Comparing Subjective Similarity of Automated Driving Styles to Objective Distance-Based Similarity

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Comparing subjective similarity of automated driving styles to objective distance-based similarity

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ABSTRACT

Objective: This study explores subjective and objective driving style similarity to identify how similarity can be used to develop driver-compatible vehicle automation..

Background: Similarity in the ways that interaction partners perform tasks can be measured subjectively, through questionnaires, or objectively by characterizing each agent's actions. Although subjective measures have advantages in prediction, objective measures are more useful when operationalizing interventions based on these measures. Showing how objective and subjective similarity are related is therefore prudent for aligning future machine performance with human preferences.

Methods: A driving simulator study was conducted with stop-and-go scenarios. Participants experienced conservative, moderate, and aggressive automated driving styles and rated the similarity between their own driving style and that of the automation. Objective similarity between the manual and automated driving speed profiles was calculated using three distance measures: dynamic time warping, Euclidean distance, and time alignment measure. Linear mixed effects models were used to examine how different com ponents of the stopping profile and the three objective similarity measures predicted subjective similarity.

Results: Objective similarity using Euclidean distance best predicted subjective similarity. However, this was only observed for participants' approach to the intersection and not their departure.

Conclusion: Developing driving styles that drivers perceive to be similar to their own is an important step toward driver-compatible automation. In determining what constitutes similarity, it is important to (a) use measures that reflect the driver's perception of similarity, and (b) understand what elements of the driving style govern subjective similarity.

Keywords: time series, distance measures, automation acceptance, trust, driver behavior

INTRODUCTION

Increasingly automated vehicles promise a safer and more comfortable driving experience. However, their success depends on user acceptance. One path to improve user acceptance is to allow personalization so that the automated vehicle's driving style matches the driver's preferred way of manual driving (Bellem et al., 2018; Hasenjäger & Wersing, 2017; Paschalidis et al., 2020; Sun et al., 2020; Trende et al., 2019). Research exploring if drivers prefer driving automation that emulates their driving style shows mixed results (Basu et al., 2017; Griesche et al., 2016; Lehsing et al., 2019). However, these explorations rely on the driver's subjective assessment of whether the driving style is like their own. While subjective similarity is important for improving vehicle personalization and predicting user acceptance, it relies on the driver's perception and comprehension. Alternatively, objective similarity measured by comparing different driving behavior dimensions (e.g., mean speed or acceleration) could provide a more unbiased view of similarity; however, it may not align with subjective measurements. Such challenges make it difficult for vehicle developers to personalize automated vehicle driving styles.

Misalignments between subjective and objective assessments show that some drivers self-rate their driving as non-aggressive when objective measures indicate otherwise (Sarwar et al., 2017). Changes in perceived aggressiveness rating depend on whether the observation was from a first, second, or third-person perspective (Kerwin & Bushman, 2020). Another study demonstrated that socio-demographics and behavioral characteristics affected perceived aggressiveness (Fountas et al., 2019). Such differences in perception highlight the need to understand subjective similarity and its alignment with objective similarity.

We seek to address these challenges by implementing objective similarity measures and investigating their alignment with subjective similarity. A straightforward objective similarity measure is the geometric distance between driving styles along dimensions such as the driving speed. The distance would then be the difference between two speed profiles at one or multiple points. However, there are many distances to choose from to capture different characteristics of similarity. Also, driving styles consist of multiple dimensions such as speed, acceleration, or headway and the effect of these dimensions on the perception of similarity may vary. For instance, when approaching stop-controlled intersections, a vehicle decelerates and stops, and then accelerates when departing the intersection. When judging if a driving behavior is like their own, drivers may assign either equal or unequal importance to the acceleration versus the deceleration behavior. Thus, when checking the alignment between subjective and objective measurements, it is important to understand the dimensions that influence them. Here, these dimensions are referred to as *driving style components*. Driving behavior (e.g., acceleration vs deceleration at a stop-controlled intersection) can be segmented into different components based on the maneuver being executed. Both the choice of driving style components and distance measures can play a crucial role in evaluating subjective and objective similarity.

Importance of similarity and its measurement methods

Similarity-attraction theory states that people are attracted to each other when they share a likeness along various dimensions (Byrne, 1971). This theory has been extended to human-automation interaction applications such as assistive robotics, intelligent virtual, and voice agents (Reeves & Nass, 1996; Vugt et al., 2008; Ziegler & Lausen, 2004). Automation that is perceived as similar leads people to evaluate the interaction positively and accept it (Bailenson & Yee, 2005; De Visser et al., 2016; Verberne et al., 2015). These potential positive outcomes warrant the exploration of similarity for drivers in highly automated vehicles.

Driving research has previously explored the relationship alignment between subjective and objective measurements. Objective measurements include driving performance and physiological measurements such as brain activity and skin conductance. Subjective measurements are derived from self-reports such as surveys and diaries. While some studies report alignment between the subjective and objective assessments, others do not (Kaye et al., 2018; Sagberg et al., 2015). The present study focuses on the alignment between distance-based objective similarity and subjective similarity.

Objective human-automation similarity measures

Previous studies explore different analytical techniques to measure various similarities in the driving domain. Strayer et al. (2006) used discriminant analysis to identify variables that compare cell phone usage to drunk driving (Strayer et al., 2006). Parmet et al. (2015) used piecewise linear regression to compare the speed homogeneity between novice and experienced drivers across different scenarios (Parmet et al., 2015). Basu et al. (2017) compared driving styles using defensiveness scores by aggregating driving variables. Others have employed machine learning techniques to cluster driving performance features to compare driving styles (K.-T. Chen & Chen, 2019; Z. Chen et al., 2022; Feng et al., 2018). Some studies have also used statistical distances between probability distributions of speed and acceleration to compute similarity and estimate and compare driving style related parameters (Wang et al., 2018; Zhu et al., 2019).

All these studies rely on aggregate measures or distributions of features to estimate similarity. However, such methods may neglect the shape of the time series profiles (J. D. Lee et al., 2021; J. D. Lee & McLaurin, 2022; Parmet et al., 2015; Wang et al., 2018). To overcome this, computing the distance between time series data, such as the variation of speed over time, offers a promising alternative in capturing dynamic behavior. As objective similarity measures, distances can be applied to driving-related time series data. We apply this by computing distances between times series data obtained from manual driving and automated driving that drivers experience. But there are many distance measures to choose from and the choice may influence the distance-based objective similarity estimate. Here, we make the distinction between *lock-step* and *elastic distance measures*. Lock-step measures calculate the distance between the i^{th} point of one series to the i^{th} point of another. Elastic measures do not adhere to the one-to-one point comparison and perform non-linear mappings to align the series. Figure 1 highlights the difference between lock-step and elastic measures when comparing two time series. In the example, the lock-step measure would indicate that the two time series are different but the elastic measure would indicate they are similar.

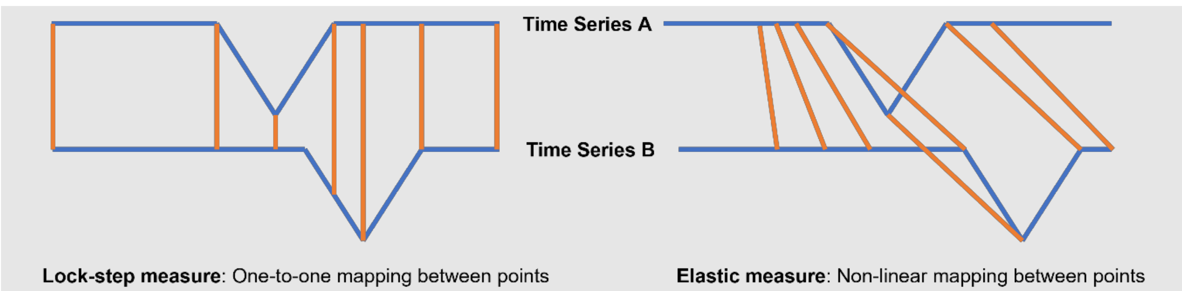

Figure 1. Lock-step vs elastic time series distance measures. (Note: the time series appear shifted in the vertical axis to demonstrate the difference in lock-step and elastic measures)

To demonstrate lock-step and elastic measures, one common lock-step measure, Euclidean distance, and two elastic measures – dynamic time warping (DTW) distance and time alignment measure (TAM) are explored (Folgado et al., 2018; Keogh & Pazzani, 2001). With Euclidean distance, the distance between the i^{th} point of series A and series B is computed and summed. Thus, the Euclidean distance between two series is,

$$d(A,B) = \sqrt{\sum_{i=1}^{n}(A_i - B_i)^2}$$

A more flexible DTW distance computes the Euclidean distance (or any type of lock-step distance) between the i^{th} point in series A and every other point in series B. This is repeated for each point to create an $n \times n$ matrix where n is the total number of points in the time series. Within this matrix, some cells contain the minimum distance. These minimum distance cells connect to form a *warping path*. The sum of the minimum distances along the warping path is the DTW distance (Giorgino, 2009). Figure 2 shows two series, A and B, along with a distance matrix heat map and the warping path overlayed. Here, multiple matrix cells can have the same minimum distance values and thus there can be more than one warping path. DTW function constraints help address warping path selection. Appendix briefly discusses these constraints.

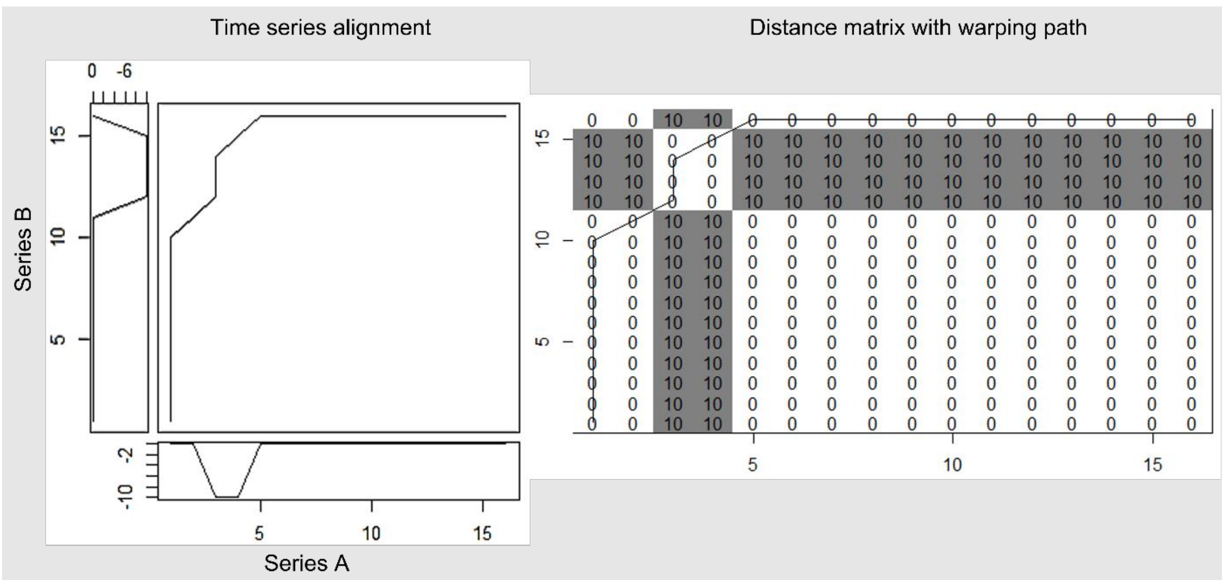

Figure 2. Dynamic time warping path between two time series (left) and the distance matrix with warping path superimposed (right).

In Figure 2, time series A and B are out of phase but have similar shapes. The DTW distance searches for shape similarity by warping the profiles. There may be instances where the degree of profile warping can indicate similarity or dissimilarity between time series. To account for this the time alignment measure (TAM) which accounts for the warping in DTW, is adopted (Folgado et al., 2018). Thus, we implement three distances for estimating similarity between time series: Euclidean, DTW, and TAM distance. Note that, distances computed will vary based on the type of measure selected and reflect different aspects of the time series (see Appendix for a demonstration). For understanding driving styles, the different aspects that the three distances capture (or other distances not presented here) can be used individually or as composite measures depending on the behavior of interest.

Research questions

We demonstrated the differences between lock-step and elastic measures that can affect distance-based objective similarity measurements and the need to understand driving style components that influence subjective similarity. These topics are investigated here in a driving simulator study where manual driving data at stop-controlled intersections was recorded. Participants experienced different automated driving styles while moving through the same intersections and self-reported subjective similarity. With the data, we examine the following questions,

(a) Do objective similarity measures of driving styles obtained using the three distance measures predict self-reported subjective similarity?

We investigate this by extracting the manual driving speed profiles and computing their distance to the automation's speed profile. While the variation of speed over position is also a suitable choice to analyze driving styles, the variation of speed over time can highlight how long the vehicle remains stopped at stop-controlled intersections, which is key to this investigation. All three distances (Euclidean, DTW, TAM) were implemented to obtain objective similarity measures and examined to see if they can predict the self-reported subjective similarity ratings.

(b) Do different components of the intersection negotiation influence subjective similarity?

We investigate this by dividing all the speed profiles during intersection negotiation into their approach and departure components. Distances are then computed using the segmented speed profiles and examined to see if one or both components predict subjective similarity.

METHODS

Participants

Twenty-four people (16 female, 8 male; aged between 25 and 55, M = 29, SD = 5) from Madison, WI participated in the study. While gender-based differences in driving styles can be expected (Taubman-Ben-Ari & Skvirsky, 2016), the experiment was not designed to investigate gender differences and so gender effects were not analyzed. Inclusion criteria required that participants drive at least 2,000 miles per year. Driving experience was verbally confirmed. Optional survey responses reported the number of miles driven in the week before the study with one participant responding “Unsure.” From this data, the yearly mileage was estimated (M = 7686, SD = 9774). Participants were required to possess a valid driver’s license for at least 2 years and be in overall good health. The participation time for each participant was approximately 2 hours and the compensation was US $30/hr. The Education and Social/Behavioral Science Institutional Review Board at the University of Wisconsin–Madison approved this study.

Apparatus

The National Advanced Driving Simulator (NADS) MiniSim™, a fixed-based simulator, was used for this study. The setup included three 43 × 25.4-in. monitors. The center monitor was placed 4.5 ft from the participant; the three monitors produced a 270° field of view. The simulated roadway was a four-lane suburban street. A proportional-integral-derivative (PID) controller modulated the accelerator and brake input based on the driving style parameters and controlled driving automation.

Experimental design

The experiment was a 4 (Intersection Type) × 3 (Automation Style) within-subject design. The presence of a stop-controlled intersection and cross-path traffic dictated the intersection type. Uncontrolled intersections did not require a response and stop-controlled intersections required the vehicle to stop. The cross-traffic passed before the vehicle reached the intersection, ensuring participants would see the traffic, but not interact with it. The automated driving styles were labeled as aggressive, moderate, and conservative. A replicated Latin square design counterbalanced the four intersection types, the intersection sequence, and the driving style order.

Procedure

Upon arrival, participants were informed about the study activities, the types of data collected, and the potential risks and benefits. After obtaining informed consent for participation, participants completed a driving demographic survey. Following this, participants practiced driving in the simulator. Once comfortable with the simulator, participants then drove the vehicle manually twice. Thus, each participant completed two manual drives and each drive had four intersection types. For this analysis, only the second manual drive was used assuming that participants were more comfortable with the simulator environment during this drive. Following the manual drives, participants experienced the three automated driving styles twice with each drive consisting of four types of intersections (see Figure 3b). Note that all the automation styles were blocked so participants experienced each style twice consecutively (see Figure 3a). Wellness questionnaires issued after each manual and automated drive monitored participant wellness. After each automated drive was complete, participants rated their trust in the automation and the driving style similarity. Thus, the trust and similarity questionnaires were completed six times. Figure 3a depicts the experiment timeline. The driving style similarity rating had a single item: “How similar to your own driving was this system?” Ratings were on a 7-point Likert scale ranging from “not at all similar” (-3 rating) to “completely similar” (+3 rating). The trust questionnaires and a final failure drive are not examined here (J. D. Lee et al., 2021).

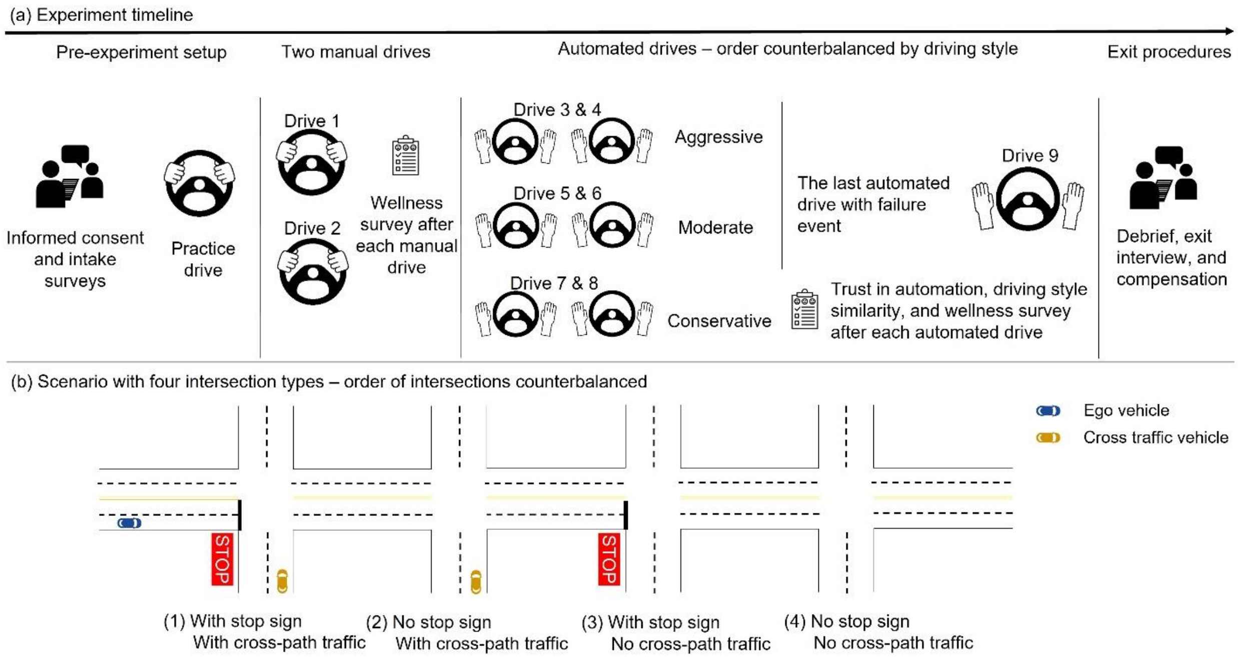

Figure 3. (a) Timeline depicting the different procedures in the experiment. (b) Driving scenario with four types of intersections.

Driving style implementation

Pilot study data from the manual driving scenarios helped develop three longitudinal control algorithms to guide automated driving modes. The aggressive, moderate, and conservative styles were determined using the 15th, 50th, and 85th percentile of drivers' manual driving's mean deceleration, mean acceleration, distance to the stop line when the speed first goes below 1 mph during approaches to stop-controlled intersections and stop duration at stop-controlled intersections. Table 1 shows these variable values for each automation driving style (J. D. Lee et al., 2021). The conservative automation style (15th percentile driving performance) reflects a conservative driver who begins to decelerate earlier than a moderate (50th percentile driving performance) or aggressive driver (85th percentile driving performance) during the approach to the stop-controlled intersection. The differences in mean deceleration values differentiate between the styles, with conservative styles having a lower deceleration compared to the moderate and aggressive styles. Next, the stop duration at the intersection varies with conservative styles stopping longer than the moderate and aggressive styles.

Finally, the aggressive style had higher mean acceleration than the moderate and conservative style when departing the stop-controlled intersection. Note that in the stop-controlled intersections, the stop sign was placed 5 feet ahead of the stop line. All automation styles stopped such that the stop sign was within the participant's field of view. Consequently, the distance to the stop line where the automation stops is exaggerated in a simulator setting and is larger than what can be observed in real world driving. While not representative of real-world driving, this was implemented so that differences between the styles were clear to participants.

Table 1. Variables differentiating the conservative, moderate, and aggressive driving styles in stop-controlled intersection negotiation.

Automation driving style	**Distance to stop line when speed first goes below 1 mph (ft)***	**Mean deceleration (ft/s^2)**	**Mean acceleration (ft/s^2)**	**Duration of the stop (seconds)**
Aggressive (85^{th})	10.5	-2.56	4.28	0.18
Moderate (50^{th})	18.2	-2.33	2.49	1.51
Conservative (15^{th})	25.2	-2.14	2.00	2.05

* Distance to the stop line measured from the front bumper of the vehicle.

Figure 4 shows the conservative, moderate, and aggressive driving styles. The automation has distinct speed profiles for the stop-controlled intersections. One of the stop-controlled intersections experiences cross-path traffic and another does not have cross-path traffic. There is no difference between the automated driving styles at the stop signs based on the cross-path traffic presence. For the remaining two uncontrolled intersections, there is no intersection negotiation. As there were no intersection negotiations at these intersections, the analysis excluded these intersections. Thus, only stop-controlled intersections (intersection 1 and intersection 3 in Figure 3b) are included in this analysis.

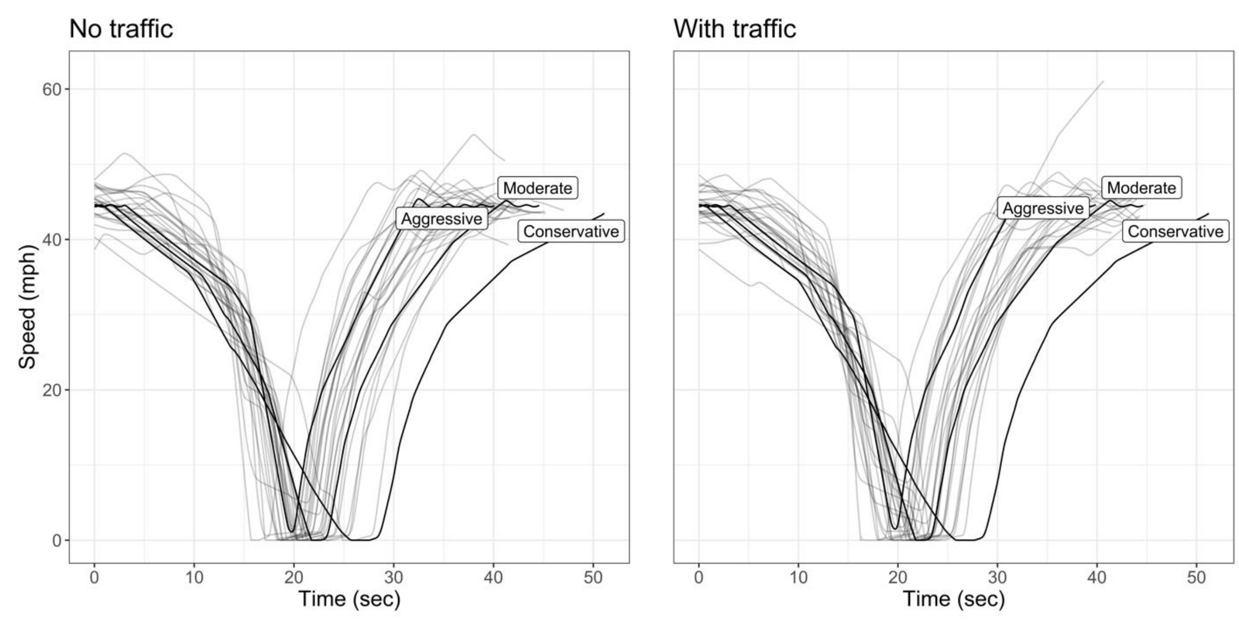

Figure 4. Speed profiles for the three styles of automation at stop-controlled intersections indicated by dark lines. Gray lines indicate the speed profile of each participant.

Segmenting speed profile into approach and departure

To analyze the approach and departure behavior components at the stop-controlled intersection, the speed profiles were divided into two respective segments. Figure 5 shows the speed profile segments for the manual and automated driving styles. Gas pedal values around the stop line indicated when the vehicle departed the intersection and helped to segment the data.

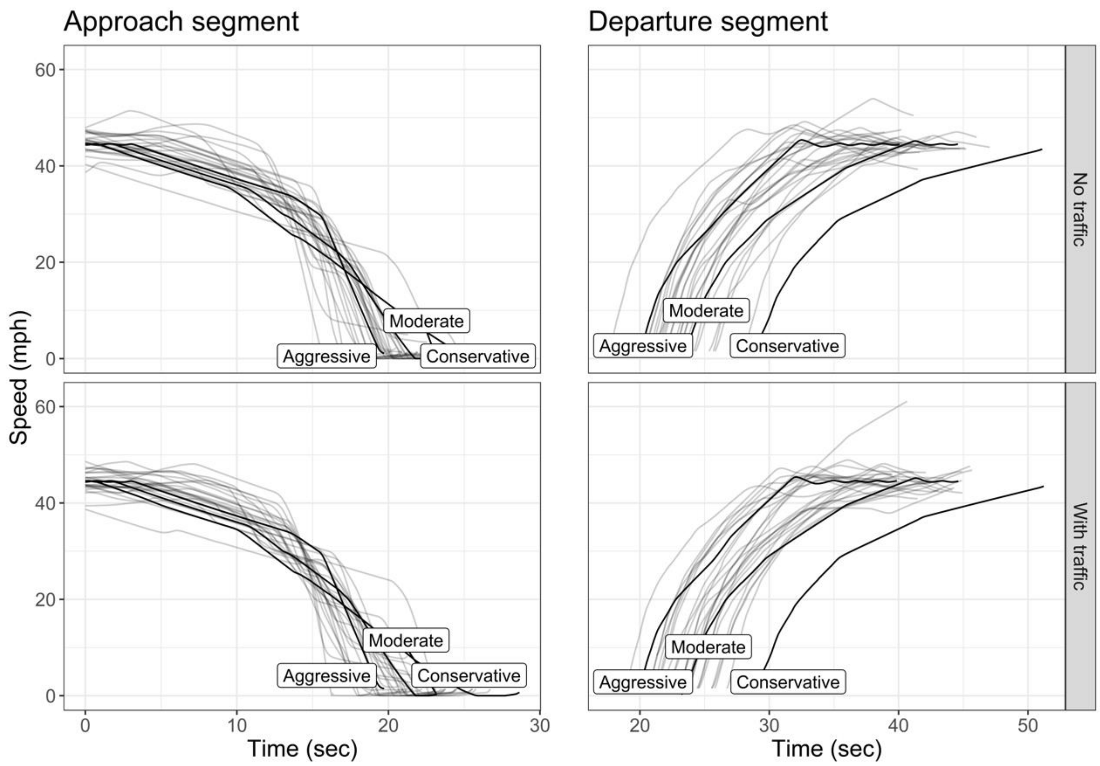

Figure 5. Speed profiles for intersection negotiation divided into approach and departure segments. Dark lines indicate the automated profiles. Grey lines indicate the speed profile of each participant. The order of lines from left to right indicates the aggressive, moderate, and conservative styles respectively.

Data processing and analysis

The distance-based objective similarity was calculated by comparing the manual and automated speed profiles from the two stop-controlled intersections (i.e., one with cross-path traffic and one without). To compute Euclidean distances, the time series being compared must be equal in length. Thus, the time series interpolation enabled Euclidean distance calculation. For the TAM distances, distances are bound between 0 and 3 with 0 indicating no warping cost and 3 indicating maximum warping cost (Folgado et al., 2018). Log transformation ensured normal distribution of the distances. Distances were scaled to 0-1 to support visual comparison.

Before data analysis, application of the interquartile range criterion identified outliers in the subjective similarity rating. This highlighted four observations across two participants as outliers. Upon inspection, we removed one participant that rated all driving styles as dissimilar. The other participant was retained as the similarity rating varied across the automation styles.

The *tidyverse* package in R was used for data wrangling and visualization (Wickham et al., 2019). The Euclidean, DTW, and TAM distance-based objective similarities were estimated using the *TSDist* package in R (Mori et al., 2016). The *stats* and *lme4* packages in R were used for the statistical analyses (Bates et al., 2014).

RESULTS

Subjective similarity ratings

Participants experienced each style twice consecutively (e.g., an aggressive automated drive immediately followed another aggressive automated drive). Thus, each participant rated the subjective similarity ratings of each driving style twice. A two-way ANOVA assessed differences between the similarity rating from the first and second drives within each automation block. Results showed that the main effect of drive order (i.e., first or second automated drive) and automation style was not significant, $F(1, 132) = 0.00$, $p > .999$ and $F(2, 132) = 1.36$, $p = 0.260$, respectively. Also, the interaction between the drive order and the automation style was not significant, $F(2, 132) = 0.19$, $p = 0.827$. As there was no significant difference between the self-reported rating within each automated driving block, the mean of the ratings was used as the subjective similarity score. Figure 6 shows the subjective similarity scores where higher ratings indicate that participants felt the automation style was more like their driving style.

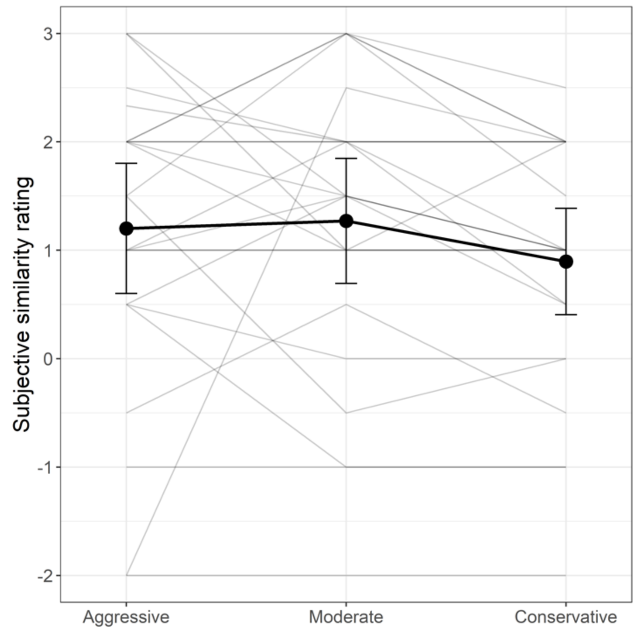

Figure 6. Slope graph of the subjective similarity ratings. Each light gray line represents one participant's rating across each automation style. Solid vertical lines show the mean and the 95th percent confidence intervals.

Subjective similarity predicted by objective similarity at stop-controlled intersections

We first investigate if the objective similarity between driving styles obtained using the three distance measures predicts the self-reported subjective similarities. Subjective similarity ratings vary substantially across participants with some rating some styles more similar than other styles, and some rating all styles as either similar or dissimilar. A linear mixed effect model predicting subjective similarity ratings across automation styles with the participants modeled as a random effect revealed an intra-class coefficient (ICC) of 0.53. This reflects substantial individual differences in how participants perceived the driving styles. To account for this, linear mixed effect models that examine subjective similarity ratings as predicted by the distance-based object similarity measures were implemented with participants modeled as a random effect.

Figure 7 shows a summary of the distances for the stop-controlled intersections as a slope graph. Each line on the graph indicates a participant's distance-based objective similarity across the three automation styles. Lower distances indicate that the participant's driving style is closer to the automation driving style and higher distances indicate that they are more dissimilar. Note that, while all distances indicate more similarity with the moderate driving style, there are differences in which style appears to be more dissimilar.

The relationship between the distance-based similarities (from Figure 7) and the subjective similarities (from Figure 6) was analyzed using two sets of linear mixed-effects models (for intersection with and without cross-path traffic). Participants were modeled as a random effect.

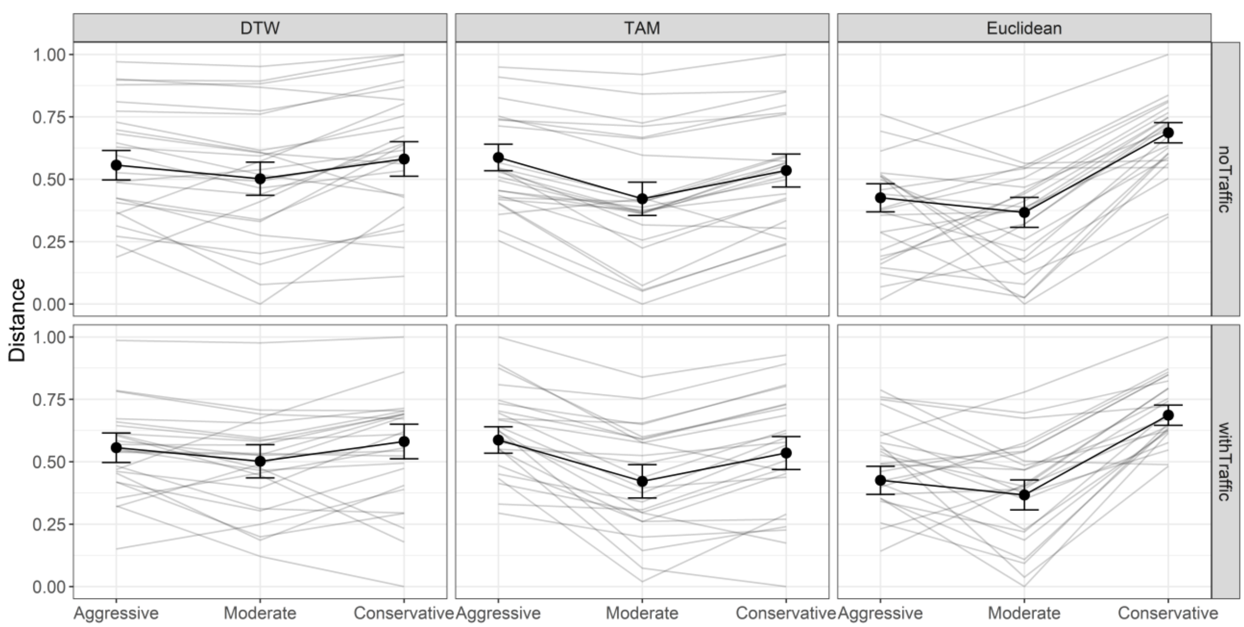

Figure 7. Slope graph of the distances between manual and automated speed profiles at the two stop-controlled intersections. Distances have been log-transformed and scaled. Higher distance values indicate dissimilarity while lower values indicate similarity. Each light gray line represents the data from one participant. Solid vertical lines show the mean and the 95th percent confidence intervals.

Table 2 shows the model formulations and all model results. The left-hand side of the model formulation is the response variable (subjective similarity). The right-hand side includes the predictors (automation style and distance-based objective similarity) and the participants modeled as a random effect. For the model analyzing intersections without cross traffic, Euclidean distance is statistically significant and negative (Table 2, model 3), indicating that increasing Euclidean distances are associated with lower subjective similarity scores. The effect of the DTW and TAM distances was non-significant (Table 2, model 1, and model 2). For intersections with cross traffic, the effect of Euclidean, DTW, and

TAM was non-significant (Table 2, model 4, model 5, and model 6) indicating that neither distance predicted subjective similarity. For these models, Figure 8 plots the relationship between subjective and objective similarity. The expected trend here is a negative slope where lower distances predict higher subjective similarity ratings. Reflecting the results from the model (Table 2, model 3), the Euclidean distance for the intersection without cross-path traffic showed a significant negative slope. Across all models, conditional R^2 values highlight the model's total explanatory power from both fixed and random effects while the marginal R^2 highlights the model's explanatory power with fixed effects alone. Note that the fixed effects had a significantly lower explanatory power than the random effects, reflecting the strong differences between participants.

Table 2. Results of linear mixed-effects models for the analysis of stop-controlled intersections with and without traffic in the cross path. σ^2 refers to the within-subject variance, $\tau_{00\ participant}$ refers to the between-subject variance, and ICC is the intra-class coefficient. Number of participants = 23, Number of observations = 69.

Fixed effects				Random effects			
Predictors	Estimates	CI	p	σ^2	$\tau_{00\ participant}$	ICC	Marginal R^2/ Conditional R^2
Intersections with no cross-path traffic							
Model 1		Subjective Similarity ~ Automation Style + DTW Distance + (1|Participant)					
Intercept	1.86	0.94 – 2.79	**<0.001**	0.63	0.71	0.53	0.055 / 0.554
Moderate	0.01	-0.46 – 0.49	0.962				
Conservative	-0.28	-0.76 – 0.19	0.237				
DTW	-0.37	-2.34 – 0.49	0.197				
Model 2		Subjective Similarity ~ Automation Style + TAM Distance + (1| Participant)					
Intercept	1.63	0.55 – 2.72	**0.004**	0.63	0.77	0.55	0.028 / 0.563
Moderate	-0.01	-0.54 – 0.52	0.971				
Conservative	-0.34	-0.81 – 0.13	0.157				
TAM	-0.53	-2.34 – 1.27	0.558				
Model 3		Subjective Similarity ~ Automation Style + Euclidean Distance + (1| Participant)					
Intercept	2.02	1.36 – 2.69	**<0.001**	0.53	0.81	0.60	0.093 / 0.640
Moderate	0.00	-0.43 – 0.43	0.988				
Conservative	0.25	-0.33 – 0.83	0.389				
Euclidean	-1.92	-3.23 – -0.62	**0.004**				
Intersections with cross-path traffic							
Model 4		Subjective Similarity ~ Automation Style + DTW Distance + (1| Participant)					
Intercept	1.27	0.29 – 2.24	**0.012**	0.65	0.74	0.53	0.022 / 0.544
Moderate	0.07	-0.41 – 0.55	0.762				
Conservative	-0.33	-0.80 – 0.15	0.173				
DTW	0.15	-1.42 – 1.72	0.850				
Model 5		Subjective Similarity ~ Automation Style + TAM Distance + (1| Participant)					

Intercept	1.05	-0.03 – 2.14	0.057	0.65	0.72	0.53	0.027 / 0.541
Moderate	0.16	-0.41 – 0.73	0.576				
Conservative	-0.28	-0.78 – 0.21	0.257				
TAM	0.48	1.12 – 2.09	0.548				
Model 6		Subjective Similarity ~ Automation Style + Euclidean Distance + (1| Participant)					
Intercept	1.78	0.90 – 2.66	**<0.001**	0.62	0.78	0.56	0.035 / 0.575
Moderate	-0.03	-0.52 – 0.46	0.910				
Conservative	-0.14	-0.70 – 0.42	0.617				
Euclidean	-0.88	-2.39 – 0.62	0.245				

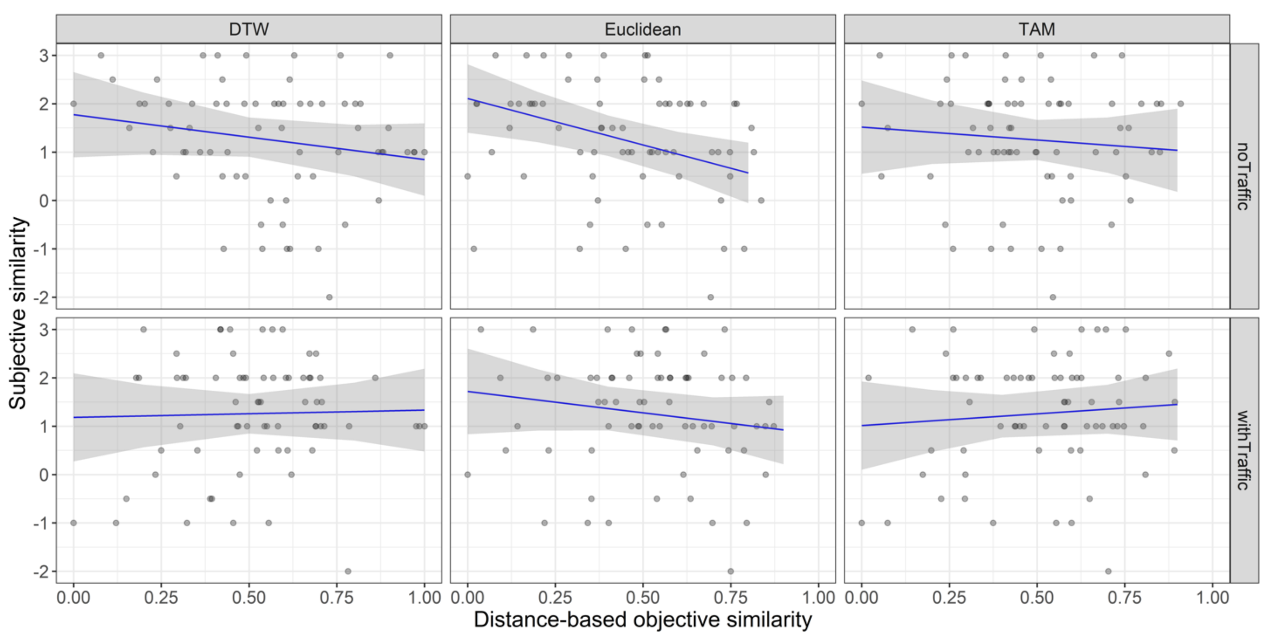

Figure 8. Subjective similarity predicted by distance-based objective similarity at the two stop-controlled intersections in situations with and without cross traffic.

Influence of driving style components on objective and subjective similarity

We now explore if one or both driving style components predict subjective similarity by using the speed profile’s approach and departure components (see Figure 5).

Approach segment

Figure 9 shows the distances for the speed profiles in the approach segment. Table 3 shows the model formulations and all model results for the approach segment analysis. For the intersections without cross traffic, the effect of Euclidean distance-based similarity was found to be significantly negative (see Table 3, model 3) while DTW and TAM-based similarity measures were non-significant (see Table 3, model 1, and model 2). For the intersections with cross traffic, the effect of all three distances was not significant (see Table 3, model 4, model 5, and model 6).

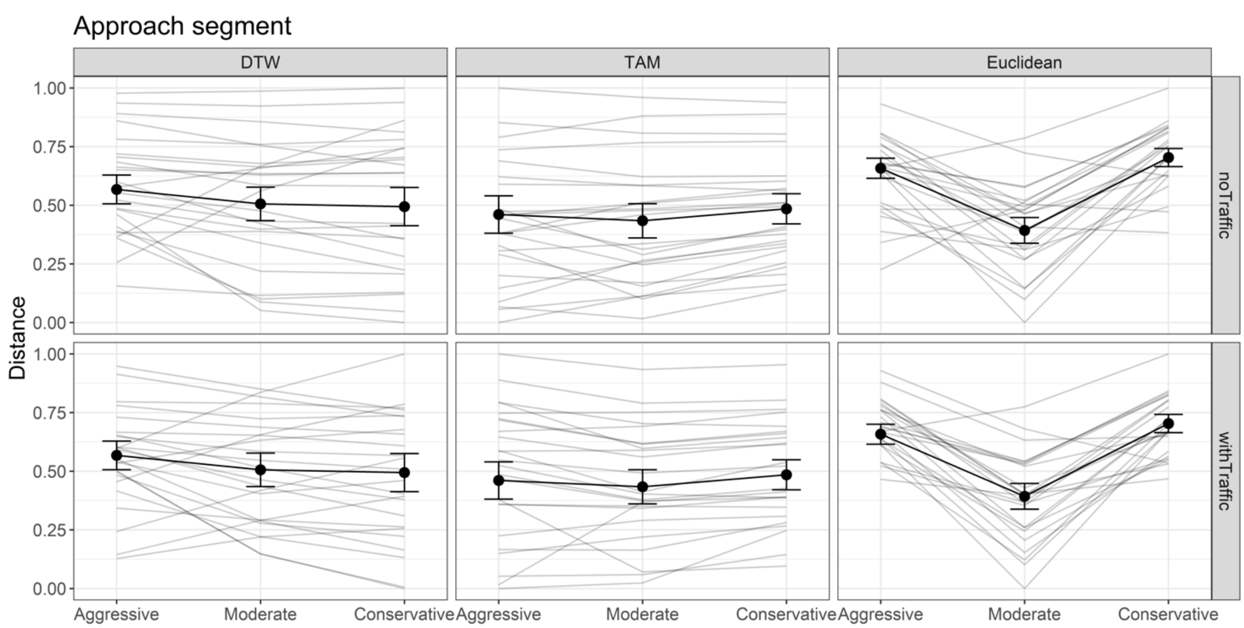

Figure 9. Slope graph of the distances between manual and automated speed profiles when approaching the two stop-controlled intersections differentiated by the presence of traffic in the cross path. Distances have been log-transformed and scaled. Higher distance values indicate dissimilarity while lower distance values indicate similarity. Each light gray line represents the data from one participant. Solid vertical lines show the mean and the 95th percent confidence intervals.

Table 3. Results of linear mixed-effects models for the analysis of the approach segment at stop-controlled intersection differentiated by the presence of cross-path traffic. σ^2 refers to the within-subject variance, $\tau_{00\,participant}$ refers to the between-subject variance, and ICC is the intra-class coefficient. Number of participants = 23, Number of observations = 69.

Fixed effects				**Random effects**			
Predictors	Estimates	CI	p	σ^2	$\tau_{00\,participant}$	ICC	Marginal R^2/ Conditional R^2
Approach Segment - Intersections with no cross-path traffic							
Model 1		Subjective Similarity ~ Automation Style + DTW Distance + (1| Participant)					
Intercept	1.75	0.86 – 2.63	**<0.001**	0.65	0.69	0.52	0.044 / 0.538
Moderate	0.02	-0.46 – 0.50	0.935				

Conservative	-0.37	-0.85 – 0.11	0.127				
DTW	-0.71	-2.03 – 0.61	0.287				
Model 2		Subjective Similarity ~ Automation Style + TAM Distance + (1| Participant)					
Intercept	1.78	0.93 – 2.63	**<0.001**	0.60	0.84	0.58	0.058 / 0.606
Moderate	0.06	-0.40 – 0.51	0.801				
Conservative	-0.27	-0.74 – 0.19	0.249				
TAM	-1.07	-2.78 – 0.64	0.216				
Model 3		Subjective Similarity ~ Automation Style + Euclidean Distance + (1| Participant)					
Intercept	2.24	1.27 – 3.22	**<0.001**	0.58	0.79	0.58	0.056 / 0.601
Moderate	-0.27	-0.82 – 0.28	0.323				
Conservative	-0.21	-0.67 – 0.25	0.372				
Euclidean	-1.45	-2.81 – -0.09	**0.037**				
Approach Segment - Intersections with cross-path traffic							
Model 4		Subjective Similarity ~ Automation Style + DTW Distance + (1| Participant)					
Intercept	1.73	0.84 – 2.61	**<0.001**	0.64	0.73	0.53	0.039 / 0.551
Moderate	0.02	-0.45 – 0.50	0.925				
Conservative	-0.39	-0.87 – 0.10	0.117				
DTW	-0.69	-2.05 – 0.66	0.312				
Model 5		Subjective Similarity ~ Automation Style + TAM Distance + (1| Participant)					
Intercept	1.42	0.52 – 2.32	**0.003**	0.64	0.76	0.54	0.022 / 0.553
Moderate	0.06	-0.42 – 0.54	0.806				
Conservative	-0.33	-0.80 – 0.15	0.173				
TAM	-0.15	-1.74 – 1.45	0.854				
Model 6		Subjective Similarity ~ Automation Style + Euclidean Distance + (1| Participant)					
Intercept	1.90	0.62 – 3.18	**0.004**	0.63	0.77	0.55	0.029 / 0.566
Moderate	-0.20	-0.92 – 0.53	0.593				
Conservative	-0.34	-0.81 – 0.13	0.152				
Euclidean	-0.79	-2.49 – 0.90	0.354				

The results indicate that the Euclidean distance for the approach segment predicted participants' subjective similarity only for intersections without cross-path traffic. Figure 10 plots the relationship between the subjective and objective similarity for the approach segment. Reflecting the results from the model (Table 3, model 3), the Euclidean distance for the intersection without cross-path traffic in the approach segment showed a significant negative slope.

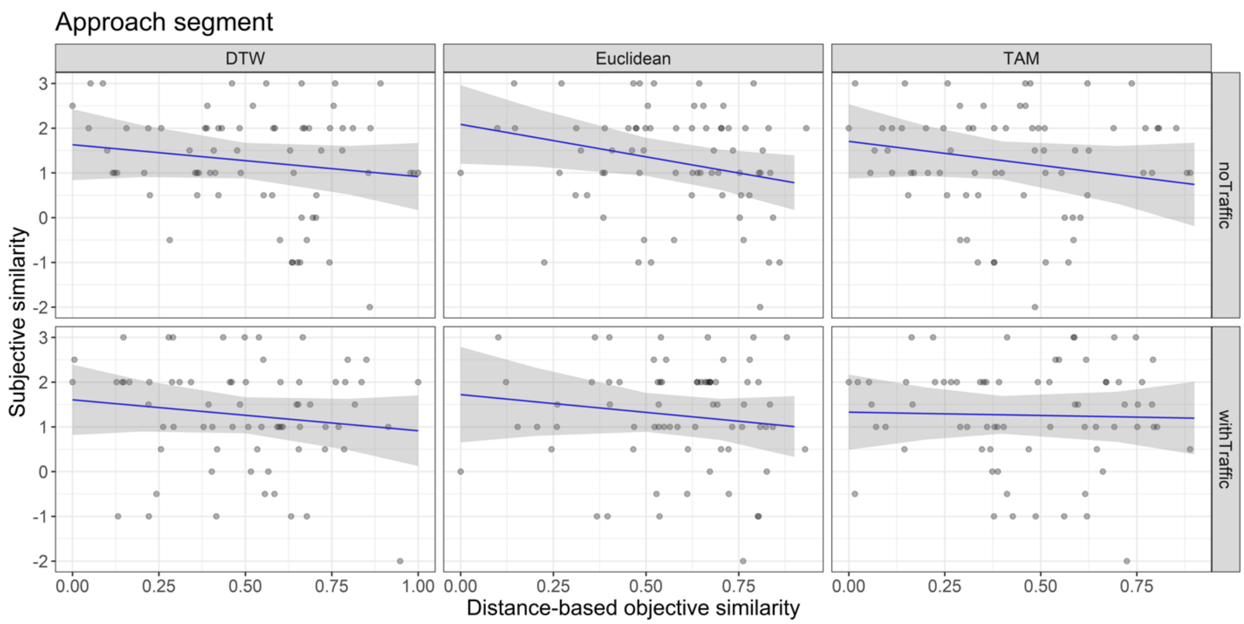

Figure 10. Subjective similarity predicted by distance-based objective similarity for approach segment speed profiles at the two stop-controlled intersections differentiated by the presence of traffic in the cross path.

Departure segment

Figure 11 shows the distances for the speed profiles for the departure segment. Table 4 shows the model formulations and all model results for the departure segment analysis. For the intersections with and without cross traffic, the effect of all three distances was not significant (see Table 4, models 1 – 6).

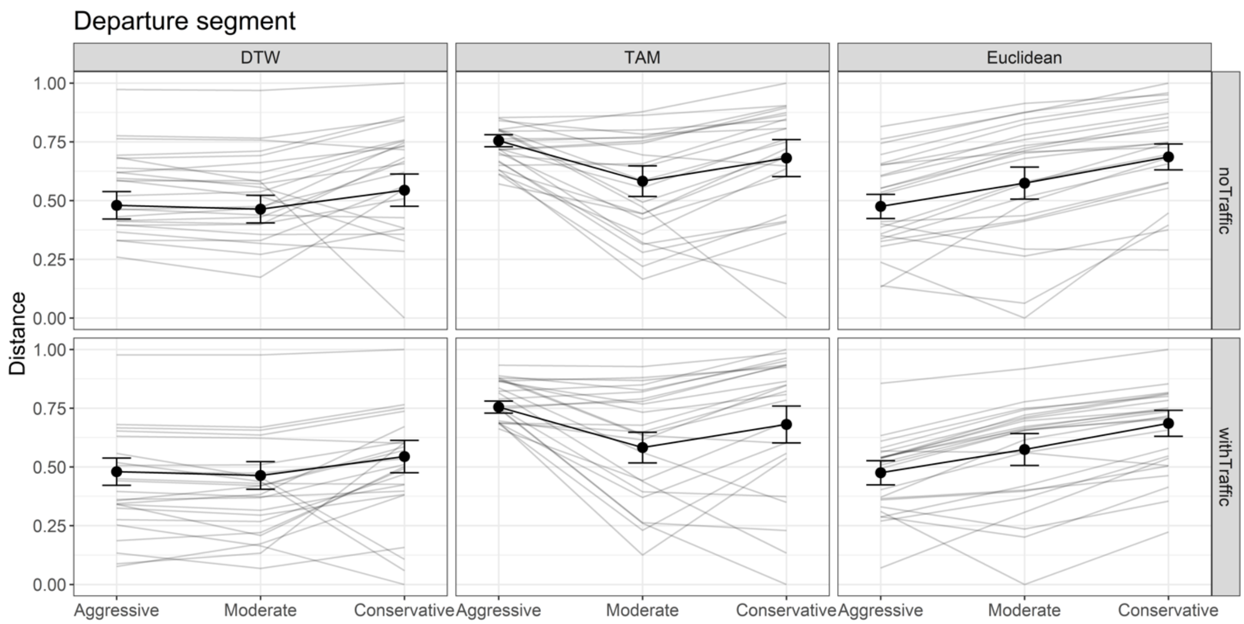

Figure 11. Slope graph of the distances between manual and automated speed profiles when departing the two stop-controlled intersections differentiated by the presence of traffic in the cross path. Distances have been log-transformed and scaled. Higher distance values indicate dissimilarity while lower distance values indicate similarity. Each light gray line represents the data from one participant. Solid vertical lines show the mean and the 95th percent confidence intervals.

Table 4. Results of linear mixed-effects models for the analysis of the departure segment at stop-controlled intersection differentiated by the presence of cross-path traffic. σ^2 refers to the within-subject variance, $\tau_{00\ participant}$ refers to the between-subject variance, and ICC is the intra-class coefficient. Number of participants = 23, Number of observations = 69.

Fixed effects				**Random effects**			
Predictors	Estimates	CI	p	σ^2	$\tau_{00\ participant}$	ICC	Marginal R^2/ Conditional R^2
Departure Segment - Intersections with no cross-path traffic							
Model 1		Subjective Similarity ~ Automation Style + DTW Distance + (1| Participant)					
Intercept	1.48	0.51 – 2.44	**0.003**	0.64	0.75	0.54	0.022 / 0.547
Moderate	0.06	-0.41 – 0.53	0.798				
Conservative	-0.31	-0.79 – 0.17	0.197				
DTW	-0.24	-1.78 – 1.31	0.759				
Model 2		Subjective Similarity ~ Automation Style + TAM Distance + (1| Participant)					
Intercept	1.27	0.12 – 2.42	**0.031**	0.65	0.74	0.53	0.021 / 0.545
Moderate	0.08	-0.45 – 0.62	0.753				
Conservative	-0.32	-0.80 – 0.16	0.192				
TAM	0.11	-1.32 – 1.55	0.877				
Model 3		Subjective Similarity ~ Automation Style + Euclidean Distance + (1| Participant)					
Intercept	1.70	0.75 – 2.65	**0.001**	0.62	0.79	0.56	0.037 / 0.574
Moderate	0.14	-0.36 – 0.63	0.577				
Conservative	-0.16	-0.76 – 0.44	0.597				
Euclidean	-0.73	-2.42 – 0.96	0.389				
Departure Segment - Intersections with cross-path traffic							
Model 4		Subjective Similarity ~ Automation Style + DTW Distance + (1| Participant)					

Intercept	1.04	0.28 – 1.80	**0.008**	0.67	0.64	0.49	0.041 / 0.512
Moderate	0.08	-0.40 – 0.56	0.753				
Conservative	-0.38	-0.87 – 0.11	0.127				
DTW	0.74	-0.67 – 2.15	0.297				
Model 5		Subjective Similarity ~ Automation Style + TAM Distance + (1| Participant)					
Intercept	0.94	-0.15 – 2.03	0.091	0.65	0.70	0.52	0.031 / 0.532
Moderate	0.16	-0.37 – 0.69	0.547				
Conservative	-0.28	-0.77 – 0.21	0.261				
TAM	0.52	-0.73 – 1.77	0.410				
Model 6		Subjective Similarity ~ Automation Style + Euclidean Distance + (1| Participant)					
Intercept	1.14	0.17 – 2.12	**0.022**	0.65	0.73	0.53	0.026 / 0.541
Moderate	0.02	-0.48 – 0.53	0.929				
Conservative	-0.41	-1.01 – 0.18	0.172				
Euclidean	0.44	-1.41 – 2.29	0.634				

The results indicate that distances obtained from the departure segments did not predict the participants' subjective similarity. Note that, in both the approach and departure segment analysis, the fixed effects had a significantly lower explanatory power than the random effects. Again, this reflects the effects of strong individual differences. Figure 12 plots the relationship between the subjective and objective similarity for the departure segment. Note that no significant negative slope was observed.

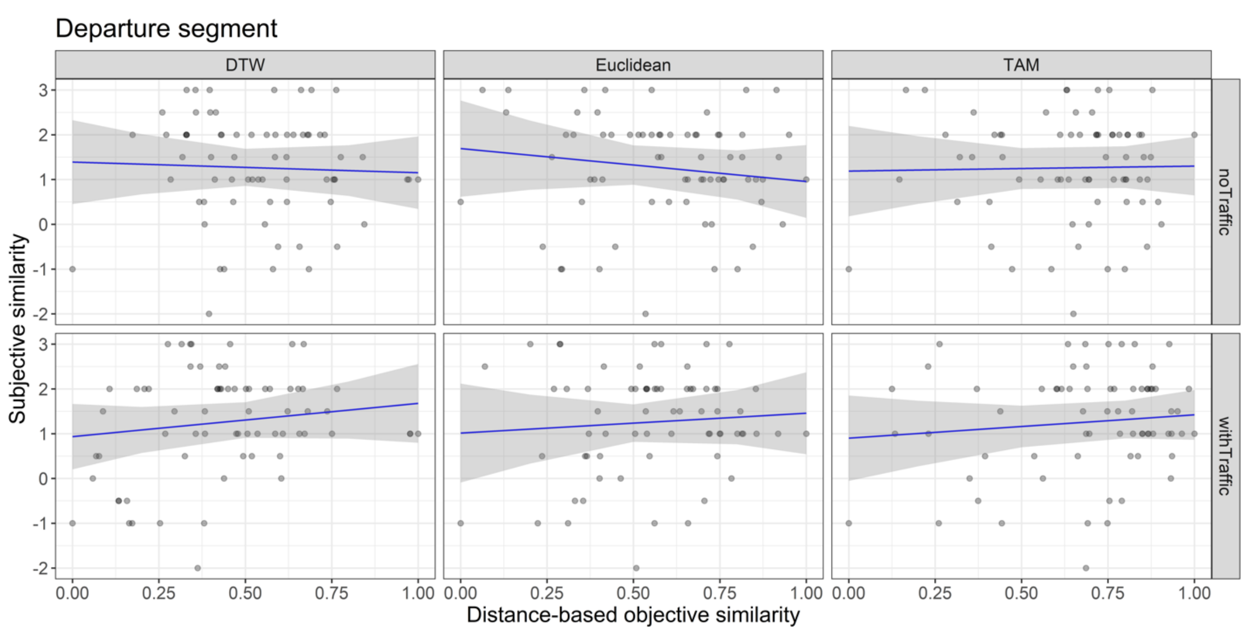

Figure 12. Subjective similarity predicted by distance-based objective similarity for departure segment speed profiles at stop-controlled intersections differentiated by the presence of traffic in the cross path.

DISCUSSION

We investigated distance-based objective similarity of driving styles at stop-controlled intersections and its relation to subjective similarity. Results showed Euclidean distance best predicted subjective similarity ratings with the approach component's objective similarity influencing subjective similarity ratings. This suggests that the Euclidean distance between the manual and automated approach speed profiles may be a metric that can be used to align driver preferences with automation. However, further investigation is warranted to assess the breadth of driving situations and components that may contribute to the subjective experience of driving styles.

Implications for research and design

Similarity through behavioral mimicry has been found to enhance trust and autonomous agent acceptance (J. D. Lee & See, 2004; K. M. Lee et al., 2011; Moon, 1996; Verberne et al., 2015). This could be attributed to the perception of decreased uncertainty in the interaction as similar interaction partners may be more predictable than dissimilar ones (Berger & Calabrese, 1974; Mitteness et al., 2016). Thus, behavioral mimicry achieved through driving style similarity could improve trust in vehicle automation (Brück et al., 2021; Ma & Zhang, 2021). However, its operationalization requires objective similarity measures that reflect the driver's subjective similarity. The distance measures explored here and the process of investigating driving style components that influence subjective similarity can help leverage the similarity effect to develop trustworthy and acceptable vehicle automation.

Of the three distance measures investigated, only the Euclidean distance predicted subjective similarity. While this may imply it is a good objective similarity indicator, this choice may differ based on the behavior being investigated. This study investigated intersection negotiation where drivers drove the same route, on the same lane, and passed through the same stopping event. Factors differentiating the automation style were the onset time for deceleration and acceleration, and the stop duration. Since DTW is time-invariant and focuses on the shape of the time series profile, it was insensitive to these differences. Shape similarity is the primary focus of some driving studies for which DTW may be more useful than Euclidean distance (Taylor et al., 2015). Additionally, some driving data (e.g., naturalistic driving study data) can benefit from elastic measures like DTW as those data are rarely formatted to enable calculating lock-step measures like the Euclidean distance. Typically, data interpolation ensures that vectors are of equal length. Such processing is unnecessary for elastic measures as they are capable of handling vectors of varying lengths. But the trade-off is that elastic measures may not capture effects such as amplitude changes that arise due to time shifts.

The result also indicates that the approach speed profile contributes to the driver's subjective similarity while the departure does not. This could be due to how driving styles were operationalized in this study and may not be the case universally. The automation style differentiation was such that the approach component depends on three factors – the stop duration, distance to halt line when speed first goes below 1 mph, and the mean deceleration. Factors like the distance to halt line were also larger than what can be observed in real-world driving to ensure participants noticed differences between the driving styles. The departure component depended only on one factor – the mean acceleration. A more complete representation of driving styles must go beyond intersection negotiations to consider turns, car following, lane changes, etc (Scherer et al., 2015). These factors will not only contribute to differences in driving behavior classification but also introduce more considerations for what driving components contribute to the driver's subjective similarity (Dettmann et al., 2021; Hartwich et al., 2015). Additionally, it may not only be profile matching that captures driving style similarity but also time series summary statistics that describe the profiles (J. D. Lee & McLaurin, 2022).

Future work

In this study, the subjective similarity uses a single-item questionnaire. As evidenced from prior and current research, similarity is assessed along multiple dimensions and therefore subjective similarity evaluations must reflect these dimensions. Future efforts will develop improved subjective similarity assessments to better understand the link between subjective and objective similarity. Furthermore, distance-based similarity measures do not explore directionality or the orientation of similarity (i.e., whether drivers exhibit behavior or show preferences that lean towards a conservative or aggressive driving style). This directionality of similarity may be another factor that influences driving style perception and will be explored in future work. This work also assumes automation that acts in a way that drivers judge as to their own driving will be viewed as acceptable. Future work should consider whether a combination of experience, as well as visual, vestibular, and haptic cues, could make automation more predictable and acceptable even if it acts very differently.

CONCLUSION

Understanding what drivers perceive to be similar can help determine appropriate methods of personalizing driving styles in automated vehicles. Thoughtful use of objective similarity, based on time series similarity measures, offers a path to better understanding the driver's subjective similarity. For intersection negotiation examined in this study, Euclidian distance outperformed Dynamic Time Warping and the Time Alignment Measure in predicting subjective similarity. This can support personalization venues for the future of automated vehicles when these drivers transition into becoming vehicle passengers.

APPENDIX

Differences in distances computed by the DTW, TAM, and Euclidean distances

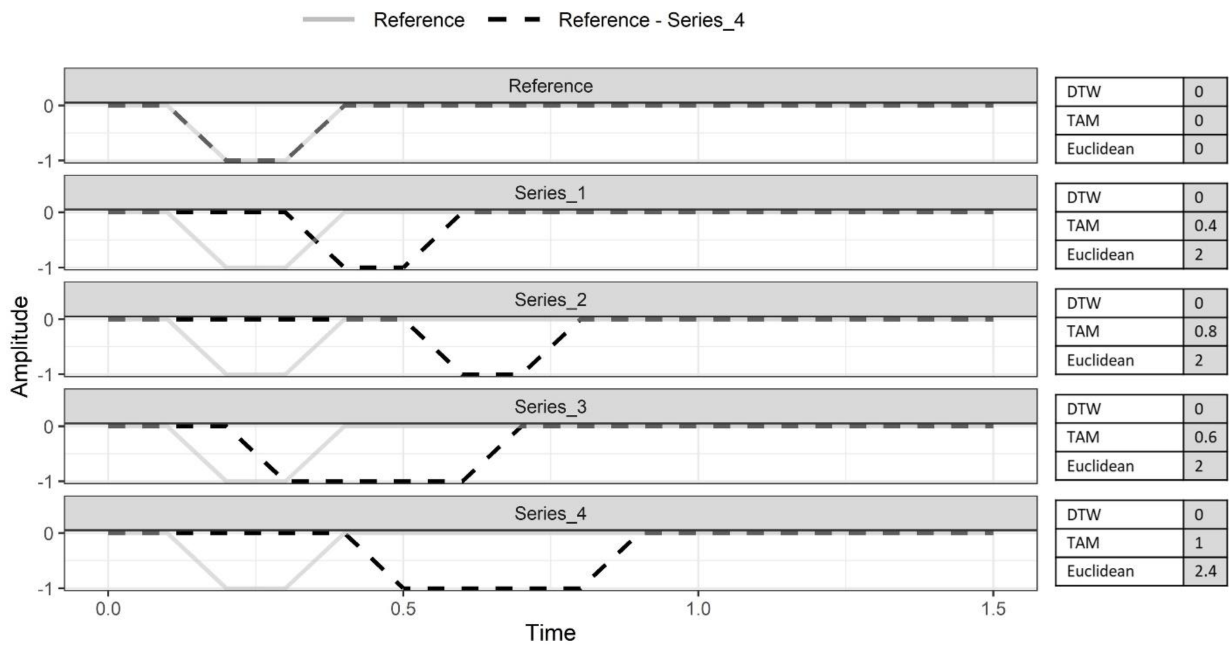

Figure 13. Variation in DTW, TAM, and Euclidean values as a series shifts in time. The tables on the right show the three distances compute between the reference and each time series (Folgado et al., 2018).

Figure 13 shows the difference in distances calculated using the Euclidean, DTW, and the TAM distance between a reference curve and four time series (series 1–series 4). Series 1 and Series 2 are the reference time series but with the dips shifted in time. Series 3 and Series 4 are similar in shape but modified by expanding the dip on the time axis and misaligned with the reference like series 1 and series 2. Note that the DTW is zero for all cases even with series 3 and series 4 where the shape is expanded in the time axis. This demonstrates the time invariant nature of the DTW distance. The Euclidean distance on the other hand shows dissimilarity due to the one-to-one mapping between points. Also, note that based on the Euclidean distance, series 1, series 2, and series 3 are equidistant from one another. While counterintuitive, this is a result of the one-to-one mapping performed by the Euclidean distance. Finally, the TAM distance can capture the degree to which the DTW distance warps the times series. In the case of series 1 and 2 where the series are shifted in time, the TAM distance reflects the warping cost due to this time shift. In series 3 and 4, there is an added cost that TAM reflects since the series are not just shifted in time but also expanded in the time axis. Thus, it is evident from Figure 13 that each of these distances produces a different value of similarity. Given these differences, the question that follows is which to use because each distance is sensitive to different aspects of the time series. The Euclidean distance measures the overall mismatch between points in a time series in a one-to-one mapping and is sensitive to misalignments. The DTW distance measures shapes differences but does not reflect the misalignment that the TAM accounts for. TAM does not account for misalignment alone but rather the warping cost and therefore does not reflect shape similarity.

DTW function constraints

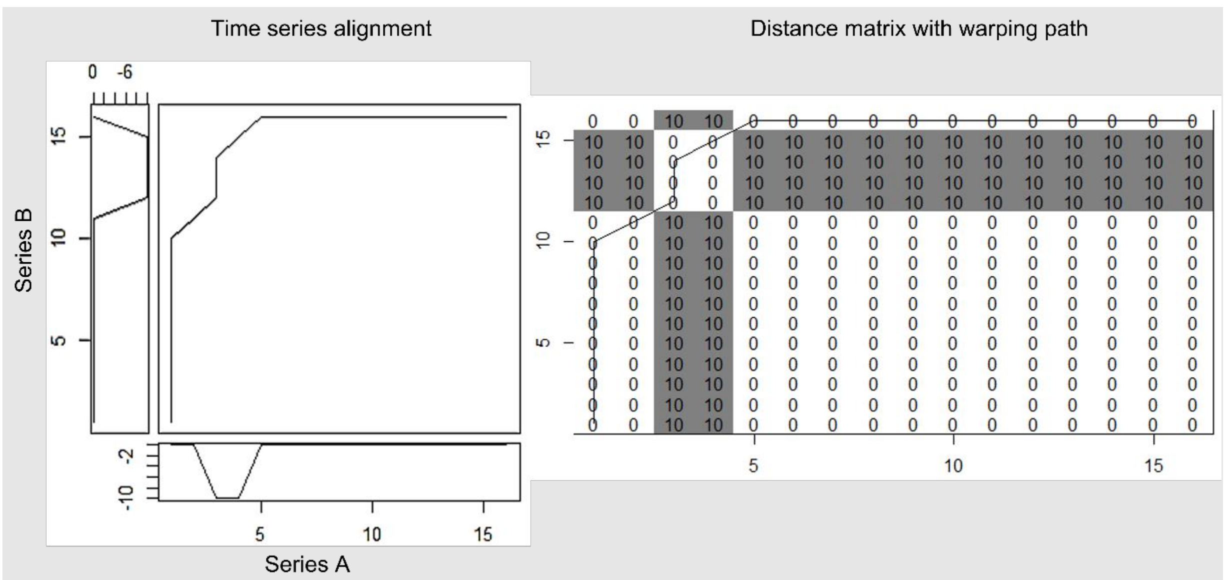

Figure 14. Dynamic time warping path between two time series (left) and the distance matrix with warping path superimposed (right).

When computing the DTW distance, note that multiple matrix cells can have the same minimum distance values (see Figure 14) and thus there can be more than one warping path. This issue of selecting a warping path is addressed by imposing constraints on the DTW function. These constraints include factors such as monotonicity, continuity, boundary conditions, and a warping window. The monotonicity ensures that the warping path does not go back in time. Continuity ensures that there is no jump between time steps. Boundary conditions make sure that the warping path starts at the bottom left of the matrix and ends at the top right and finally, a warping window is imposed to make sure the warping path stays close to the diagonal.

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KEYPOINTS

- Time series data analyzed with a variety of distance measures can generate objective similarity measures for assessing human-automation interaction.
- Understanding which distance measures reflect subjective similarity is an important step in supporting the development of human-compatible automation.
- Selection of the distance measure depends on multiple factors including driver behavior, driving setting, and the research question.

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