQ1 be defined and evaluated?

RQ 2.2: Can the predictive performance be pushed beyond the level of performance achieved by static and aggregate models by successfully leveraging the information available in the individual data?

The paper is structured as follows: We will first introduce the relevant data. Afterwards, we introduce a meaningful discomfort measurement feature representation. Based on this we derive our predictive modeling task. We approach this modeling task, by using a user-based recommender method for predicting individual discomfort. Finally, we present and discuss the results of the prediction of discomfort in autonomous driving.

Data

The present data set was collected by Beggiato, Hartwich, et al. (2020). 40 participants took part in the stationary driving simulator experiment. The study was conducted in 2 sessions, separated by two months. The participants were presented with identical driving scenarios for both sessions, where they experienced the simulation of driving in a fully automated car that is approaching a truck on a straight rural road three times and they had no possibilities to influence the ego car's behavior (see Figure 1). The approaching speed was about 102 km/h whilst the speed of the truck was constantly 80 km/h. At a minimum distance of 4 meters the ego car was slowing down to 60-70 km/h and increasing the distance again. Afterwards the next phase begun by accelerating to the original speed again. The overall time for the scenario was about three minutes. Altogether, in both sessions each participant experienced six minutes of autonomous driving including six discomfort inducing events.

Figure 1: Ego perspective of the participants car approaching the truck

During the whole driving session the participants had the task to indicate their perceived level of discomfort with a handset controller. So according to the deflection of the controller lever the amount of felt discomfort could be recorded.

At the beginning of each session the participants were asked to push the discomfort lever for testing and synchronization purposes. Thus, these first 15 seconds, 1000 data points, are excluded from the used data set. Additionally, all measurements beyond second 157, the 10500th data point, are not considered due to demounting noise after the driving session.

Furthermore we excluded two participants as outliers from our final data set, because their single discomfort events could not be distinguished from each other, which leaves 38 available participants. In the following, we refer to the 3 discomfort inducing events from the first session as Event 1–3 and from the second session, Event 4–6.

Discomfort Measurements Representation

Telpaz et al. (2018) performed an on-road wizard-of-oz study in an urban area focusing on exterior features related to other road users. The subjects were asked to indicate their comfort by using a potentiometer dial ranging from one to ten. They found that car and context related features, are a main factor to identify discomfort inducing events. Specifically, they showed that vehicle dynamics, i.e., speed under consideration of external features like velocity or position of other traffic participants are a main factor for classifying comfort and respectively discomfort in autonomous driving.

Following that, we found that the ratio between the ego car speed and distance to the vehicle in front is a good approximation of the aggregate discomfort among all participants as shown in Figure 2.

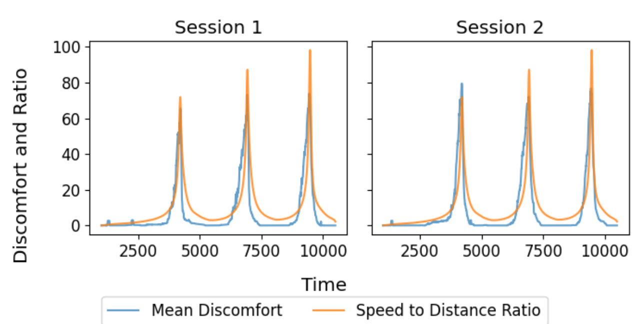

Figure 2: Mean discomfort and the speed-to-distance ratio

However, on an individual level this ratio does not always depict the events in an adequate way as shown in Figure 3 for a selected participant as an example. For example, the ratio underestimates the intensity experienced discomfort in Event 1, and it cannot pinpoint the moment in time when the discomfort started in Event 4.

Within the data set we found a wide variety between the measurements of expressed discomfort by participants (cf. Figure 4). A static model like the speed-to-distance ratio can obviously not represent every individual accurately.

The standard deviation of discomfort for all participants over time is shown in Figure 5 and equals $sd = 12.058$ over all

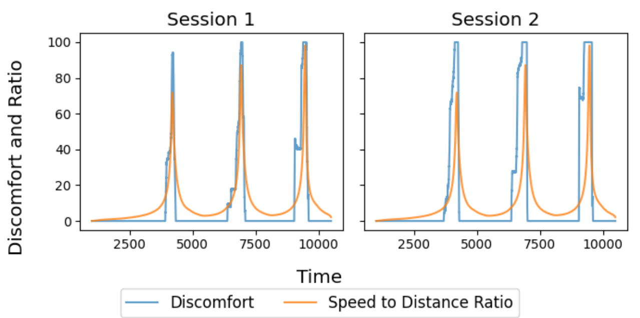

Figure 3: Example difference between speed to distance ratio and a participant's discomfort

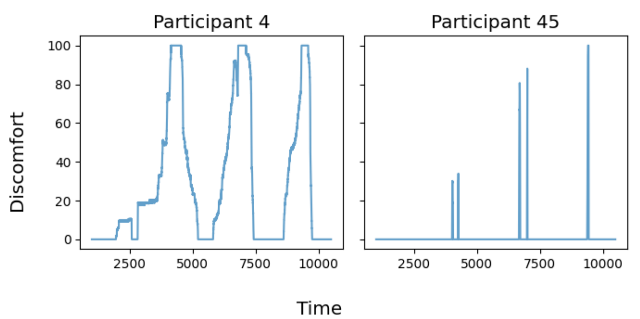

Figure 4: Example for variety in discomfort between two participants for the same driving session

events. This observation can be explained by the fact, that discomfort is a very subjective feeling that differs between individuals (Kuijt-Evers, Groenesteijn, de Looze, & Vink, 2004).

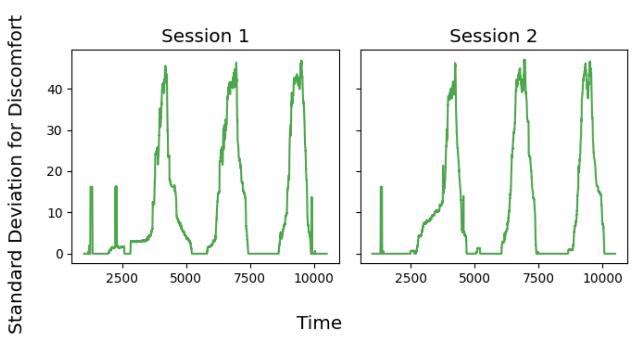

Figure 5: Standard deviation of discomfort over time for all participants

Given this extent of variability among the discomfort curves, a prediction focusing only on the presence or absence of discomfort is not sufficient. Therefore, in contrast to simply binarizing the events, we introduce a representation of discomfort based on meaningful curve features, that we will use for our predictive modeling task, as described in the following section. Given a discomfort curve, such as the one depicted in Figure 4, we describe it using the following five features. Starting with the *area under the curve* (AUC) which describes the amount of discomfort overall. Then, *global maximum* is the maximum intensity of the experienced discomfort. The *onset* tells us when the discomfort feeling started. *Slope* indicates how fast is the maximum discomfort reached. And, finally, *duration* explains how long did the discomfort last. A visual representation of these five features applied on an individual's discomfort curve is shown in Figure 6. With these features, a discomfort curve during a single event can be represented numerically, facilitating the modeling and prediction process, while additionally answering questions that provide more detailed insight into describing the experienced discomfort.

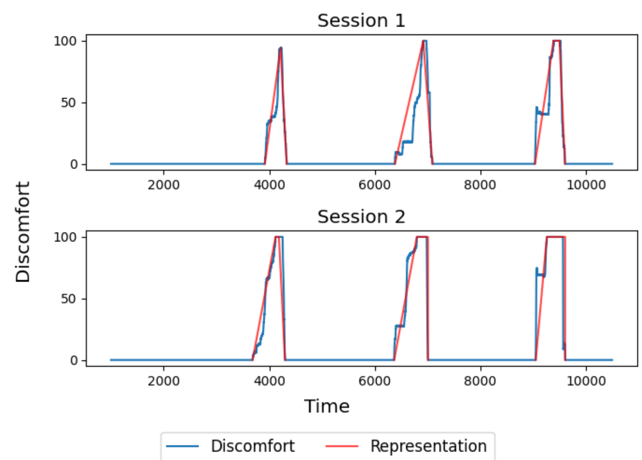

Figure 6: Representation of an example participant's discomfort curve using the five derived features. This representation is used as a ground truth for modeling

Predictive Modeling Task

The main objective of the predictive modeling task is predicting an individual's discomfort curve. We represent a discomfort curve using the 5 features as described previously: the AUC, global maximum, onset, slope, and duration. When a discomfort inducing event occurs, an individual's reaction is obtained, which is then used to predict discomfort curves for future events, through our 5-feature curve representation. In order to evaluate a model's individual predictive performance, we calculate the root mean squared error (RMSE) between the predicted values, and the true values for the 5 features representing the individual's discomfort curve, for each participant. Finally, the mean of all RMSE values is taken to determine the model's overall performance. In the following, we propose a new modeling approach which is based on the k-nearest neighbors algorithm.

k-Nearest Neighbors

k-nearest neighbors (k-nn) is a learning algorithm used for classification and regression that predicts a target value for unseen data based on previously learned data points. For a new data point, a neighborhood consisting of the k near-

Table 1: Predictive performance of all models: Mean RMSE values for the predicted discomfort curve feature values across all participants for each event. Speed-to-Distance Ratio – The 5 feature values of the speed-to-distance ratio curve; Aggregate Discomfort – The mean values of every other participant for a specific event; Individual Discomfort – The mean values of previous experienced events by the individual; *k*-Nearest Neighbor Model – Our approach based on the *k*-nearest neighbors model

	Event						
Approach	1	2	3	4	5	6	Overall
Speed-to-Distance Ratio	0.427	0.408	0.425	0.408	0.409	0.424	0.417
Individual Discomfort	0.374	0.206	0.261	0.204	0.111	0.213	0.228
Aggregate Discomfort	0.134	0.129	0.164	0.124	0.134	0.132	0.136
k-Nearest Neighbor Model	0.134	0.118	0.126	0.108	0.101	0.096	0.114

est (most similar) known data points is created. The similarity is thereby determined based on a set of features describing the instances. The prediction is then calculated by building the average target value of the neighbors. In order to select a model that represents the data well enough, but does not overfit and can perform accurately against unseen data, the value for k is often determined using cross-validation (Kramer, 2013), where the data is split into training and validation sets. In the specific case of smaller data sets, in order to maximize the number of training instances, leave-one-out cross-validation (LOO-CV) is used, where k-nn models with different k values are fit on every data point (*training set*) except the one whose target value is to be predicted (*validation set*). This process is repeated for each data instance. The prediction on the validation set is evaluated and based on the overall lowest validation error, the best performing k is chosen. Given the chosen k, we have a k-nn model that is ready to be applied to new, unseen data (*test set*).

Given an individual's discomfort curves, using k-nn we find the nearest neighbors who reacted in a similar manner to all events until now and then make a prediction for the individual's future reactions. More specifically, the exact features that the k-nn algorithm trains on are the five features describing discomfort curves. As the model relies on similarity measures, the interval ranges of the feature values are of utmost importance, as for adequate results they should be on the same scale (Aggarwal, 2016). Therefore, we normalized the feature values, i.e. their value ranges are in the [0, 1] interval.

In our data scenario, we iterate over the 6 events, trying to predict an individual's 5-feature representation of their discomfort curves for each one of them, using the knowledge about the neighbors with most similar reactions to all already recorded events. E.g., when making a prediction for Event 3, k-nn looks for the individual's nearest neighbors for both events 1 and 2 together.

Naturally, with this approach it is expected that as more events are recorded, the predictions should have a better accuracy, given that the participant's neighborhood becomes more well-defined. One drawback, however, is the lack of information to make a prediction for the very first event, which is common in such neighborhood recommender approaches and is referred to as the cold start problem (Aggarwal, 2016). In order to overcome this, we use the aggregated discomfort curve feature values of *all* other participants, in contrast to a refined neighborhood.

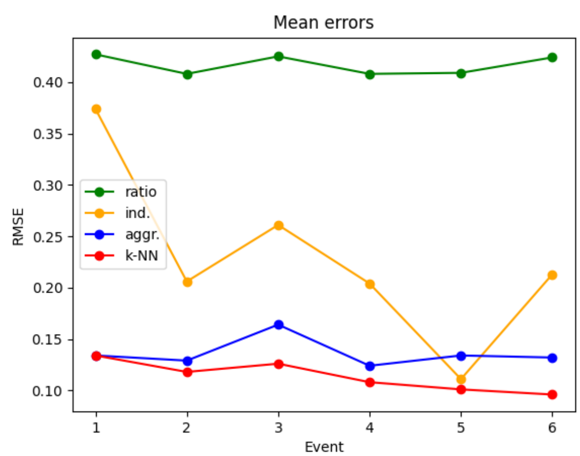

Figure 7: Mean RMSE values of predicted discomfort curve feature values across all participants for each event. ratio - speed-to-distance ratio; ind. - individual; aggr. - aggregate; k-NN - *k*-Nearest Neighbor Model

In order to determine which value for k is best suitable for our scenario, we followed the standard procedure (Dangeti, 2017) to randomly assign the data into a 70% training set and a 30% test set, leading to 26 and 12 participants respectively. Given the small data set size, we performed LOO-CV on the training set and determined the validation errors using the root mean squared error (RMSE) metric. We calculated the average RMSE value between the model's predictions and the individuals' true discomfort curve feature values, for each value of k. Performing LOO-CV on 26 data points means we have 25 participants in the training set, leading to the maximum possible number of neighbors for the validation data point to be 25, which sets the possible values of k in the interval [1, 25]. The best performance was achieved with $k = 11$, based on the minimal validation RMSE value of 0.071. Applying the model on the unseen test set delivered an RMSE of 0.113. Therefore, in our approach we use the 11-nn model. `Python`'s `scikit-learn` library[1] was used for data splitting, RMSE calculations and *k*-nn regression with multiple outputs.

Results

In this section we report our evaluation outcomes, mainly through root mean squared error (RMSE) values.

In a previous section we showed a representation of discomfort measurements using the ratio of the car's velocity and the distance to the vehicle in front. We calculated the RMSE between the area under the curve values for the ratio curve and the true mean discomfort curve (Figure 2), leading to a value of 0.127 – as usual an RMSE of 0 is a perfect fit. In order to confirm that this is not a good representation on an individual basis, we also calculated the RMSE between the ratio curve and each participant's discomfort curve (e.g. Figure 3) which is 0.200. Moreover, we evaluated our proposed 5-feature curve representation in the same manner, for each participant, leading to a much better mean RMSE value of 0.102, proving that this is indeed a more accurate way of representing the individual's discomfort curve.

Following is the performance evaluation of our approach for the predictive modeling task based on RMSE values between the model's predictions and the true individual values for each of the five features representing a participant's discomfort curve. First, we establish a baseline by using three other models. The first baseline model is the five feature representation of the speed-to-distance ratio curve as a predictor. This is a static predictor that cannot adapt to an individual. Following is a model based on an individual's experienced discomfort. For each event, the mean of the previous events' five feature representation values is taken as a predictor. Naturally, given the fact there is no available information for the first event, the prediction is that there is no discomfort. Finally, the last baseline model is based on the aggregate discomfort amongst all other participants. For each event, the means of the five feature representation values of every other participant for the to-be-predicted event is taken as a predictor. Similarly to before, the RMSE values we evaluate are based on scaled feature values in the interval [0, 1]. All RMSE values for each model overall and every event separately are reported in Table 1.

In our approach the overall mean RMSE across all participants and events is 0.114, outperforming the speed-to-distance ratio curve (0.417), the individual model (0.228) and the aggregate model (0.136). Given the nature of our approach, a meaningful point to consider is the evaluation of the predictive performance for each event separately and how they compare to each other. When examining Figure 7 it becomes apparent that once the model starts gathering information about the individuals, it is capable to understand and predict their discomfort reaction much more accurately in the subsequent events, which is noticeably shown through the overall improvement in the RMSE values over the course of the events. Particularly the reduction from a starting RMSE of 0.134 for Event 1 to 0.096 for Event 6. Naturally, such a trend can not be found when analyzing the separate event RMSE values for the speed-to-distance ratio as a predictor, as it is a static model that does not take individuals into account. The individual and aggregate discomfort models do not display such improvements as well.

Comparing our *k*-nn approach to the aggregate discomfort model more closely, we see an improvement overall and per event. The improvement is significant on the individual RMSE values achieved by both models (Wilcoxon $W = 38$, $p = .0000014212$).

In addition, we also analyze the results visually by reconstructing the discomfort curve using the predicted feature values for each participant. An example is shown in Figure 8 for a selected participant, which shows the ability of our approach to reconstruct an individual's discomfort curve using our five feature representation.

Discussion and Conclusion

The quest to predict individual discomfort in autonomous driving lead to two research questions. Firstly, we focused on finding a suitable representation of measurements of human's experienced discomfort in an autonomous vehicle (**RQ 1**). Given measured discomfort over time, a discomfort curve can be represented by using five features: *Area under curve* (AUC), *global maximum*, *onset*, *slope*, and *duration*. With these expressive features, we can not only characterize attributes, such as the discomfort intensity and rapidity, but also generate both – a numerical and geometrical depiction that assists in modeling the discomfort. Most importantly, we showed that with this approach the differences among individuals can be effectively captured. Using this representation, we formulated a predictive modeling task, addressed in our second research question.

Following is **RQ 2.1**: Given information regarding an individual's discomfort reaction to a driving scenario, how well can we predict their discomfort in future events? Having the ability to make an accurate prediction would aid the automated vehicle to tailor its actions to accommodate the individual's preferences and increase their feeling of comfort and safety. We presented our method of predicting an individual's discomfort reaction to 6 events using data from an experimental driver study (Beggiato, Hartwich, et al., 2020). Our model is based on the *k*-nearest neighbor algorithm which takes into consideration the neighborhood of individuals who during previous events reacted most similarly to the individual whose discomfort we are aiming to predict. This approach is capable of adapting to individuals, shown through the improvement of the prediction error over time. This also confirms that the more information about an individual is gathered, a better neighborhood is found. The used data con-

[1] `https://scikit-learn.org/stable/`

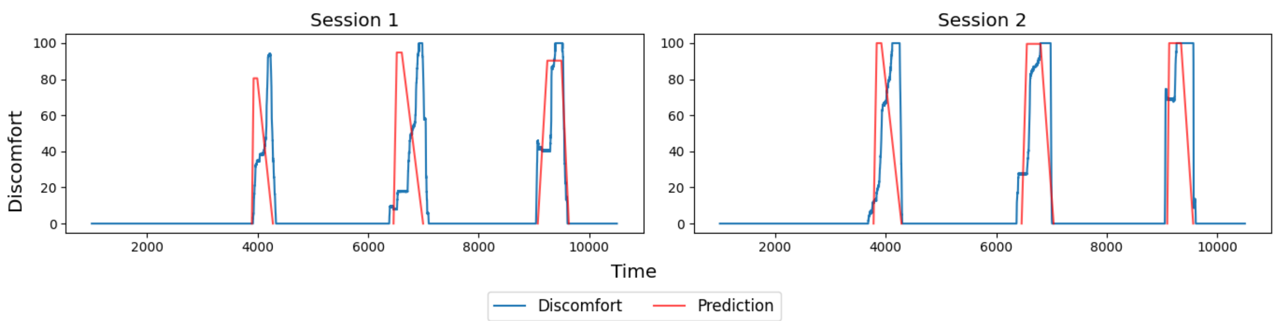

Figure 8: Example of a reconstructed predicted discomfort curve for a selected participant

tained only 38 participants and their discomfort reactions to 6 events. With a smaller number of individuals, there is a bigger chance for some participants to not have neighbors that are similar enough. Technically, they would be "outliers" in the current scenario, but with more data, that would not necessarily be the case. The availability of more participants and events would provide an opportunity to refine an individual's neighborhood and therefore increase the prediction accuracy. Moreover, it would be of interest to research how to handle and adapt to an individual when the neighbors are not doing enough. The detection of such situations could be done through e.g. setting a similarity value threshold.

We tackled the cold start problem by relying on all available participants for the prediction of the first event, which gives a good starting point if there is no individual information is available. However, once the information is available, the model performance improves substantially. In regard to **RQ 2.2**, we were able to demonstrate that our model can leverage the additional information available in the data when considering individuals instead of the aggregate.

The participants in the experiment were constantly exposed to the same discomfort inducing scenario, which naturally rises the question of possible habituation effects. Such effect was not found among the participants (Beggiato, Hartwich, & Krems, 2018, p.3):

> "The main reasons for inviting the participants twice were to: (a) obtain a higher overall number of discomfort situations per person; and (b) assess habituation effects within subjects over short and longer time periods (3 min vs. 2 months). Evaluation of habituation effects resulted in small to almost no effects, both for short- and long-term periods. Thus, all situations were included in the subsequent analyses."

However, this is not something that would be an issue for an approach like *k*-nn. If a habituation effect would have been found among some individuals, they would be present in each other's neighborhoods.

This paper focused on the close vehicle approach scenario, which is just one of several potential discomfort inducing situations. We demonstrated that – even for the same scenarios – a users' experienced discomfort can differ vastly from the discomfort others experience and from the discomfort the same user has experienced in events before. In fact, the speed-to-distance ratio is the worst predictor, then even the individual predicting itself, then the aggregate of all drivers. By employing methods from machine learning it was possible to improve considerably the predictions of an individual's discomfort based on the identification of similar drivers profiles. Even more so, participants could in fact be better predicted by their neighbors than by their own history of previous events. This indicates that the neighborhood indeed captures characteristics of the individual in a meaningful way.

This is only a starting point for the individual discomfort predictive task. Future models using these data could include additional sensor data such as body movements, heart rate, pupil dilation and eye blink frequency (Beggiato, Hartwich, et al., 2020; Dommel et al., 2021) as well as facial expressions (Beggiato, Rauh, & Krems, 2020).

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