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Perceived Comfort Prediction by Occupants Package Layout and Vehicle Seat Engineering Factors

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ABSTRACT

Perceived comfort is one of the most important factors in automotive engineering, but it is also a very complex and difficult to define. Consumer survey and expert evaluation is the mostly used to determine the subjective comfort level. As technology advances, engineering becomes increasingly important during the design review phase. The aim of this study is to define a conceptual framework of the consumers' perceived comfort, which is related to various engineering factors, and to develop a ML-model (Machine Learning Model). The conceptual framework from various factors to perceived comfort was introduced to develop a ML-model. Three major parts – occupants package layout, seat shape, and seat properties - were considered as objective inputs to predict perceived comfort. The predicted value CI which stands for Comfort Index were calculated by more than 100 subjective questions. Sedans and SUVs from various segments were included in the dataset for development of the machine learning model. Generally used three method – Linear Regression, Ridge Regression, and Elastice Net – were used to develop a ML model. Totally, 11 independent variables were survived during the development of the machine learning model. The R-square values of the models were from 0.623 to 0.651. The RMSE was distributed from 0.132 to 0.389. Ridge regression model showed the minimum RMSE values, 0.132 and the Linear regression model showed the maximum R-square value, 0.651. And, an absolute coefficient values of the model were from 0.004 to 0.629.

Keywords: Vehicle seat comfort, Human system integration, System engineering, Machine learning model

INTRODUCTION

Past studies have been interested in finding, clarifying, and defining the relationship between objective measures from vehicle seat itself and subjective measures from consumer. Body pressure distribution is the mostly considered objective measures. Because the body pressure is well reflected and interacted tools between vehicle seats and human body/posture (Naddeo et al., 2018; Zhongliang et al., 2009; Kolich & Taboun, 2004; Wegner et al., 2020).

Seat engineers and researchers focused on how much deflected into the seat cushion and seat back. Because the amount of the deflection into the seat represents lots of hidden facts like as feeling of hardness, support, sinking, and uniformly support as well. The amount of deflection is mainly measured through BPD, which represents the interaction between the occupants or the dummy and the vehicle seat and indenter. Some engineers perform a CAD work to determine and predict the comfort level with OSCAR and/or their own human dummy.

Another research trend in vehicle (seat) comfort is CAE-based comfort engineering through the development of the Human body modelling. Simulating and evaluating the comfort level using the provided human body model is one important trend for comfort engineering and research. It mostly focused finding the mechanical properties of the seat and prove occupant posture and their sitting location. Developing a finite element human body model is, also, the major roots of CAE-based comfort research (Ile et al., 2014; Choi et al., 2006).

The majority of vehicle-level seat comfort research concerns vibration ride comfort. SEAT index is mainly used to define the level of vehicle ride comfort quality under driving condition (Jang, 2005; Aniruddha, 2019).

However, due to the complexity of the comfort itself, it was difficult matters that defining and determining the level of the (vehicle) seat comfort. This is why many researchers and engineers rely on subjective surveys. There is a problem with evaluations that rely on human emotions because they cannot guarantee accuracy and requires large number of participants. Recently, research has been conducted on algorithms that define and explain overall comfort levels. It suggested well-defined conceptual frame which all included vehicle, seat itself, and occupant. And conducted to predict comfort levels using these factors (Mike, 2008; Sunwoong, 2023).

The aim of this research is to define a conceptual framework of the consumers' perceived comfort, which is related to various engineering factors, and to develop a ML-model.

METHOD

Overall comfort levels were affected by both psychological and physical factors. However, it is difficult to define and/or explain with mathematical functions to psychological factors. It was performed that defining the conceptual framework of the consumers' perceived comfort level from various physical factors like as seat aspects, vehicle environment, and interaction between occupants and seat.

Based on this conceptual framework, it was conducted that a developing the database structure and gathering the dataset.

From a seat mechanical properties aspect, seat mechanical properties were gathered from 8 mechanical test methods – initial and long-term SLD (Static Load Deflection), HSLD (Head restraints SLD tests), HP (Hardness Profile), LSP (Long-term Sitting Properties), Impact Damping Tests, Vibration Transmissibility, and SBC (Seat Back Compliance) as well.

Data which can describe occupants package layout was gathered through Benchmark SgRP process (SAE J3103), from a vehicle environment aspect.

General seat dimensions and interacted dimensions between SAE J826 and STO (Seat Trim Outline) dataset was gathered by SAE J2732 and our internal procedure, as interaction with dummy/human aspects.

Sedans and SUVs from various segments were included in the dataset for development of the machine learning model.

Four methods were considered to develop the ML model: Linear regression, Ridge regression, Elastice Net, and Lasso. However, finally, the Lasso model was removed due to the quite lowered R-squared value of the Lasso model.

RESULTS

At first, 23 factors were converted and calculated from 13 major test methods from 3 major comfort aspects. Generally used values from each method and some internal specific values were used to determine the 23 factors. Finally, the 11 major factors survived after statistical analysis. The consumers' perceived comfort is predicted by these 13 major factors. These are illustrated below Figure 1. Where the CI (Comfort Index) value, perceived comfort, is overall values for each comfort from a perceived comfort aspects like as feeling of support, irritation, pressed, firmness, sinking, and so forth.

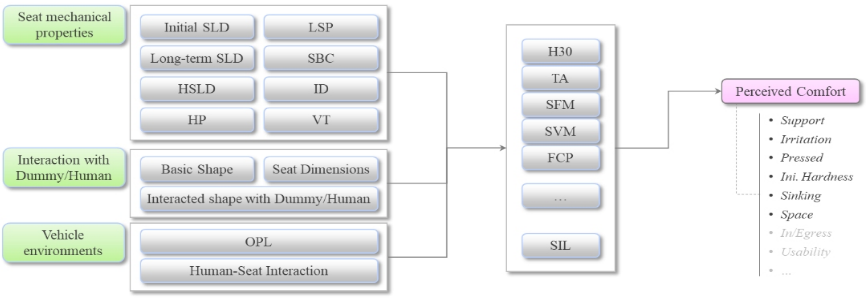

Figure 1: Conceptual framework from objective dataset to perceived comfort.

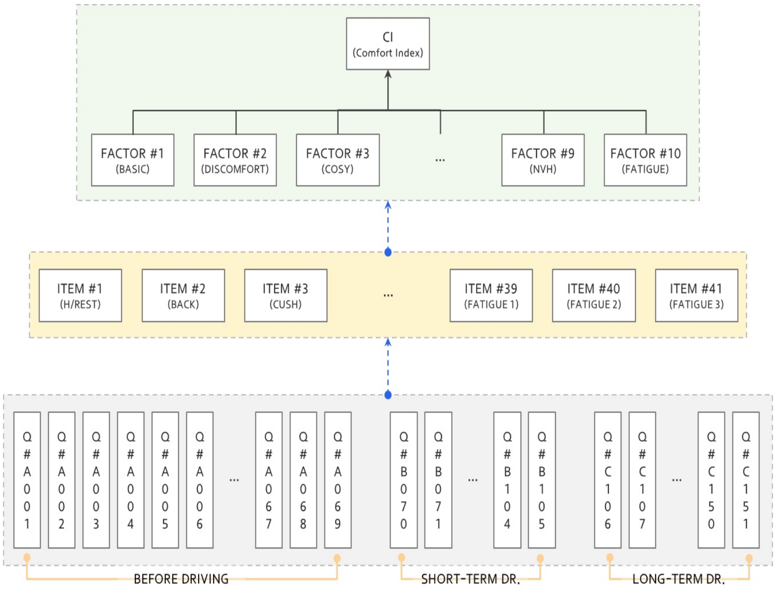

Figure 2: Basic conceptual framework to calculate a CI index by consumers' subjective response (Sunwoong, 2023).

Figure 2 showed that the basic conceptual model to calculate CI of a vehicle seat from subjective response. At first, the evaluated value for 41 items were calculated by 151 subjective responses. Finally, an overall comfort index was calculated by scores of these 41 items.

Table 1. Effects of multicollinearity by VIF.

Factors	**H30**	**SVM**	**FCP**	**FBP**	**HLRC**	**HLRB**
[1]**VIF**	4.64	4.34	2.43	1.52	3.32	3.62
Factors	**USIC**	**USIB**	**ALS**	**SIS**	**SIL**	-
VIF	7.78	7.26	3.11	4.32	5.56	-

[1]VIF : Variance Inflation Factor

Linear correlations between all independent variables were confirmed, and factors with high linear correlations between independent variables were first removed.

H30 and other 10 factors were survived after iteration field from developing the ML model and checking the validity for all three ML methods.

As shown in Table 1, all the survived factors have no problem with multicollinearity by calculating the VIF.

Developed three ML models showed relatively high R-squared value, 0.623 ~ 0.651. And, showed relatively low root mean square errors from 0.132 to 0.374 (Table 2). All three models developed were found to have similar predictive performance.

Table 2. R-square value and RMSE (root mean squared error) of developed ML model.

Factors	**Linear Regression**	**Ridge Regression**	**Elastice Net**
R-square	0.651	0.628	0.623
RMSE	0.374	0.132	0.389

DISCUSSION AND CONCLUSION

It was suggested that the predicting the comfort score by occupant package layout and vehicle seat engineering factors, and the predictive model showed quite good performance (Kim, 2023).

In this study, it attempted to develop a machine learning model using a wider range of factors. All three developed ML model showed the good validation of R-square values and RMSE.

As a result of analysis of the coefficient values, it was confirmed that the sinking factor had a much lower impact on the CI than other factors.

H30, USIC, ALS were the highest impact factors to CI for negative direction.

One result is that the influence of sinking factors was found to be very low. The amount of change in the data itself may have been small, but since the sinking factor is a factor that is perceived through relatively long-term driving, it may have been difficult for passengers to distinguish the differences in sinking amount.

H30 is one of the highest impact factors to CI for negative direction. This means that as the H30 value increases, the seating position also higher accordingly. The recommended joint angle is that the least discomfort was within a neutral range for the tissue stresses are minimized (Keegan, 1953; Reed, 2000). The higher sitting position can lead to further than a neutral range of trunk-thigh angle.

Occupants prefer to more uniformly support on the seat cushion, feeling of seat cushion and back padding. Occupant seems to prefer feeling properly supported by a seat cushion rather than feeling elasticity when sitting.

Table 3. Comparison of the coefficient's values of developed ML model.

Factors	Linear Regression	Ridge Regression	Elastice Net
H30	−0.574	−0.578	−0.431
SVM	−0.167	−0.176	−0.033
FCP	0.278	0.279	0.200
FBP	0.112	0.122	0.119
HLRC	0.251	0.267	0.184
HLRB	−0.250	−0.271	−0.196
USIC	−0.617	−0.629	−0.413
USIB	0.326	0.346	0.142
ALS	−0.424	−0.456	−0.325
SIS	−0.004	−0.015	0.030
SIL	0.008	0.090	0.000

DEFINITIONS/ABBREVIATIONS

SLD – Static Load Deflection
HSLD – Head restraint SLD test
HP – Hardness Profile
LSP – Long-term Sitting Properties
ID – Impact Damping tests
VT – Vibration Transmissibility
SBC – Seat Back Compliance
STO – Seat Trim Outline
H30 -Vertical distance between heel point and SgRP
SVM – Amount of Seat Vertical Movement
FCP – Feeling of seat Cushion Padding
FBP – Feeling of seat Back Padding
HLRC – Hysteresis Loss Ratio of seat Cushion
HLRB – Hysteresis Loss Ratio of seat Back
USIC – Uniform Support Index of seat Cushion
USIB – Uniform support Index of seat Back
ALS – Area of Lumbar Support
SIS – Sinking Index during Short-term driving.
SIL – Sinking Index during Long-term driving.

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