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Motion Sickness Prediction Based on Passenger's Self Evaluation

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***Abstract*—Passengers performing non-driving related tasks in a self-driving vehicle, e.g., working on a laptop, are at high risk of developing symptoms of motion sickness. In the future, intelligent vehicles will use their own strategies and new technologies to prevent motion sickness and therefore enable the benefit of autonomous driving for the passengers. The current methods of objective assessment, modeling, prediction, and prevention of motion sickness show good performance applied to a group of passengers, but have difficulties when applied on an individual level. Therefore, pasenger's subjective self-assessment remains difficult to replace as a reference in motion sickness research and will likely be required in future intelligent vehicles. We demonstrate that the susceptibility, intensity, and onset of motion sickness can be predicted based on passenger's self-assessment using data collected in three real-world driving experiments. This way, we show that the concept of classifying motion sickness based on questionnaire results can be successfully applied, not only in virtual reality scenarios, but also in car sickness situations. As a result, future intelligent vehicles could adapt model parameters or choose avoidance strategies for respective passengers, based on classification algorithms using information derived from a questionnaire.**

***Index Terms*—motion sickness, modeling and simulation, intelligent vehicle, autonomous vehicles, human factors.**

I. Introduction

DURING non-driving related tasks, e.g., reading a book, the risk of developing motion sickness (MS) symptoms (like nausea, vomiting, headache, facial pallor, and cold sweating) increases significantly, see [1]–[3]. In the future, autonomous cars are expected to avoid MS with on-board technical solutions to allow the driver, who switches to the passenger position as soon as the driving task is handed over to the car, to engage in such activities. Since 1974, it is known that amplitude and frequency of vertical acceleration influence the passenger's well-being and provoke MS symptoms [4]. Based on these findings, the sensory conflict theory [5]–[7], describing the mismatch between the sense of balance and the internal expectation of actual body movements, has resulted in several models successfully predicting MS incidence [6]–[10], but still fail in predicting individual MS symptoms. A large number of findings on newly discovered or further disaggregated MS influencing factors have not yet been incorporated into the development of MS models, e.g., the effect of seating position [11], [12], display position [13], sound environment [14], [15], and motion anticipation. In addition, there is a lack of research trying to integrate known factors, such as gender, age [18], or MS experience [19], in existing MS models. Besides medication, known to have negative side effects, no other investigated method for MS prevention have been able to reliably prevent MS symptoms. While many systems show positive effects on the incidence of MS, see [11], [13], [14], these effects vary greatly between individuals. Each individual shows an unique physiological response to MS. Therefore, physiological MS indicators cannot be generalized, although there are still many approaches to find a way to measure MS objectively [20]–[22]. In a large number of subjects, electrodermal activity, heart rate, as well as heart rate variability show correlations with MS [20], [21]. Although, further research is carried out to better specify symptoms of passengers with additional physiological correlates, such as contactless measurement of sweat gland activity [25], MS experiments still rely on questionnaires and subjective rating scales as gold standard to evaluate MS, see [10], [11], [14], [15], [22]–[24]. Since driving dynamics-based MS models calculate MS incidence and physiological MS correlates are currently difficult to scale, taking into account subjective passenger information could significantly improve the reliability of MS predictions and thus enable successful use in series vehicles. It is conceivable that the first generation of intelligent vehicles will focus on avoiding MS among passengers who use the vehicle daily, so MS models could take into account individual, unique recorded passenger information, e.g., a short questionnaire. 2021, Golding et al. successfully showed that predicting virtual reality sickness based on questionnaires is possible [24]. Therefore, it is likely that data from questionnaires are necessary for reliable individual MS models in cars, for the time being. We evaluate the possibility of estimating the susceptibility, intensity, and onset of MS in a real-driving situation only based on questionnaire data collected in three independently conducted driving experiments.

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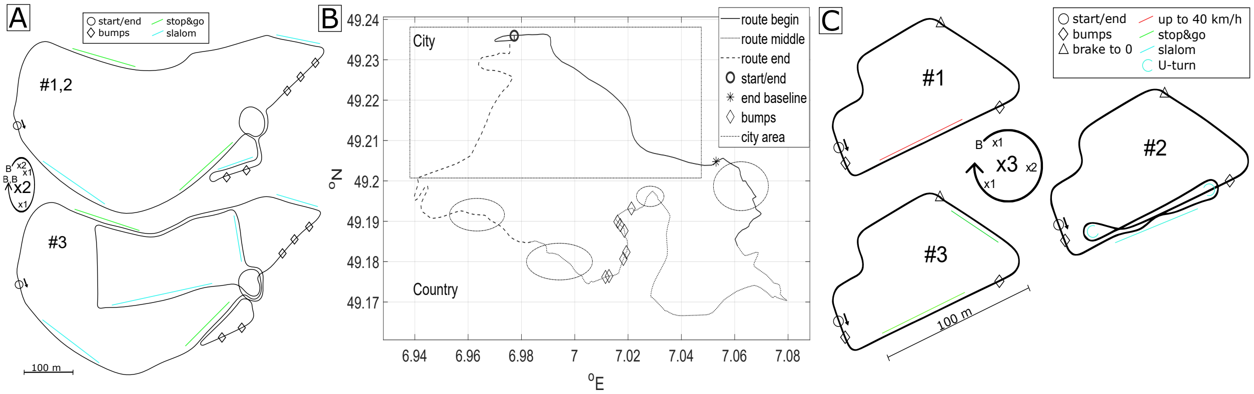

Fig. 1: Experimental routes: A: Route of study[A] with 11 laps driven on a closed test area (geographically predefined route) including hard maneuvers. Maneuvers of round #2 and #3 are designed to provoke 0.2 Hz in car's chassis during slalom and stop & go maneuvers. B: One-way route of study[B] driven in mixed real road traffic. C: Route of study[C] with 12 laps driven on a closed test area including clean maneuvers (driving dynamic separation).

II. Method

A. Conducted Driving Studies

The evaluation includes three separated real-world driving studies (see marking: [A],[B],[C]) focused on provoking MS through hard maneuvers[A]; driving in daily traffic[B]; and provoking MS through specific, selected maneuvers[C] driven by pre-trained drivers, see Fig. 1 and [10], [20], [26]. The data collection was conducted over a total period of 3.5 years. A family VAN (Ford Galaxy 3rd gen.[A], VW Touran, 2nd gen.[B,C], see Fig. 2) was used to drive:
[A]: 11 laps on a closed 22.5 km circuit over 1 h;
[B]: a 40 km one-way route in a total of 50 minutes in real traffic across countryside and through the city;
[C]: 12 laps on a closed 6.1 km circuit over 25 minutes.
All experiments included standing and easy driving as baseline phases about at least 300 s.

Fig. 2: Research vehicle used in study[B,C]. Left: Participant solving non-driving related tasks on a tablet-PC. Right: Trunk of the vehicle including measurement equipment.

B. Participants and Studies Design

28[A]; 22[B]; 29[C] volunteers (mean (std.) age: 24.3[A] / 23.5[B]/ 25.1[C] (4.3[A]/ 2.7[B]/ 2.5[C]) y.; 18[A]/ 13[B]/ 18[C] males; 10[A]/ 9[B]/ 11[C] females) participated in the study. The participants were placed on the rear left[A,B]/ rear middle[C] seat. With lowered gaze the participants played mini-games[A,B]; read texts[A,B,C]; watched silent videos[A,B,C]; and answered questions[A,B,C] about the content of the presented text and video on a center placed display. Every 2[B]/ 5[A,C] minutes the task changed and the participants rated their subjective motion sickness level (SMSL) based on a visual analogue scale between 0 and 10. All participants were aware that they could abort the measurement at any time without reason. Completely resistant as well as very susceptible participants were excluded from the measurement[B,C]. This research complied with the tenets of the Declaration of Helsinki and was approved by the Institutional Review Board "Ethikkommission der Ärztekammer des Saarlandes", Saarbrücken, Germany, Identification Number: 199/17 and 181/18. Informed consent was obtained from each participant prior to each measurement.

C. Subjective Motion Sickness Evaluation

To analyze self-evaluated MS susceptibility, a questionnaire, based on [23], was filled out prior to each experiment. To reduce the degrees-of-freedom of the possible answers in the questionnaire, detailed and specific answers were simplified to a mere yes-or-no categorization. Resulting, we considered eight multiple-choice questions for the evaluation (see Table I) and a score value was assigned for each possible answer. Afterwards, the final score, also referred to as Q-Score, was calculated as the summation of all the individual score values.

D. Subject Classification

Subjects rating their SMSL at least 7 at any point of the measurement were defined as motion sick, corresponding to a symptomatology of the rating "nausea, fairly" of the misery scale by [27]. The elapsed time to the onset of MS was defined as time to sick (T2S). Abortion of the drive due to

TABLE I: MS questionnaire including scoring

Question	Answer [Score]
1. Do you see yourself as prone to motion sickness?	No [0]; Low [1]; Moderate [2]; High [3]
2. Can you read or watch videos during a car trip without getting sick?	Yes [0]; No [1]
3. How severe are your symptoms when they occur (on a scale 0 to 10)?	0-1 [0]; 2-5 [1]; 6-8 [2]; 9-10 [3]
4. Do you have ever taken medication for motion sickness symptoms?	No [0]; Yes [1]
5. Do you have any tricks to avoid the occurrence of motion sickness?	No [0]; Yes [1]
6. Does sitting in the front or back seat of the car affect motion sickness?	No [0]; Yes [1]
7. Does the way of sitting affect motion sickness?	No [0]; Yes [1]
8. Do factors such as attention or fatigue influence motion sickness?	No [0]; Yes [1]
	[max. Q-Score = 12]

severe symptoms is automatically assessed with an SMSL of 10. If MS did not occur, T2S is set to the duration of the measurement ($\geqslant$ 50 min) in the first two studies[A,B] and to n/a in the third study[C], which was significantly shorter and thus not comparable to [A] and [B].

Three classification methods have been tested to predict whether a subject is *susceptible* or *resistant* to MS:

1) Classification using individual answers: Table II lists the distribution of responses related to the available options and the corresponding percentage of sick subjects. Some answer options were chosen more often by subjects who became motion sick in the experiment, see question no. 4 as an example. Therefore, to examine the features, i.e. the individual questions of the questionnaire, for their categorization potential, the subjects were separately categorized based on every single answered question. Hereby, the choice of the examined answer option leads to the categorization into the group *susceptible*, whereas the choice of another answer leads to the group *resistant*. Then, the categorization accuracy of the answer option is calculated.

TABLE II: Responses of the questionnaire

Question	Responses [number of subject ratings/ thereof proportionately sick]
1.	No [9/ 11.1%]; Low [27/ 40.7%]; Moderate [24/ 66.7%]; High [19/ 94.7%]
2.	Yes [24/ 66.7%]; No [47/ 72.3%]]
3.	0-1 [11/ 18.1%]; 2-5 [35/ 51.4%]; 6-8 [30/ 76.7%]; 9-10 [3/ 100%]
4.	No [68/ 52.9%]; Yes [11/ 90.9%]
5.	No [34/ 38.2%]; Yes [45/ 73.3%]
6.	No [33/ 39.4%]; Yes [46/ 71.7%]
7.	No [40/ 47.5%]; Yes [39/ 69.2%]
8.	No [37/ 37.8%]; Yes [42/ 85.7%]
	n = 79; motion sick (46/ 58.2%)/ not motion sick (33/ 41.8%)

2) Threshold-classification: Mean and standard deviation of the calculated Q-Scores of the subjects getting motion sick (red) and subjects do not (blue) are calculated and assumed to be normally distributed, see Fig. 3. The Threshold-classification (TC) process is based on the division of the subjects according to the intersection of the Q-Score distributions at the value 5.61 (Fig. 3, green). Subjects who exceed this value are therefore categorized as *susceptible*.

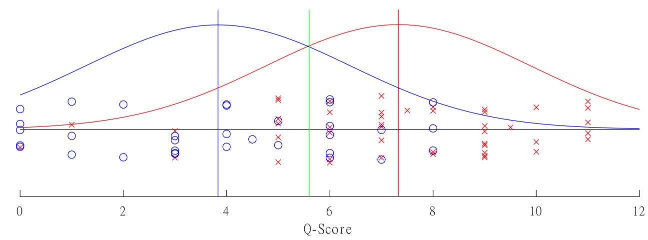

Fig. 3: Calculated Q-Score separated in subjects getting motion sick (red x) and not motion sick (blue o). Estimated normal distribution with mean value (μ) of 3.83 (2.56) (blue) and 7.33 (2.57) (red). Intersection of the distributions at 5.61 (green).

3) Classification using Support-Vector-Classifier: In order to apply a machine-learning approach, the resulting dataset is processed as follows: Because only three subjects answered the question no. 3 with "9-10" (see Table II) this category is clearly underrepresented and was therefore included in the group of answers in the range of "6-8". To avoid local minima due to randomly selecting training (n = 48 /60%) from test data (n = 31 /40%), 100 distinct splits were generated at once, maintaining class distributions. Consequently, support vector classifiers (SVCs) were fitted to these datasets (with the score of the eight answers as model input $x_n \in \{0, 1\}$ whereby $n \in [1, 8]$ and $x_{1,3} \in \{0, 1/3, 2/3, 1\}$) in an attempt to predict subject's MS susceptibility $y \in \{0(resistant), 1(susceptible)\}$. The SVC algorithm is implemented in Python (scikit-learn toolbox) using a gaussian kernel with fixed coefficient equal 1. In addition, the balanced class weight is activated.

III. Results

A. *Q-Score correlation*

The highest rated SMSL showed strong negative Pearson correlation coefficients with the T2S (r = -0.87[A]/ -0.83[B] / -0.47[C] / -0.87[A-C]), see Fig. 4A. The SMSL (Fig. 4B) and T2S (Fig. 4C) show correlation coefficients clearly different from 0 to the Q-Score (r = 0.66[A]/ 0.71[B] / 0.47[C] / 0.59[A-C]); (r = -0.61[A]/ -0.53[B] / (-0.07[C]) / -0.47[A-C]). Hereby, study[C] shows the lowest values.

B. *Classification using individual answers*

The examination of the single questions shows that the question no. 8 has the highest classification potential, 69.3% of the subjects were correctly classified based on this question, see Table III. Note, accuracies below 50% can be complemented, classifying subjects as *resistant* instead of being classified as *susceptible*.

This increases the classification accuracy, based on the relationship: $P(resistant) = 100\% - P(susceptible)$

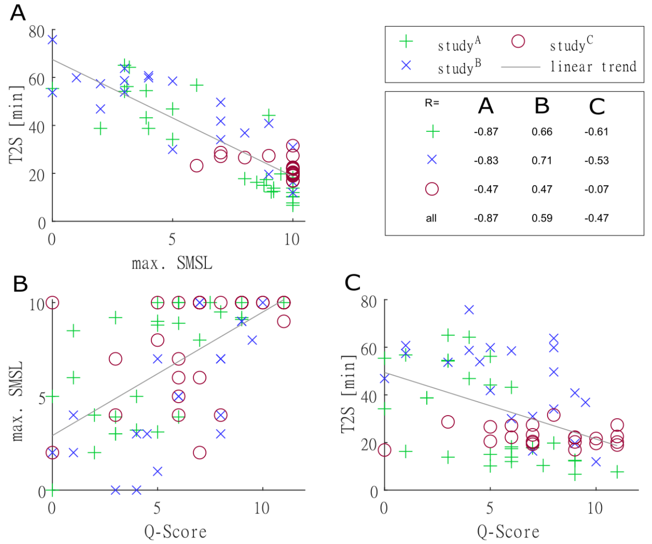

Fig. 4: Correlation between (A) the maximum SMSL and T2S; (B) the calculated Q-Score and maximum SMSL; (C) the calculated Q-Score and T2S separated in the three driving studies (green^{A}, blue^{B}, red^{C}). Linear approximation is colored in grey.

TABLE III: Categorization using each single answer option

Question	answer option [number of correct classified *susceptible* subjects]
1.	No [33.3%]; Low [34.6%]; Moderate [51.3%]; High [62.8%]
2.	Yes [32.1%]; No [67.9%]
3.	0-1 [33.3%]; 2-5 [42.3%]; 6-8 [61.5%]; 9-10 [44.9%]
4.	No [47.4%]; Yes [52.6%]
5.	No [32.1%]; Yes [67.9%]
6.	No [33.3%]; Yes [66.7%]
7.	No [39.7%]; Yes [60.3%]
8.	No [30.7%]; Yes [69.3%]

C. *Results of the Threshold-classification*

72.2% of the subjects were correctly classified by TC, see Table IV (30.4% correct *resistant* + 41.8% correct *susceptible*). The proportion of subjects falsely classified as *resistant* is 10.1%, while 17.7% were falsely classified as *susceptible*.

TABLE IV: Categorization using each single answer option

no. subjects (percentage)	class *resistant*	class *susceptible*	sum
not MS 33 (41.7%)	24 (30.4%)	14 (17.7%)	38 (48.1%)
MS 46 (58.2%)	8 (10.1%)	33 (41.8%)	41 (51.9%)
sum	32 (40.5%)	47 (59.5%)	79 (100%)

D. *Results of the Support-Vector-Classifiers*

The median of the applied SVCs is 69.0%, which is 4.2% lower than the 72.2% accuracy of TC, see Fig. 5. The classification results of the best SVC are shown in Table V. 87.1% of the subjects were correctly classified (35.5% correct *resistant* + 51.6% correct *susceptible*). The proportion of subjects falsely classified as *resistant* is 9.7%, while 3.3% were falsely classified as *susceptible*.

TABLE V: Results of the best SVC

no. subjects (percentage)	class *resistant*	class *susceptible*	sum
not MS 33 (41.7%)	11 (35.5%)	1 (3.3%)	12 (38.7%)
MS 46 (58.2%)	3 (9.7%)	16 (51.6%)	19 (61.3%)
sum	14 (45.2%)	17 (54.8%)	31* (100%)

*test data, 40% of the complete dataset

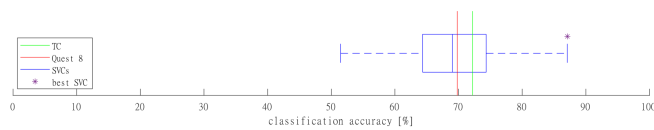

Fig. 5: Accuracy of the applied SVCs (blue) compared to the Threshold- (green) and question no. 8 (red) classification accuracy.

IV. Discussion

Categorization of subject's MS susceptibility based on just one single question only shows a maximal accuracy of 69.3%, see Table III (question no. 8). However, there can be more information in a single question, which can be seen in the example of the question no. 4: Only 52.6% of the subjects were correctly classified based on the question no. 4 alone, see Table III. Incorrectly, this result suggests that the question no. 4 is a useless feature for the machine learning approach, but that is a fallacy because only eleven subjects responded with "Yes" and 90.9% of them became motion sick in the experiment, see Table II. This question thus makes a reliable statement about a small subset of the subjects, which can also be seen in the answers of question no. 1 and 3. Individual questions are often weighted more heavily in questionnaires. However, the results indicate that a weighting of individual answer options should be undertaken in an evaluation of MS questionnaires, in future.

The TC classification (using the Q-Score threshold) achieves an accuracy of 72.2%, see Table IV (30.4% correct *resistant* + 41.8% correct *susceptible*). The accuracy is thus slightly higher than the best single-question-classification using the question no. 8 (see 69.3% on Table III). TC falsely classified 10.1% of the subjects as *resistant* (see Table IV). Such a classification arises when passengers clearly overestimate their own MS resistance answering the questionnaire. It might be possible that the subjects have no, little, or no recent experience with MS situations. However, overestimating passengers can be an issue for future vehicles, which, would expect a *resistant* passenger and not apply prevention strategies, resulting in sudden and unexpected MS symptoms. The opposite group of passengers who are falsely classified as *susceptible* (17.7%) can be handled more easily by an intelligent vehicle. If the vehicle detects that its own classification was wrong, e.g., due to objective indicators, it can switch off MS countermeasure strategy and continue normal driving.

Machine learning approaches show the potential to map the relationships of individual answer options and thus obtain further information from the questions. Although the median accuracy of all pre-learned SVCs is 69.0%, the best SVC achieved 87.1% accuracy, see Table V (35.5% correct *resistant* + 51.6% correct *susceptible*). This SVC also has some problems with 9.7% of the subjects (overestimating themselves) being misclassified as *resistant*, similar to 10.1% of TC, see Table IV. On the other hand, only 3.3% of the subjects were misclassified as *susceptible*, which is an improvement of the machine-learning approach compared to the TC, misclassifying 17.7%. Consequently, the machine-learning approach finds combinations in the contradictory responses of the subjects that indicate a MS resistance and enable a better classification result.

Because some of the answer options only given by a very small number of subject (see Table II, e.g., 3rd question answer option "9-10"), it should be checked by additional measurements whether the calculated MS incidence is correct. Additionally, the effect of pre-experiment questionnaires on the experimental results cannot be ruled out, see [28]. Our results suggest, that a classification of car sickness susceptibility is possible using MS questionnaires, similar to [24] showing that questionnaire scores indicate the MS susceptibility of participants in virtual reality. Since the sample refers to 79 people between the ages of 18 and 35, an extension to older people would be useful to see if there is an effect of age on the classification or self-evaluation. The intensity (SMSL) and the onset (T2S) of MS also show high correlation coefficients with the Q-Score (see Fig. 4B and 4C) and correlate with the results presented in [23]. However, the data show a high variance: E.g., subjects with a Q-Score of 6 rated a SMSL between 4 to 10 (see Fig. 4B) and reached a T2S between 15 to 60 minutes (see Fig. 4C). Routes with stronger driving dynamics ($\text{study}^{A,C}$) provoke a larger SMSL and lower T2S (see Fig. 4B and 4C, green and red markers), compared to a softer drive (study^{B} marked in blue). Resulting, questionnaire based MS models show potential for improvement through combination with MS models based on driving dynamics.

Nevertheless, at the moment, models based on passenger information, offer a simpler and currently more reliable solution than models based on driving dynamics or physiological data. Probably, also the combination of physiological and driving data will not be able to gain reliable results without taking additional passenger information into account.

V. Conclusion

Eight questions asking about MS experience enable a successful classification of 72.2% of car passengers in MS *susceptible* or *resistant* using a threshold classification. Machine learning methods, approximating the relationship of the individually given answers, might allow to classify even more (in our case up to 87.1%) passengers correctly. Such pre-classification of passengers, using self-evaluation, could initialize MS models or avoidance strategies in advance and improve their accuracy or effectiveness. Intelligent vehicles would thus lose less time for adjusting to a new passenger in the future and increase the driving comfort significantly.

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References

[1] J. F. Golding, "Motion sickness susceptibility", Autonomic Neuroscience: Basic and Clinical, vol. 129, pp. 67-76, 2006.
[2] J. Iskander, M. Attia, K. Saleh, D. Nahavandi, A. Abodakr, S. Mohamed, H. Asadi, A. Khosravi, C. P. Lim and M. Hossny, "From car sickness to autonomous car sickness: A review", Transportation Research Part F, vol. 62, pp. 716-726, 2019.
[3] T. Wada, "Motion Sickness in Automated Vehicles", In Proc. 13th International Symposium on Advanced Vehicle Control, 2016, pp. 169-176.
[4] J. F. O'Hanlon and M. E. McCauley, "Motion sickness incidence as a function of frequency and acceleration of vertical sinusoidal motion", Aerospace Medicine, vol. 45, pp. 366-369, 1974.
[5] J. T. Reason, "Motion sickness adaptation: a neural mismatch model", Journal of the Royal Society of Medicine, vol. 71, pp. 819-829, 1978.
[6] C. M. Oman, "A Heuristic Mathematical Model for Dynamics of Sensory Conflict and Motion Sickness Hearing in Classical Musicians", Acta Oto-Laryngologica, suppl. 392, pp. 4-44, 1982.
[7] W. Bles, J. E. Bos, B. de Graaf, E. Groen and A. H. Wertheim, "Motion Sickness: Only one provocative conflict?", Brain Research Bulletin, vol. 47, no. 5, pp. 481-487, 1998.
[8] J. E. Bos and W. Bles, "Modelling motion sickness and subjective vertical mismatch detailed for vertical motions", Brain Research Bulletin, vol. 47, no. 5, pp. 537-542, 1998.
[9] N. Kamiji, Y. Kurata, T. Wada and S. Doi, "Modeling and Validation of Carsickness Mechanism", In Proc. SICE Annual Conference, 2007, pp. 1138-1143.
[10] B. Buchheit, E. N. Schneider, M. Alayan, F. Dauth and D. J. Strauss, "Motion Sickness Prediction in Self-Driving Cars using the 6DOF-SVC Model", IEEE Transactions of Intelligent Transportation Systems, vol. 23, no. 8, pp. 13582-13591, 2022.
[11] S. Salter, C. Diels, P. Herriotts, S. Kanarachos and D. Thake, "Motion sickness in automated vehicles with forward and rearward facing orientations", Applied Ergonomics, vol. 78, pp. 54-61, 2019.
[12] H. Konno, S. Fujisawa, T. Wada and S. Doi, "Analysis of Motion Sensation of Car Drivers and Its Application to Posture Control Device", In Proc. SICE Annual Conference, 2011, pp. 192-197.
[13] O. X. Kuiper, J. E. Bos and C. Diels, "Looking forward: In-vehicle auxiliary display positioning affects carsickness", Applied Ergonomics, vol. 68, pp. 169-175, 2018.
[14] O. X. Kuiper, J. E. Bos, C. Diels and E. A. Schmidt, "Knowing what's coming: Anticipatory audio cues can mitigate motion sickness", Applied Ergonomics, vol. 85, 2020.

[15] Y. Sawada, Y. Itaguchi, M. Hayashi, K. Aigo, T. Miyagi, M. Miki, T. Kimura and M. Miyazaki, "Effects of synchronized engine sound and vibration presentation on visually induced motion sickness", Scientific Reports, vol. 10, no. 1 ,2020

[16] T. Wada, H. Konno, S. Fujisawa and S. Doi, "Can Passengers' Active Head Tilt Decrease the Severity of Carsickness? Effect of Head Tilt on Severity of Motion Sickness in a Lateral Acceleration Enviroment", Human Factors, vol. 54, issue. 2, pp. 226-234, 2012.

[17] J. Maculewicz and P. Larsson, "Intuitive and subtle motion-anticipatory auditory cues reduce motion sickness in self-driving cars", Int. J. Human Factors and Ergonomics, vol. 8, no. 4, pp. 370-392, 2021

[18] J. T. Reason and J. J. Brand, "Motion Sickness", Academic Press, London, 1975.

[19] M. Turner and M. J. Griffin, "Motion sickness in public road transport: the relative importance of motion, vision, and individual differences", British Journal of Psychology, vol. 90, pp. 519-530, 1999.

[20] E. N. Schneider, B. Buchheit, P. Flotho, M. J. Bhamborae, F.I. Corona-Strauss, F. Dauth, M. Alayan, F. Dauth and D. J. Strauss, "Electrodermal Responses to Driving Maneurvers in a Motion Sickness Inducing Real-World Driving Scenario", IEEE Transactions on Human-Machine Systems, vol. 52, no. 5, pp. 994-1003, 2022.

[21] J. Smyth, S. Birrell, R. Woodman and P. Jennings, "Exploring the utility of EDA and skin temperature as individual physiological correlates of motion sickness", Applied Ergonomics, vol. 92, 2021.

[22] T. Irmak, D. M. Pool and R. Happee, "Objective and subjective responses to motion sickness: the group and the individual", Experimental Brain Research, vol. 239, pp. 515-531, 2021.

[23] J. F. Golding, "Motion sickness susceptibility questionnaire revised and its relationship to other forms of sickness", Brain Research Bulletin, vol. 47 , no. 5, pp. 507-516, 1998.

[24] J. F. Golding, A. Rafiq, and B. Keshavarz, "Predicting Individual Susceptibility to Visually Induced Motion Sickness by Questionnaire" frontiers in Virtual Reality, vol. 2, 2021,

[25] M. J. Bhamborae, P. Flotho, A. Mai, E. N. Schneider, A. L. Francis and D. J. Strauss, "Towards Contactless Estimation of Electrodermal Activity Correlates". Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2020, pp. 1799–1802, 2020.

[26] B. Buchheit, E. N. Schneider, M. Alayan and D. J. Strauss, "Motion Sickness related Route Profiling for Evaluation of the Sensory Conflict in Real-Driving Studies", Annual International Conference of the IEEE Engineering in Medicine and Biology Society 2022, pp. 816–819, 2022.

[27] J. E. Bos, S. N. MacKinnon and A. Patterson, "Motion Sickness Symptoms in a Ship Motion Simulator: Effects of Inside, Outside, and No View", Aviation, Space and Environmental Medicine, vol. 76, no. 12, pp. 1111-1118, 2005.

[28] S. D. Young, B. D. Adelstein and S. R. Ellis, "Demand Characteristics in Assessing Motion Sickness in a Virtual Environment: Or Does Taking a Motion Sickness Questionnaire Make You Sick?", IEEE Transactions on Visualization and Computer Graphics, vol. 13, no. 3, pp. 422-428, 2007.

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