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ARTIFICIAL NEURAL NETWORKS AS A TOOL FOR ERGONOMIC EVALUATIONS OF VEHICLE CONTROL PANELS

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Abstract

Unreadable and inconveniently arranged instruments make it difficult for the driver to accurately read signals and understand the relayed information. They can distract the driver and prolong response times, thus posing a risk to traffic safety. Designers also have to account for customer expectations, including a demand for esthetically appealing dashboards that incorporate vast amounts of data in limited space since such dashboards appear to be maximally adapted to the driver's needs. However, attractive dashboards are not always adapted to human perceptual abilities. A neural model was developed in the study to objectively assess dashboard ergonomics in passenger cars. The data were used to determine the correlations between subjective driver impressions and the functionality and ergonomics of dashboards evaluated objectively based on the adopted criteria. With the best-learned networks, 3 conformance classes were obtained for the predicted cases. However, taking into account the ±1 class, as many as 3 of the preserved ANN gave correct answers in all 6 cases.

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List of acronyms

ANN – Artificial Neural Networks
EBEC – Evaluation Based on Ergonomic Criteria
MLP – Multilayer Perceptron
RBF – Radial Basis Functions
SIE – Subjective Interval Evaluation

Introduction

The control process is a dialogue between the vehicle (machine) and the operator (driver). From this point of view, factors that promote reliable flow of information, data processing and optimal decision making play the most important role in the control process (MARCUS 2015). Humans and machines interact through computerized devices which are attuned to the human sensory system and through control systems which collect information about motor performance. Information is received via receptors or sensory organs, and decision-making is influenced by the operator's ability to accurately read signals and understand the relayed information.

The human sense of sight provides approximately 80% of all information about the surrounding world. The second most important sense is hearing, whereas the remaining senses play a less significant role. During driving, visual stimuli are the key determinants of the driver's safety as well as the safety of other traffic participants. A well-designed and functional dashboard provides the driver with rapid and accurate access to visual information and plays a very important role in this process. Solutions that obstruct the smooth flow of information can distract the driver, prevent reliable assessment of the driving situation and prolong response times, which poses a risk to traffic safety (BHATTACHARYA, BISHT 2021, GIBSON 2016, KLAUER 2014, OU et al. 2013).

There are no universal guidelines for designing vehicle dashboards. However, analyses of human responses to signaling devices in the control process provide valuable inputs for dashboard design (BURNETT, POTTER 2001, CARVALHO, SOARES 2012, GIBSON et al. 2016, GUKOUSKOS et al. 2014, LANDAU 2002). The significance of that information is evaluated instinctively by the designer. Designers also have to account for the growing demand for esthetically appealing dashboards, and they are faced with the challenging task of designing dashboards that match the unique style of a vehicle brand or model and incorporate vast amounts of data in limited space. The resulting solutions do not always contribute to the reliable receipt of sensory data, but they increase the appeal of new vehicles as products that are maximally adapted to the driver's needs. Many drivers are unaware that attractive dashboards are not always perfectly adapted to their perceptual abilities (BHATTACHARYA, BISHT 2021, FRANCOIS et al. 2021).

There is a lot of research into the design of cars and their individual components. However, it is difficult to find current research that focuses on the design of dashboards that take into account the needs and capabilities of users. However, many researchers emphasize the importance of incorporating behavioral data into engineering design. (NANDY et al. 2022, RAHMAN et al. 2019, SHA et al. 2015, TANG et al. 2020, YU et al. 2016)

In recent years, one of the most interesting studies into dashboard design was conducted by GIBSON et al. (2016). The authors surveyed 35 drivers who were asked to evaluate various aspects of dashboard ergonomics in a questionnaire containing 50 questions. Most drivers positively reviewed the physical ergonomics of their vehicles, but they also reported a host of problems. More than a third of the respondents claimed that excessive data displayed on the control panel caused distraction during driving, whereas more than half of the surveyed subjects were unsure of the purpose of some of the displays. Nearly half of the respondents would redesign their dashboards to a certain extent. It should be noted that more than 70% of the participants were drivers with less than 5 years' driving experience, and their dashboards were relatively simple. The respondents were also asked to evaluate their own cars; therefore, their opinions were highly subjective. Despite the above, the study provides valuable tips for improving the ergonomic design of vehicle dashboards. In another study (CARVALHO, SOARES 2012), the ergonomics of three vehicle cockpits with basic, average and luxury features were analyzed based on observations, photographs, notes, an open interview, a questionnaire and user tests. The study also revealed various problems in every analyzed case. The results were used to formulate recommendations for dashboard design. The usability of car dashboard displays for elderly drivers has also been researched (BALDWIN 2002, KIM et al. 2011, YANG, COUGHLIN 2013). Other researchers argue that the aesthetic forms and functional features of a product are certainly important, the decision to buy or not to buy a product often depends on more, namely, the experience or feel of use (NANDY, GOUCHER-LAMBERT 2022, PARK et al. 2019, TOVARES et al. 2014).

Artificial Neural Networks (ANNs) were used to analyze subjective impressions regarding the ergonomics of various vehicle dashboards. Artificial Neural Networks are sets of interconnected objects (neurons). Every connection is assigned a specific weight, and weights are modified during ANN training. As a result, ANNs are sets of objects (neurons) that process data by serial-parallel transmission (depending on the selected topology and network type) (YEGNANARAYANA 2009). Artificial Neural Networks are inspired by biological neural networks in the human brain, which explains their name. The operations of ANNs are based on the black box model. The model relies on the correlations between input and output data in the training process, but it does not take the form of a mathematical equation (PATTERSON 1995, ZHANG 2018). Artificial Neural Networks model complex non-linear processes, including physical phenomena and processes that have not been fully explored. They are also used for prediction, classification (WANG et al. 2015, YADAV, CHANDELL 2014), modeling dynamic phenomena in process and electric engineering, as well as for pattern, face and image recognition (ALMONACID et al. 2011, KRÓLCZYK et al. 2008, KWATER 2001, RUTKOWSKA et al. 1997, RUTKOWSKI et al. 1996). Artificial Neural Networks are also useful tools for modeling and solving designs problems. ANN found applicationin order to generate designs of new car that elicit targeted style goals from consumers (TSENG et al. 2011).

In the literature, they have been applied to predict the risk of driving operations (OU et al. 2013), monitor driver alertness (SWINGLER, SMITH, 1996), evaluate the comfort of automobile seats (KOLICH et al. 2004), analyze driver's cognitive workload levels (TJOLLENG et al. 2017) and anticipate the health risks associated with whole body vibration in mining truck drivers (RAHIMDEL et al. 2017). It is also worth mentioning groundbreaking works in which ANN was used to determine the level of discomfort at work (HAJ MAHMOUD et al. 2021), the development of safety management systems in a production company (MENANNO et al. 2021), and research on optimizing the „positioning layout of central control screen" in vehicles (MA et al. 2021).

Artificial Neural Networks have numerous applications in ergonomics research, and they have been used to predict the anthropometric parameters of children for school furniture design (AGHA, ALNAHHAL 2012) and to forecast workplace hazards and safety-related behaviors (GHASEMI et al. 2017).

Aim and scope of the study

The aim of this study was to develop a tool for rapid and objective evaluations of dashboard functions based on ergonomics principles and drivers' subjective opinions. The criteria for evaluating dashboard ergonomics in passenger cars were developed. Selected dashboards were analyzed based on the adopted criteria. Dashboard functions were then evaluated subjectively by drivers in a questionnaire designed for the needs of the study.

As shown in the introduction, the literature lacks methods to objectively assess the functionality of dashboards. In this situation, the use of Artificial Neural Networks was proposed as a new tool. ANNs were trained on a set of test results according to ergonomic criteria and a set of answers obtained from drivers in surveys. For the research, the following research hypothesis was formulated: the responses obtained from a well-learned ANN may constitute an objective assessment of the quality of the dashboard, due to its functionality related to the arrangement and readability of signaling devices.

In the available literature, no solution to a problem similar to the one presented in this study has been found. The developed method of objective assessment of dashboards is original.

Methods

In the first stage of the study, dashboards in selected passenger cars were evaluated, based on the ergonomic criteria developed by the authors of the study based on a review of relevant literature (Evaluation Based on Ergonomic Criteria, EBEC) (BASTIEN, SCAPIN 1992, KUMAR et al. 2002, WULFF et al. 1999). The development of criteria for the assessment of product ergonomics is an important solution that is used in science. It is used in situations where unambiguous criteria do not exist or are scattered. Defining them is already a help for potential designers (LIN et al. 2019, LIU et al. 2020).

This approach supported the identification of the top 11 criteria for assessing dashboard functions relating to the location and legibility of dashboard displays and the displayed information. Every criterion was evaluated on a grading point scale with intervals of 0.5 points, where 0 points denoted the absence of functional problems. The maximum scores differed across the evaluated criteria. Dashboards that scored 0 points were most functional, and dashboards that scored the maximum number of 27.5 points were least functional. The scores were awarded based on direct evaluations of dashboards in 44 passenger cars.

The next stage of the study involved a survey questionnaire. One of the stages in many ergonomic studies is user surveys. It is difficult to otherwise define their preferences, which are essential for design (LIN et al. 2019).

Based on detailed photographs of dashboards in the 44 analyzed vehicles, the participants were asked to select a response that best matched their impressions regarding dashboard functionality and the ease of controlling the instrument panel. All components that were assessed during the EBEC were presented in photographs and, if necessary, less legible solutions were additionally presented in enlarged photographs. The respondents graded their answers on a five-point scale where: A – completely unsatisfactory, B – not satisfactory, C – acceptable, D – quite functional and I could use it in my car, E – highly functional and I would like to have it in my car. The questionnaire was completed by 40 drivers with 1 to 40 years' of driving experience. All respondents were daily drivers, and occasional drivers were not included in the study. Among the participants were 12 women and 28 men aged 27 to 48.

In the next stage of the research, a neural model was developed to objectively assess dashboard ergonomics based on the functionality, location and legibility of dashboard displays. To determine the correlations between driver impressions and the analyzed solutions, the neural model was built based on the results of the EBEC of 44 dashboards and the results of the survey questionnaire which produced more than 1,760 subjective evaluations.

Results and data analysis

Evaluation based on ergonomic criteria (EBEC)

The EBEC scores for the evaluated dashboards ranged from 2.5 to 11 points, where 2.5 points denoted dashboards that were most functional in view of the adopted criteria. The average score for 44 dashboards was 6.45 points. The proportions [%] of scores awarded to each criterion are presented in Figure 1.

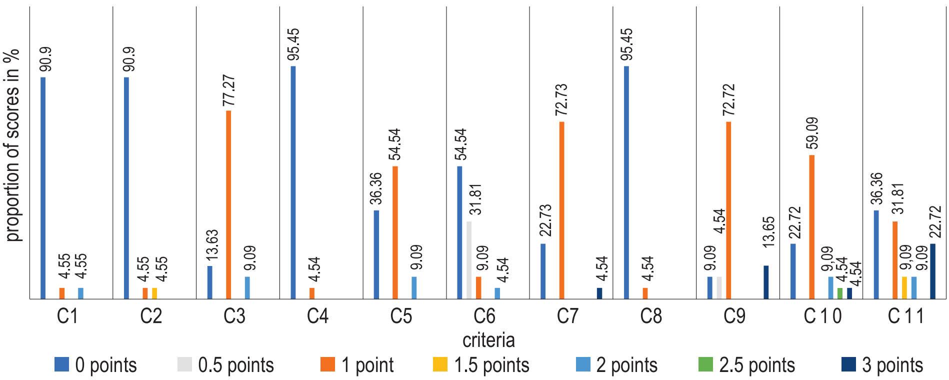

Fig. 1. Proportions of scores for each criterion (in %)

Criterion C1 was the location of the main control panel on the dashboard. The panel was regarded as most functional when situated in the main display zone in the horizontal plane, perpendicular to the axis of the driver's body at an angle of ±15°. In 90.90% of the cases, this criterion was adequately met and was awarded 0 points. The remaining dashboards scored 1 and 2 points (4.55% each).

Criterion C2 was the type and shape of the speedometer, and analog speedometers with a round face were regarded as most ergonomic. This solution was present in 90.90% of the cases, and the remaining speedometers scored 1 and 1.5 points (4.55% each).

Criterion C3 was the location of the main speedometer. To best accommodate human perceptive ability, the main speedometer should be located in the center of the main display zone, at eye level in the horizontal plane, below eye level in the vertical plane at an angle of ≤30°, with a head tilt angle of ≤5° relative to the vertical axis of the driver's body. The above parameters were satisfied in

13.63% of the cases. In 77.27% of the cases, dashboards scored 1 point, mainly because the speedometer was situated on the right or left side of the main display zone. The remaining 9.09% of the cases scored 2 points.

Criterion C4 was the linearity of the speedometer scale which influenced the accuracy of speed readouts. Only two options were available: a linear scale which received 0 points in 95.45% of the tested dashboards, and a non-linear scale which received 1 point in 4.54% of the cases.

Criterion C5 was the scale interval on the speedometer. Speedometer scales with smaller intervals corresponding to a speed of 5 km/h and larger intervals corresponding to a speed of 10 km/h were regarded as the optimal solution, and these parameters (0 points) were met in 36.36% of the analyzed cases. 54.54% of dashboards scored 1 point, and 9.09% dashboards scored 2 points. Intervals corresponding to a speed of 20 km/h and other features obstructing accurate speed readouts detracted from the score.

Criterion C6 was the marking on speedometer scales which also influenced the accuracy of speed readouts. Speedometers with number marks every 20 km/h or every 10 km/h (if they did not compromise legibility) were regarded as the optimal solution. The respondents pointed to various factors that compromised readout accuracy, including number marks next to scale intervals inside the wheel, number marks every 50 km/h, differently-sized numbers on the same scale, and graphic obstacles. In this evaluation, 54.54% of dashboards scored 0 points, 31.81% scored 0.5 points. 9.09% scored 1 point, and 4.54% scored 2 points.

Criterion C7 was the type, shape and legibility of the tachometer. In this evaluation, 22.73% of dashboards scored 0 points, 72.73% scored 1 point, and 4.54% scored 3 points. Most often, tachometers displayed only critical values without gear shift suggestions, and the structure and location of some tachometers compromised their legibility.

Criterion C8 was the legibility and location of the fuel gauge. In this evaluation, 95.45% of dashboards scored 0 points, and 4.54% scored 1 point.

Criterion C9 was the legibility and location of the engine temperature gauge. In this evaluation, only 9.09% of dashboards scored 0 points, 72.72% scored 1 point, 4.54% scored 0.5 points, and 13.65% scored 3 points.

Criteria C10 and C11 were the legibility of information displayed by the main dashboard indicators during driving. C10 was the location of the zero point, and indicators with a similar location of the zero point were regarded as most functional. In this evaluation, 22.72% of dashboards scored 0 points, 59.09% scored 1 point, 9.09% scored 2 points, 4.54% scored 2.5 points, and 4.54% scored 3 points. C11 was the direction of dial movement in dial indicators, and dials moving clockwise were regarded as the optimal solution. In this evaluation, 36.36% of dashboards scored 0 points, 31.81% scored 1 point, 9.09% scored 1.5 points, 9.09% scored 2 points, and 22.72% scored 3 points.

The number of points scored by dashboards in every evaluated category, including the maximum individual scores for every criterion, is presented in Figure 2.

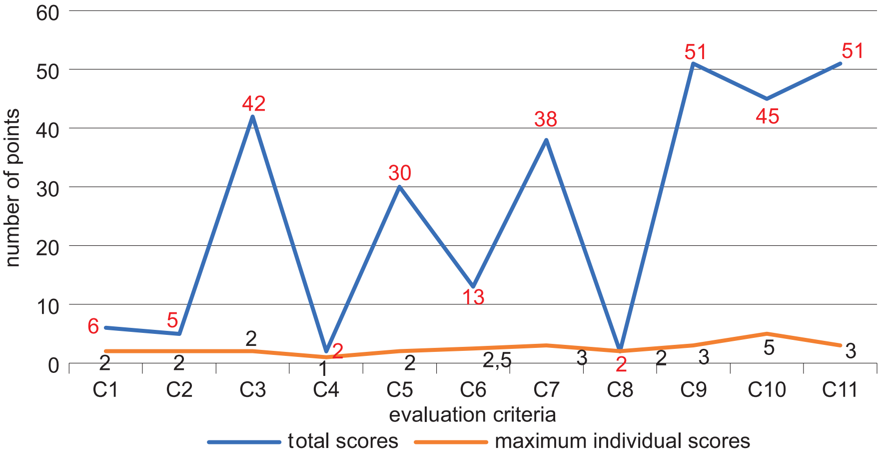

Fig. 2. Total scores and maximum individual scores for each criterion

The highest number of objections regarding the functionality of the evaluated dashboards were voiced in relation to criteria C9 and C11, where the combined score was 51 points. The following criteria also scored a high number of points in terms of solutions that compromised the legibility of the displayed information during driving: C10 (45 points), C3 (42 points), C7 (38 points) and C5 (30 points). The respondents voiced the least number of objections in relation to criteria C4 and C8 (2 points each).

The maximum individual scores were determined by the number of objections per criterion; therefore, they differed across the evaluated criteria.

Questionnaire survey

The results of the questionnaire survey were used to calculate the average scores for the tested dashboards. As described in the Methods section, the respondents graded their answers on a scale of 1 to 5 points. The results were arranged in the corresponding point intervals. The lowest average score was 1.60 points, and the highest average score was 3.91 points. The wording of questions influences the answers given by the respondents; therefore, every interval was described in words to better express the respondents' intentions. The average scores of the evaluated dashboards and the description of point intervals are presented in Table 1.

Table 1

Proportions [%] of average scores in each interval

Interval	Interval range [points]	Description	Proportion of average scores [%]
A	1.00 – 1.80	completely unsatisfactory	4.54
B	1.81 – 2.60	not satisfactory	18.18
C	2.61 – 3.40	acceptable	45.45
D	3.41 – 4.20	quite functional, I could use it in my car	31.81
E	4.20 – 5.00	highly functional, I would like to have it in my car	0

The highest number of the tested solutions (45.45%) were evaluated as acceptable and were ranked in interval C ("acceptable"). A total of 31.81% dashboards were ranked in interval D ("quite functional, I could use it in my car"). Below-average scores were awarded to 18.18% of dashboards in interval B ("not satisfactory") and to 5.54% of dashboards in interval A ("completely unsatisfactory"). None of the evaluated dashboards were ranked in interval E ("highly functional, I would like to have it in my car"). All of the tested dashboards elicited more or less critical responses from the participants. It can be assumed that 68.17% of dashboards from intervals ABC met at least average functionality standards. The most prevalent scores in every interval were compiled in a separate figure drawing. The average scores and the most prevalent scores are presented in Figure 3.

Similarly to the previous analysis, 45.45% of the tested dashboards were evaluated as "acceptable", 22.73% were ranked in interval B, 22.73% were ranked in interval C, whereas 9.09% of the analyzed dashboards were regarded as "completely unsatisfactory". Significant differences were observed in the

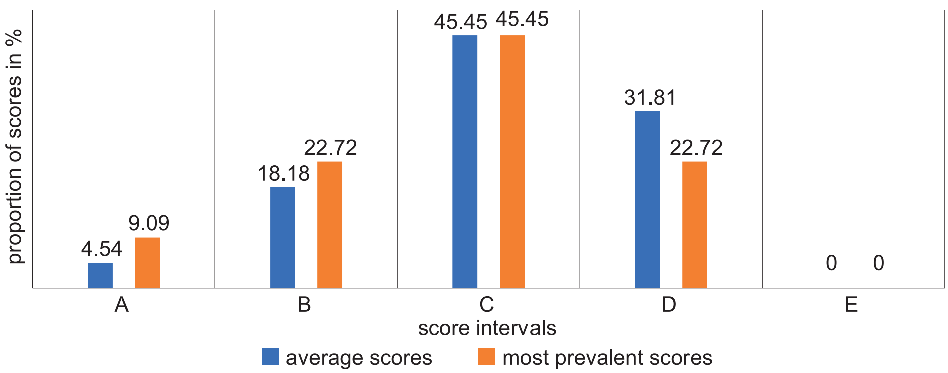

Fig. 3. A comparison of average scores and the most prevalent scores

number of extreme scores. The evaluated dashboards received the smallest number of extreme scores in interval C and the highest number of extreme scores in interval D. None of the tested dashboards were ranked in the highest interval E.

The use of ANNs in evaluations of dashboard ergonomics

In the next stage of the study, a training set for ANNs was developed based on the described dataset. The set of input data was divided into 3 parts: training, testing, and validation. Respectively: 70%, 15%, 15% of cases. MLP (Multilayer Perceptron) and RBF (Radial Basis Functions) networks with a minimum number of neurons in the hidden layer were taught. The activation function in the hidden and input layers was used: linear, logistic, tanh, exponential, and sinusoidal. The sum of squares was used as the measure of error. 1,000 nets were trained, of which the best 5 were retained. The isolated networks were used in the tests. The calculations were performed several times until a set of 5 ANNs with the best prediction was obtained for the randomly left 21st case, which was not used in the training data.

The criteria for evaluating 44 dashboards (C1-C11) were the input variables. The scores awarded by 40 drivers in a subjective evaluation were the output variables. Because the results of a research according to ergonomic criteria concerning a randomly selected 21st car were not used in the ANN learning process, 1,720 data records (43×40=1,720) were ultimately used for this purpose.

The data were divided into a training set and a test set. Different ANN topologies (MLP and RBF) with a varied number of neurons in hidden layers and different activation functions were tested. The five best-performing ANNs with the smallest training and testing errors were used in further analysis. The training and testing results for the selected ANNs, the applied training algorithms, activation functions and error functions in each ANN are presented in Table 2.

It should be emphasized that ANNs with higher learning, testing, and validation quality factors were also tested. However, the best prediction result was obtained for networks with quality factors of approx. 44-47%. This may be because higher-quality ANNs are overtrained, i.e. they represent the training cases well but lose the ability to extrapolate knowledge (generate correct answers for cases that were not used during training). Due to the 100% match of the prediction obtained for 3 ANNs at ±1 class, it was decided to leave this set of learned ANNs.

A global sensitivity analysis was performed for the selected ANNs to determine the extent to which an input variable contributes to the correct value of the output variable. The results of the sensitivity analysis are presented in Table 3.

Table 2

Selected ANNs

ANN ID	ANN name	Quality (training)	Quality (testing)	Quality (validation)	Training algorithm	Error function	Activation (hidden)	Activation (output)
1	RBF 11-23-5	43.96226	43.36283	31.85841	Raft	SOS	Gauss	Linear
2	RBF 11-23-5	43.39623	34.51327	37.16814	Raft	SOS	Gauss	Linear
3	RBF 11-22-5	35.09434	23.00885	37.16814	Raft	Entropy	Gauss	Soft ax
4	MLP 11-4-5	46.41509	45.13274	37.16814	Begs 126	Entropy	Exponen-tial	Soft ax
5	MLP 11-9-5	46.79245	44.24779	37.16814	Begs 59	SOS	Tan	Tan

Table 3

The results of a sensitivity analysis for selected ANNs and input variables

Net-work	C11	C6	C1	C2	C9	C7	C3	C8	C4	C5	C10
RBF 11-23-5	1.7575	2.6162	1.5951	1.5915	1.6313	1.5943	1.6041	1.5983	1.6027	0.8029	0.7680
RBF 11-23-5	1.7865	1.6063	1.7280	1.6495	1.6488	1.6263	1.8134	1.6073	1.6040	1.6123	1.6169
RBF 11-22-5	1.6076	1.5998	1.6229	1.6054	1.5993	1.6014	1.6037	1.5928	1.5892	1.6028	1.5939
MLP 11-4-5	6.8639	5.6679	4.2441	2.7088	2.5178	2.5136	1.9478	1.9756	2.7280	1.6032	1.3633
MLP 11-9-5	1.9383	1.6238	1.6503	1.6425	1.6477	1.6094	1.6267	1.6093	1.6031	1.6548	1.6364
Aver-age	2.7907	2.6228	2.1681	1.8396	1.8090	1.7890	1.7191	1.6767	1.8254	1.4552	1.3957

The higher the sensitivity value, the greater the influence of the input variable on the correct value of the output variable during training and testing. Sensitivity values below 1 indicate that the ANN would operate more effectively without the given variable. The sensitivity analysis was performed for all five selected ANNs and all input data. The data were arranged from the most to the least significant for most ANNs. An analysis of Table 2S indicates that variable K11, followed by variable K6 were most significant for four of the selected ANNs. These variables are related to the direction of dial movement (C11) and the speedometer indicator scale (C6). Based on the respondents' subjective opinions, these variables were most important ergonomic features of a dashboard. Variable C10 (location of the zero points on a dial display) was regarded as least significant. This criterion was regarded as least important for the prospective users.

In the next stage of the study, the influence of every variable on the value of the output variable was analyzed. Selected results are presented in Figures 4-7.

Figure 4 indicates that the most satisfactory parameters of variables C3 and C11 were classified as the optimal solution by the network with the highest sensitivity index (Table 3S). Variables with the least satisfactory parameters (2.2 and 3.5, respectively) were classified as the least desirable solution. These observations are consistent with the results of the expert evaluation. However, when the value of C11 was least satisfactory, and the value of C3 was most satisfactory, the relevant solution was still classified as suboptimal. When the value of C11 was optimal (close to 0) and the value of C3 was least satisfactory (2.2), the solution was positively evaluated. The above could imply that C3 was not an important criterion for drivers. According to the most sensitive ANN, the location of the speedometer was a less significant criterion that the direction of dial movement in a speedometer.

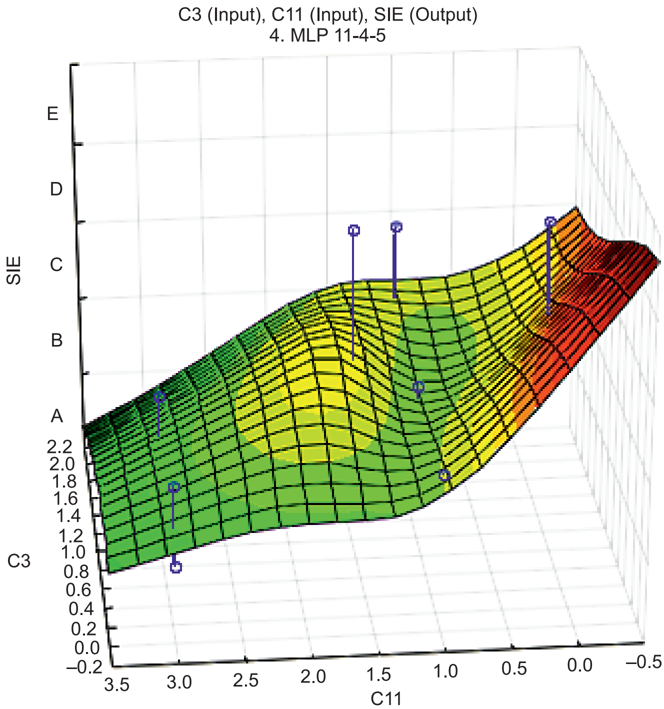

Fig. 4. A graphic representation of the correlations between subjective interval evaluation (SIE) and variables C3 and C11 for MLP 11-4-5

In the second variant (Fig. 5), variables C3 and C11 were tested with the use of network RBF 11_23_5. The solution with the least satisfactory values of C3 and C11 was also evaluated as least desirable, whereas the solution with the optimal values of these variables was evaluated as average.

The solution was regarded as optimal when C11 had the lowest (satisfactory) value and C3 had the value of 1-1.2, which implies that the speedometer is positioned on the right or left side of the main display zone. The solution where the speedometer was located outside the main display zone was evaluated as unsatisfactory. In this case, network prediction was not fully consistent with the results of the expert evaluation.

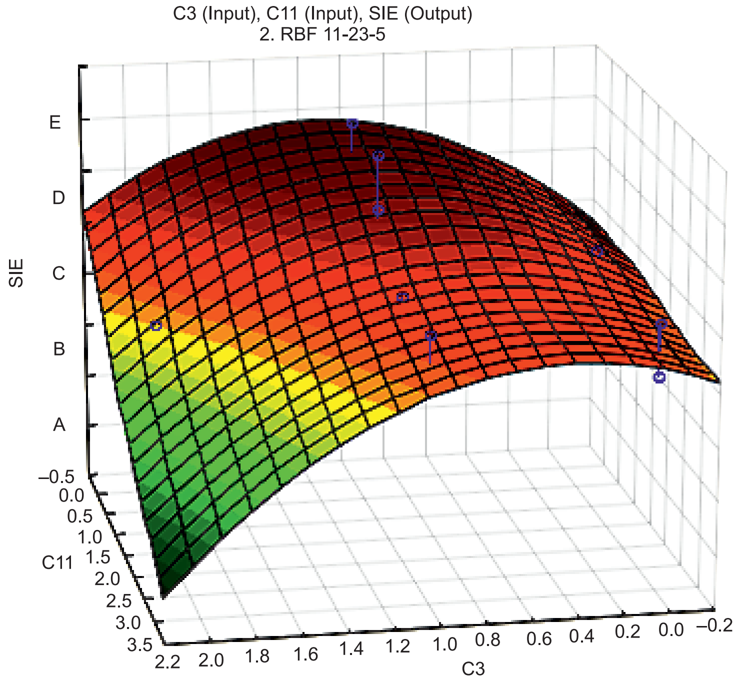

Fig. 5. A graphic representation of the correlations between subjective interval evaluation (SIE) and variables C3 and C11 for RBF 11_23_5

The results of a dashboard evaluation performed by the best network (MLP 11-4-5) based on criteria C5 and C10 are presented in Figure 6. According to the results of the sensitivity analysis, parameters C5 and C10 were least important for network prediction (sensitivity index of around 1.5). Despite the above, prediction results were consistent with expert opinions.

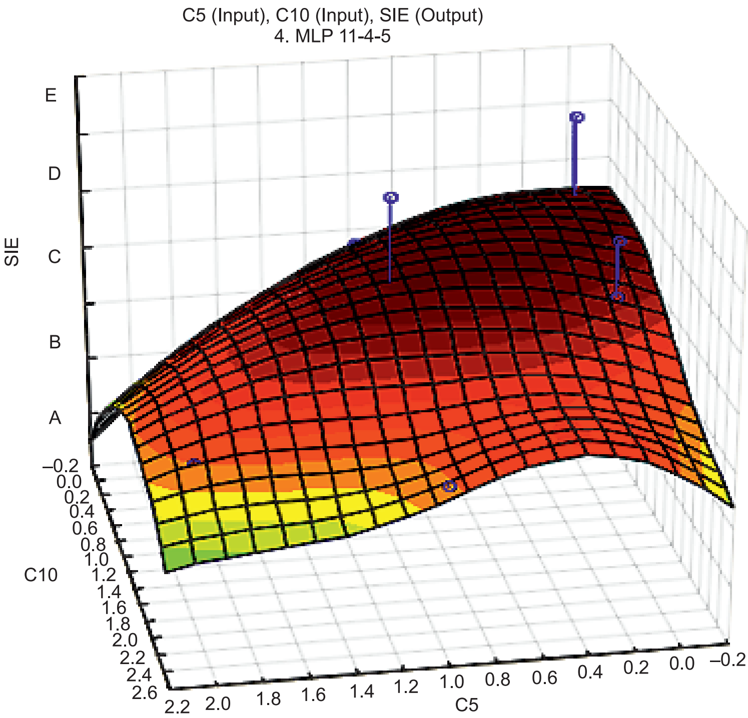

Fig. 6. A graphic representation of the correlations between subjective interval evaluation (SIE) and variables C5 and C10 for MLP 11-4-5

The solution where C5 and C10 had the most satisfactory values (close to interval D) received a better, but not the highest score. When the value of C5 was highly unsatisfactory, the influence of C10 was not important, and the solution was ranked between intervals A and B. Criterion C5 (speedometer scale interval) was least important in this evaluation.

In Figure 7, variables C5 and C10 were input into network MLP 11-4-5. This solution was evaluated as least satisfactory when the values of C5 were least satisfactory and the values of C10 were optimal. When the values of C10 were least satisfactory, the solution was evaluated as average regardless of the value of C5.

When the value of C5 was optimal, the solution was evaluated as satisfactory regardless of the value of C10. These results could indicate that C10 did not significantly influence the final score. When the values of C10 were least satisfactory, the solution was also evaluated as average regardless of the value of C5. This prediction is not fully consistent with expert opinions, which can probably be attributed to the fact that C5 is one of the several criteria evaluating the legibility of the speedometer as the main display indicator. For this reason,

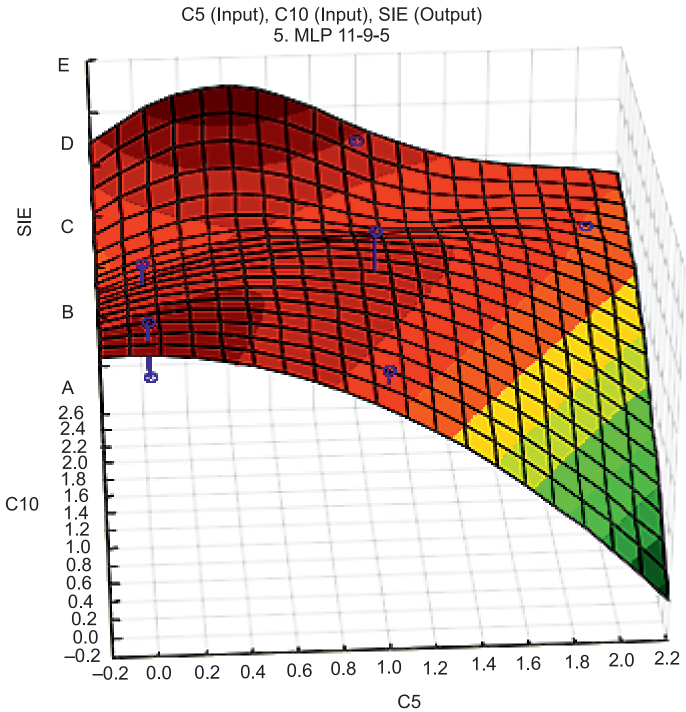

Fig. 7. A graphic representation of the correlations between subjective interval evaluation (SIE) and variables C5 and C10 for MLP 11-9-5

the correlations between criteria C5 and C6, both of which address speedometer legibility, were analyzed. The results are presented in Figure 8.

An analysis of Figure 8 indicates that the solution was most highly evaluated when C6 had the lowest (satisfactory) value, whereas the value of C5 did not significantly influence the final score. The solution was evaluated as least desirable when the values of C6 were least satisfactory. The above suggests that variable C5 did not significantly contribute to this prediction, which could explain the results noted in the previous case.

In the next stage of the study, the developed ANNs were used to evaluate dashboards that were not included in the training set. The scores awarded to the dashboard in vehicle XXI (evaluated in the questionnaires) were combined with the data describing 5 dashboards in different variants of the EBEC, from the most to the least satisfactory. Prediction results, the results of the EBEC and the average score for vehicle XXI are presented in Table 4.

The fourth network (MLP 11-4-5) produced the correct answer in three cases, and in the remaining two cases, the error spanned only one interval. An analysis of the correct answers (±1 interval) indicates that three ANNs correctly predicted all answers.

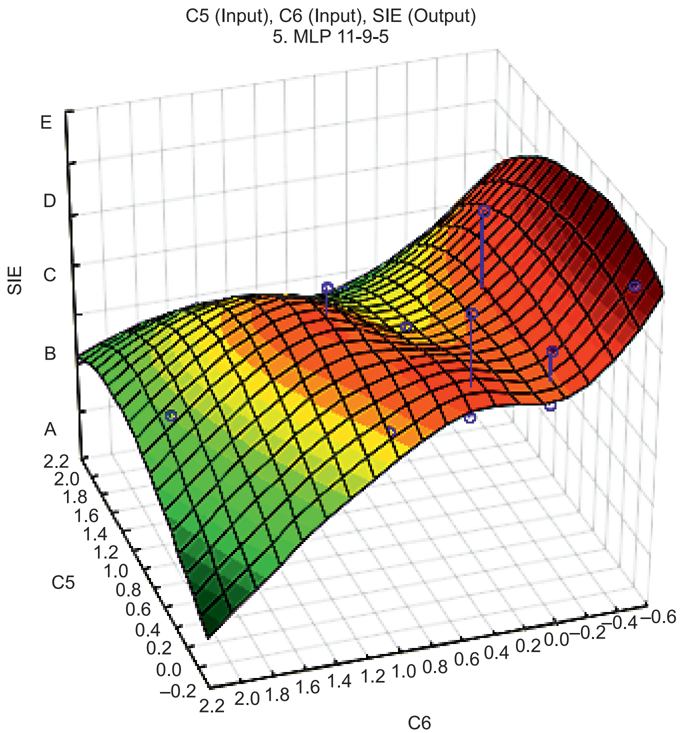

Fig. 8. A graphic representation of the correlations between subjective interval evaluation (SIE) and variables C5 and C6 for MLP 11-9-5

Table 4

Predictions for new cases in every ANN

Expert opinion	RBF 11-23-5	RBF 11-23-5	RBF 11-22-5	MLP 11-4-5	MLP 11-9-5
A	C	B	C	B	A
B	C	B	C	C	C
E	C	D	D	E	D
D	C	C	C	D	C
C	D	D	D	B	C
C	C	C	C	C	D
Consistent answers	1	2	1	3	2
Consistent answers ±1	4	6	5	6	6

Summary and conclusions

Forty-four dashboards in different passenger car makes were evaluated in the study. The dashboards were assessed by relying on the ergonomic criteria that had been developed based on a review of the literature (EBEC) to describe 11 functional criteria relating to the location and legibility of dashboard displays. The most functional dashboard scored 2.5 points, and the least functional dashboard scored 11 points. The dashboards were also evaluated by 40 drivers. The respondents filled out a questionnaire in which they described the extent to which the tested solutions approximated their idea of the perfect dashboard. Subjective driver evaluations and the results of the EBEC were used to generate datasets for a neural network analysis. The datasets were divided into two groups. One group (1,720 records) was used to develop neural models combining the values of every criterion with subjective driver evaluations. The second group (6 records) was used to evaluate the predictive capabilities of the developed models.

Five ANNs characterized by the lowest training and testing error were selected for further analysis. The tested ANNs accurately predicted subjective opinions regarding the analyzed dashboards, which implies that ANNs can be effectively used to evaluate dashboards during the design process. Because of the above, it can be assumed that the research hypothesis has been confirmed, and the developed tool can be used to objectively assess the functionality of dashboards. The sensitivity analysis identified the criteria which exerted the greatest influence on the users' subjective opinions.

The results of this study indicate that ANNs are a helpful tool for incorporating prospective users' preferences in dashboard design.

Because of the shortcomings in the study of the ergonomics of dashboards in vehicles indicated in the introduction, further research should be aimed at, among others, the development of further tools for the objective assessment of dashboards. It should be noted that the silhouettes of vehicles from different manufacturers have become more and more similar in recent years. The reason for this situation is undoubtedly the latest research on the physical and functional characteristics of individual solutions. There are repeated ones that may affect safe and comfortable driving, e.g. reducing air resistance, better visibility, or the functionality of external signaling devices, lights, etc. The design of dashboards should also aim at unification. In this case, it is about optimal functionality resulting from the evaluation by objective ergonomic tools developed as a result of subsequent studies. The advantage of similar dashboards would also be the ease of adaptation of the driver in the event of a sudden change of vehicle

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