

This study investigates the workload on the locomotive driver while driving a train. Up to now, research into the influence of the human factor on train control has not been fully completed. The reasons are the multifactorial nature of the driver's activity, the limited statistical data, as well as the difficulty of determining the psychophysiological state of a person. A serious issue is the lack of a scientifically substantiated method for determining the level of the driver's workload during trip. This work addresses this problem and defines quantitative characteristics of the state of the human operator while operating traction rolling stock. By determining the parameters of the environment in which the "driver-train" ergatic system operates and the factors affecting the driver's workload, it was possible to solve the task. Based on these data, a criterion has been devised to define the workload.

The method is based on an additive approach that combines the flow of information, the complexity of external conditions, as well as the factor of decision-making speed. The advantages of this approach are the relative simplicity of calculations, which ensures the ease of implementation of monitoring the driver's condition on board the locomotive in real time. It has been established that the total number of signals affecting the driver reaches 20300, of which 165 are critically important. It has been found that the main reserve for reducing the load on a person in the "driver-train" ergatic system is to reduce the amount of information received by the train driver.

In the future, the results of this study could be used to assess different modes of movement along different routes to identify the most dangerous values of the load on the driver. In addition, the research could lay a groundwork for implementing and adjusting the functions of locomotive decision support systems

Keywords: *railroad transport, traffic safety, traction rolling stock, cognitive load, ergatic system*

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DEVISING A METHOD FOR DETERMINING THE WORKLOAD ON A LOCOMOTIVE DRIVER BASED ON A MULTICRITERIA ADDITIVE MODEL TO IMPROVE RAILROAD TRANSPORT SAFETY

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1. Introduction

The current operating conditions of Ukrainian railroad transport have revealed several important limitations that reduce the efficiency of transportation and its safety. Such

problems include, first of all, the conduct of hostilities on the territory of the country and the constant danger of damage to the transport infrastructure and rolling stock. Under such conditions, the "human factor" becomes even more important for all operational managers in transport, from the dispatcher

to the locomotive driver. It is the driver who is able to correct the mistakes or negligence of other transport workers, but there is no one to correct the driver's mistake.

At present, the introduction of intelligent agents to control vehicles, technological processes, social processes, etc. is gaining traction. In the future, intelligent control systems should also be used to control locomotives to completely eliminate humans and secure the transportation process. However, there are still enough unresolved technical, legal, theoretical, and technological issues on this path. In addition, intelligent systems will be trained, including based on examples of driver control.

In this context, it is important to thoroughly understand how a human operator controls and what the quality of his/her control depends on. Thus, it is a relevant and extremely important task to assess the quality of control over traction rolling stock and the state of a human operator when driving a train. Solving this complex task will ultimately contribute to both the efficiency and safety of the transportation process.

2. Literature review and problem statement

Research into human control activities in the "driver-train" ergatic system is currently being conducted in several areas. The main ones are determining the psychophysiological state of the driver, modeling and formalization of the load, defining the reliability of the ergatic system as a whole, as well as ergonomic analysis of the operator on railroad transport.

Studies in the field of ergatic systems is aimed at examining physiological and psychological indicators of a person. In [1, 2], such parameters as heart rate variability, electroencephalogram, and electrocardiogram were used. They allowed the authors to sufficiently monitor and determine the current state of a person. In [3], it was proposed to determine human drowsiness using the PERCLOS index (time with eyes closed). In work [4], an approach is described that uses the galvanic skin reaction to determine the state of a person. All these methods give fairly accurate results. This is difficult to implement under current conditions because of the use of additional equipment that comes into contact with a person. Under the conditions of work of a locomotive driver, this can cause additional inconvenience and further reduce the quality of work. In the future, these and other human parameters should be tried to be obtained in a contactless way, without influencing and preparing the driver for measurement.

The most promising methods for now are those of mathematical modeling of the state of a locomotive driver. For example, in work [5], fatigue and mental load are determined. The disadvantages of the approach described include the fact that the study is based exclusively on subjective self-assessments. Worth mentioning is paper [6], in which the mathematical apparatus of Petri nets was used to describe multitasking in the work of a train driver and assess his/her workload. But the methodology of the cited work does not make it possible to obtain quantitative parameters for mathematical models of the human state. In work [7], electrocardiogram signals of human operators were collected and processed. To train the parameters of the modified hidden Markov model of vigilance assessment, heart rate variability was measured. The data were collected to train the model using the Baum-Welch algorithm and to construct a matrix of state transition probabilities. The model showed a reasonable level of accuracy but did not take into account external influences on train drivers, such as increased information flow, travel time, current

speed, etc. In addition, to date, approaches to increasing the efficiency of operation and management of railroad transport infrastructure have been developed [8]. In [9], an improved E-SHERPA method was devised for analyzing the reliability of the human factor in railroad engineering. However, in such studies, the human factor is considered to be an external disturbance and is not investigated by building a full-fledged model and testing it.

A systematic review of the characteristics of the psychological load of drivers and dispatchers was given in [10, 11]. The studies were conducted on the basis of interviews with experts. In general, the complaints of drivers about fatigue and the need for recovery after work were comparable to those of other workers. However, severe drowsiness and a high need for recovery affected a significant part of train drivers. The ability to remain attentive, anticipate, maintain concentration and cope with fatigue are psychological and cognitive skills necessary for adequate and safe performance of the work of a train driver. The study did not reveal the reasons and did not identify ways to reduce the load on drivers; the authors limited themselves to recommendations to drivers.

A promising way to improve the quality of traction rolling stock management is to eliminate (or minimize) the human factor by devising intelligent models and their self-learning systems [12]. However, the human operator is considered in the cited work to be a constant component, although practice shows that the driver's state during the trip changes significantly. When devising control systems [13] and designing systems for recognizing technical malfunctions [14], the role of the theory of artificial intelligence and pattern recognition for predicting both maintenance and control operational decisions was also determined. But the papers did not determine the influence of the human factor on the quality of technological processes of control and maintenance. The authors mainly focused on modeling technical objects.

Thus, our review of current research allows us to state that most studies consider technical aspects of improving transport operation, without determining the influence of the human factor. That did not make it possible to fully assess and propose improvements to transport ergatic systems. Analysis of available literature allows us to offer a general assumption: the influence of the human factor on the processes of locomotive control has not been fully investigated. Both the form of determining the negative influence of the human factor and its sources require clarification. The key aspect of the human factor is the driver's cognitive and informational load, which needs to be described and evaluated.

3. The aim and objectives of the study

The purpose of our study is to devise a method for assessing the load on the locomotive driver during movement. This will make it possible to significantly improve automated systems and processes for controlling train traffic by minimizing the harmful effects of the human factor. In the future, this is the basis for increasing the efficiency and safety of rail transportation.

To achieve the goal, the following tasks were set:

- to determine the parameters of the environment in which the "driver-train" ergatic system operates;
- to model the driver's information load;
- to assess the complexity of the external conditions of train movement;

- to assess the factor of decision-making speed;
- to experimentally substantiate the weight (importance, intensity) of the influence of each factor on the load of the locomotive driver.

4. The study materials and methods

The object of our study is the load on the locomotive driver while driving a train.

The principal hypothesis assumes that the driver's load parameter is complex, depends on several interrelated factors. This makes it possible to theoretically substantiate different directions of load reduction and assess the effectiveness of using each direction separately. To assess the load, the following assumption was adopted in the work: all factors affecting the driver's activity should be divided into information flow, the complexity of external traffic conditions, and limited time for decision-making.

In the process of building a model, the following simplifications were accepted. When assessing the information load, the number of information signals was taken in accordance with the number of all stimuli located on the train's path. However, during the trip, the driver may be distracted and not perceive some information stimuli. Therefore, the actual information load may be less than calculated. This does not affect traffic safety because the maximum load is taken into account in the calculation, and in reality it will be the same or less, which creates an additional reserve for the driver in real trips. This reserve is estimated at 6% of the calculated (maximum).

The next assumption is that when calculating the information flow, an average signal probability of 0.5 is assumed. This value will need to be further clarified by recalculating the probability of each information signal based on statistical data. This is the subject of a separate future study.

When defining the principle that underlies a mathematical model to be built, the following approaches were considered:

1. Multiplicative approach. The model is formed by simply multiplying the partial criteria if they all have the same importance [15]. The advantage of the multiplicative criterion is that when using it, normalization of the partial criteria is not required. Disadvantages of the criterion: the criterion compensates for the insufficient value of one partial criterion with an excessive value of another.

2. Minimax (maximin) approach. In this case, there is a danger when overestimating one criterion inevitably leads to a decrease in the values of the remaining criteria. But when performing certain operations, it is possible to achieve a certain degree of equalization of contradictory (conflicting) partial criteria, which is the purpose of the maximin principle.

3. Additive approach. In this case, the function is formed by adding the normalized values of the partial criteria. Partial criteria have different physical nature and, accordingly, different dimensions. Therefore, when forming a generalized criterion, one should operate not with "natural" criteria but with their normalized values. Normalized criteria represent the ratio of a "natural" partial criterion to some normalizing quantity measured in the same units as the criterion itself. In this case, the choice of the normalizing divisor must be logically justified [16, 17]. Several approaches to the choice of the normalizing divisor are possible.

A first approach suggests taking the directive values of the parameters specified by the customer as a normalizing divisor. The logical weakness of this approach is the implicit assumption that the optimal values of the object parameters are deter-

mined in the task for the designed computing system, and that the set of specified criteria values is considered exemplary.

A second approach involves choosing the maximum values of the criteria that are achieved in the area of existence of design solutions (in the compromise area) as normalizing divisors. An approach is possible in which the difference between the maximum and minimum values of the criterion in the compromise area is chosen as the normalizing divisors.

The choice of an approach to forming a dimensionless form of partial criteria is sometimes subjective and must be justified in each specific case. Let there be n partial criteria when modeling the load on a locomotive driver. Then the function is defined as follows

$$F(X) = \sum_{i=1}^n w_i \frac{F_i(X)}{F_i^{(0)}(X)} = \sum_{i=1}^n w_i f_i(X), \quad (1)$$

where w_i – weight coefficient of the i -th partial criterion; $F_i^{(0)}(X)$ – i -th normalizing divisor; $f_i(X)$ – normalized value of the i -th private criterion.

Such a function allows for a compromise in which the improvement of the value of one normalized partial criterion compensates for the deterioration of the values of others. The introduction of weight coefficients should take into account the different significance of the partial criteria when forming the additive criterion. The determination of weight coefficients faces serious difficulties and usually comes down to either the use of formal procedures or the application of expert assessments [18]. It is the additive approach to building a mathematical model of the load on a locomotive driver that is most suitable for solving this task.

5. Results of devising a method for determining the load on a train driver

5.1. Determining the parameters of environment in which the ergatic system "driver-train" functions

When considering the locomotive driver as an operator of the control system, it can be noted that s/he is the manager of two separate systems: the train and the locomotive. According to classical definitions, the locomotive is a part of the train. But when considering control processes, it turns out that each of the specified systems has its specific feedback channels, its specific control parameters, its specific separate objects of influence.

Our work considers each of these large control systems in detail. When controlling a train, the driver mainly controls parameters associated with the external environment and the interaction of the controlled system with this environment. The basic parameters controlled by the driver in this case:

- technical condition of the track;
- accuracy of the laid route (position of switches);
- readings of traffic lights; control of the space near the track (presence of people or animals that may interfere with traffic, control of unclear signals or actions of people near the track);
- track clearance (including at crossings);
- traffic on adjacent tracks;
- track profile;
- current train speed;
- availability of brakes on the train;
- military influence factor on train movement (presence of air alert, presence of UAVs in the field of view, hostilities, explosions, etc.);
- current weather conditions.

The main channel for perceiving all these parameters is vision. With the help of vision, the driver perceives all the information about the state of the track, signals, space near the track, etc. The volume of this information for the operator is quite large. The total amount of stimuli acting on the driver during one trip is 18–20 thousand, of which only 10% are of critical importance (traffic lights, crossings, speed limiters, track profile indicators, etc.) [19].

Other stimuli, while not being of critical importance, can become of them at any time.

Simultaneously with the factors described, the driver controls those factors that enable direct control over the locomotive and its main systems. In this case, the locomotive driver is obliged to monitor the following parameters: the position of the controls (driver's controller, brake controller, instrument displays on the remote control, noise level, and vibration level during locomotive operation, etc. Thus, in addition to vision, the driver also uses the senses of hearing and touch. Regulatory influences in this control circuit are transmitted directly – through the corresponding levers, and indirectly – through the driver's assistant.

While handling these two large systems (train and locomotive), the driver has images (models) of the states of these systems in his/her mind, which the driver considers most acceptable in the current situation, to which s/he strives during the movement. In addition, the driver is considered as an operator of a semi-automated system. Thus, a professionally important information model for an electric locomotive driver is a model of the locomotive electrical circuit, in particular, the circuit of the high-voltage chamber. The model of the position of the main relays and contacts of this circuit (as, indeed, other units) is the basis for controlling the operation of machines.

In the human mind, an imaginary reproduction of an object occurs, thereby managing models of those objects that are not currently in front of the eyes. And these information models are necessary when various kinds of problems and malfunctions arise. Since without the elimination of such malfunctions, driving itself could not be carried out, such diagnostic operator activity when controlling complex objects becomes a component of the driving process. The quality of these models is determined by the experience and level of training of each driver.

The perception of this rather large amount of information by the locomotive driver is periodically complicated by additional adverse factors, such as darkness, bad weather conditions, poor health, poor mood, etc. These factors directly affect the quality and timeliness of management decisions when driving a train, so they are taken into account in the model.

Fig. 1 shows the structure and interaction of factors influencing the locomotive driver when driving a train.

The driver's assessment of the current train situation depends primarily on how correctly s/he is able to compare different spatial quantities under normal conditions. The information-motor system formed during industrial training allows the driver to perceive the size of the path segment at each given moment of the trip.

In the classical literature, the relationship between the efficiency of the human operator and the level of his/her workload is given [20], namely the curve shown in Fig. 2.

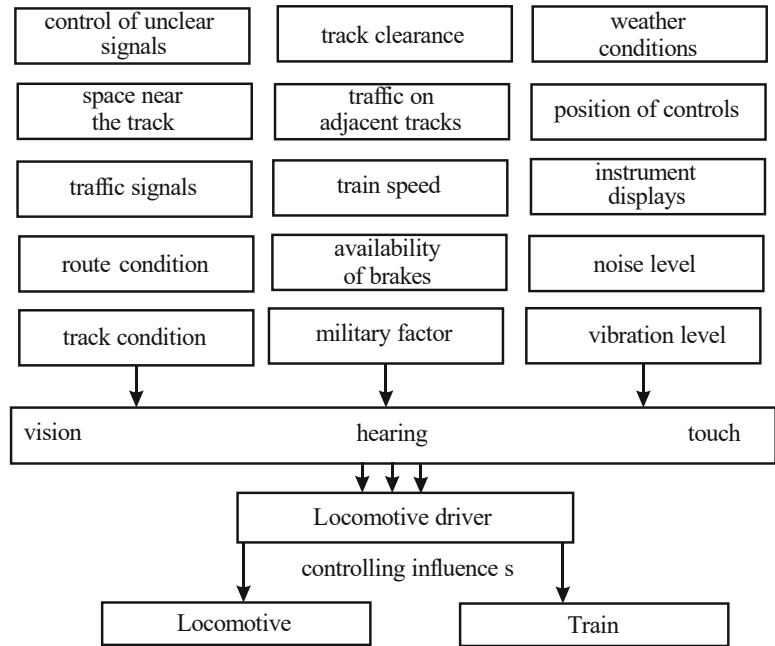


Fig. 1. Structure of the information load on a locomotive driver

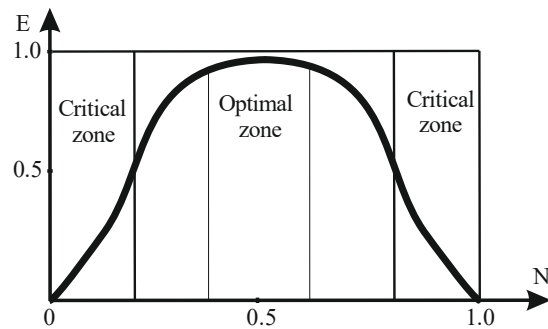


Fig. 2. Dependence of the efficiency of human operator's work on his/her workload level

Fig. 2 shows the optimal zone, which is the zone of the most effective human work. This zone is characterized by psychophysiological balance, that is, the level of human stress sufficient for concentration but not enough to block or inhibit decision-making in the human brain. Under this mode, the time between receiving information and reacting to it is minimal, and the emotional state of the operator remains stable. At a very low level of load, most operators act inefficiently because the work does not arouse interest. At an average level of load, the quality of the operator's work increases, but a further increase in the load leads to a deterioration in work efficiency, which is explained by an increase in stressful situations: fear, fatigue, etc.

Thus, an important task for assessing and predicting the quality of the "driver-train" system is the description and formalization of the concept of "driver's work tension" (in other words, the level of current load on the human operator).

Driver tension is the result of increased load during the trip. It is considered as a dynamic, latent state, which is formed under the influence of prolonged mental load, various stress factors, and limited opportunities for recovery. Tension directly affects the quality of decision-making, reaction speed, and the risk of making errors when driving a train; therefore, it is of significant importance for the safety of locomotive operation [21, 22].

The driver load assessment in this work is represented by the following expression

$$L_c(k) = w_1 N_{info}(k) + w_2 C_{env}(k) + w_3 T_{DS}(k), \quad (2)$$

where $N_{info}(k)$ – information flow (track signals, devices, radio exchange); $C_{env}(k)$ – complexity of external conditions (track profile, weather, traffic); $T_{DS}(k)$ – decision speed factor; k – discrete travel time interval; w_i – weighting factors, $\sum w_i = 1$.

These components are considered and formalized separately in our study.

5. 2. Modeling the driver’s information load

Our work analyzed the activities of locomotive crews in freight traffic from the point of view of information load. The total observation time was 67 hours. During operation, the locomotive crew receives a variety of information. To formalize the problem, it is necessary to express the amount of information in the number of signals that a person receives. Any new information or update of old information was considered as a new signal. The signals are divided into groups, given in Table 1.

According to our study, the average value of the total number of signals affecting the locomotive crew during movement is $N_{tot} = 20300$ per trip, and the number of signals indicating an abnormal situation is $N_{as} = 165$ per trip. In this study, a trip was considered to be the time from the moment the locomotive (or locomotive with a train) was accepted by the locomotive crew until the locomotive was uncoupled at the arrival station. The average trip time was 4.5 hours.

To assess the information load on the locomotive crew during movement, the density of the input flow from a sep-

arate group of signals was determined using the following formula

$$\lambda_e(k) = \frac{N_e}{k}, \quad (3)$$

where N_e is the number of signals of the e -th group received by the locomotive crew; k is the discrete time interval of the locomotive crew in motion, min.

As a result of the classification, the number of signal groups in this study is 10. The total input flow density for the locomotive crew is given by

$$\lambda(k) = \sum_{e=1}^n \lambda_e(k), \quad (4)$$

where n is the number of signal groups, (where $e \in [0;10]$).

During the study, it was found that the number of signals in different groups changes over time. As an example, Fig. 3 shows the change in λ_e signals over 0.5 hours of travel. Here you can see that when driving a train along a section, the total number of signals received by the locomotive crew is about 75 per minute, and when passing a station it reaches 150 per minute. Thus, we can conclude that the driver works in a very busy information space and cannot always react and evaluate the entire volume of signals received from the outside.

The amount of information received by the driver is estimated using information theory methods in binary units per second [23, 24] using the following expression

$$I(x_i) = -\log_2 \rho(x_i), \quad (5)$$

where $p(x_i)$ is the probability of the i -th event.

Table 1

Groups of signals that are received for processing by the locomotive crew

Group ID	Characteristics of the group	Total number of signals received	Number of signals characterizing the abnormal state of the system
Preparatory operations	Medical examination, receipt of documents, briefing, receipt of task	60	–
External factors	All signals that externally affect train control, such as the condition of the rail surface, time of day, current and next track profile and plan, weather and climatic conditions	1550	–
Technical condition of the locomotive	Determined by the locomotive crew during acceptance of the locomotive and parking lots awaiting work	150	5
Technical parameters of the train	Determined during coupling of the locomotive to the train, testing of the braking equipment and obtaining documentation for the train	80	–
Locomotive operating parameters and train condition during movement	Determined by monitoring all types of measuring and signaling devices in the locomotive cab, available to the locomotive crew during movement, monitoring the condition of the brake line and inspecting the train when passing through curves	10200	110
Status of track section at station	Determined by obtaining information about the movement of shunting trains along station tracks, the position of switches, monitoring track clearance, availability of dimensions, movement of people	3500	25
Track section condition on the stretch	Determined by monitoring the track clearance and the condition of the track superstructure over a considerable distance	1400	10
Signal positions	Determined by monitoring the condition of traffic lights, signal indicators, radio communication information, hand signals	510	5
Rules of Procedure	Number of signals received by the crew while executing the negotiation regulations	2500	10
Other	All other signals not related to train movement and locomotive maintenance	50	–

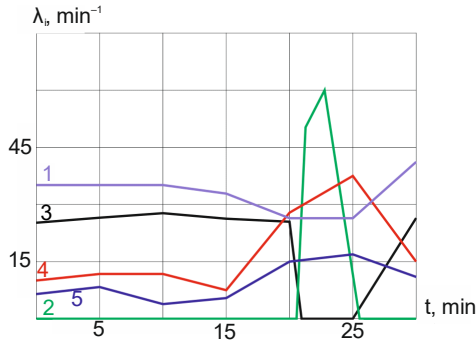


Fig. 3. Change in the density of the incoming flow during the trip: 1 – parameters of the locomotive operation and the state of the train during movement; 2 – state of the track section at the station; 3 – state of the track section on the stretch; 4 – signal position; 5 – negotiation regulations

However, there are a number of signals, the probability of which is very high, and in some cases approaches unity. These include the track clearance on the section, the serviceable condition of the track superstructure and contact suspension, visual signs of the integrity of the train carriages. If we assume that the average probability of each signal is 0.5, then it is possible to estimate the information load on the locomotive crew depending on the number of signals per minute.

In general, the information flow (rate of information receipt) is determined using the following formula

$$N_{info}(k)' = -\log_2 \rho(x_i) \cdot \frac{\lambda(k)_{max}}{60}. \quad (6)$$

To use these data in the formula for estimating the driver's workload, it is necessary to normalize the value obtained from expression (6). When determining the maximum $N_{info}(k)_{max}$ value, the maximum values of $\log_2 \rho(x_i)$ and $\lambda(k)$ obtained during experimental trips were used. The information signal with the lowest probability turned out to be the information signal "obstacle at the crossing"; its probability is $p(x_i) = 0.00072$. The maximum recorded value is $\lambda(k)_{max} = 39$ bits per minute.

Expression (6) produces the value of $N_{info}(k)_{max} = 6.79$.

The normalization of the information flow indicator occurs according to the well-known formula

$$N_{info}(k)' = \frac{N_{info}(k)_{max} - N_{info}(k)}{N_{info}(k)_{max}}, \quad (7)$$

where $N_{info}(k)_{max}$ is the maximum value of the information load flow for the time period k ; $N_{info}(k)$ is the current value of the information load flow for the time period k .

At a minimum information flow, the $N_{info}(k)$ value tends to zero.

5. 3. Assessing the complexity of external conditions of train movement

A study was conducted on the influence of natural and climatic conditions by month on traffic safety violations in operation based on the analysis data [28].

At Ukrzaliznytsia, based on six-year observations, the situation with passing prohibitory signals looks as shown in Fig. 4. The most violations are in May, July, and especially in October. This is explained by the heat, which affects the driver's reaction

time, the transitional state between the warm and cold periods of the year, when the day begins to shorten significantly and weather conditions worsen. In addition, according to statistics, an increase in the number of incidents was observed in May, which is characterized by good climatic conditions and the presence of holidays.

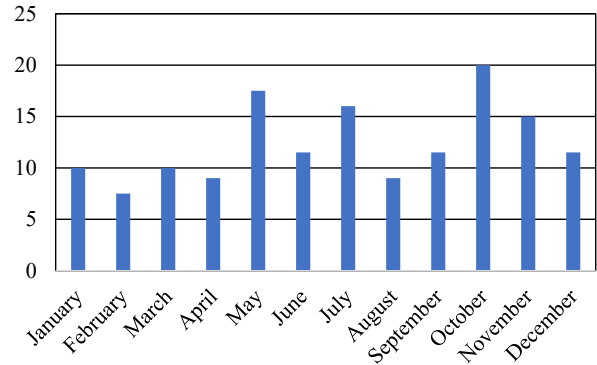


Fig. 4. Distribution of transport incidents in the railroad locomotive fleet by month

Statistics confirm that the most unfavorable for the driver are morning hours. The number of violations during this period is determined both by the psychophysiological state of the driver and the technology of the transportation process in a particular type of traffic. Data from AT "Ukrzaliznytsia" are shown in Fig. 5.

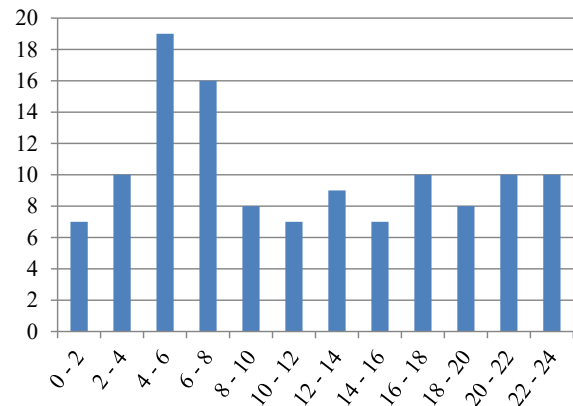


Fig. 5. Distribution of cases of passing a prohibitory signal in the railroad locomotive fleet by hours of the day

According to a survey of drivers:

- every fifth driver is dissatisfied with sleep at home, not to mention the conditions at the points of turnover. Approximately 15% of working drivers do not get deep enough sleep and the same number have a shortened sleep, that is, almost a third of drivers have deviations in sleep quality;
- drowsiness during daytime trips is noted by 4.4–6%, and at night – by about a third of drivers;
- during the day, the greatest drowsiness is observed around 9.00, 15.00, and 18.00, or at the end of the trip. At night, drowsiness occurs at 3–4 hours of work (in 69%) or in the interval of 4.00–7.00;
- increased drowsiness is observed after suffering from the flu;
- drowsiness strongly depends on the season: it is the least in summer, the greatest in winter;

– moderate eating during the day increased drowsiness in 23% of the surveyed drivers, and at night it decreased it in 25% of the surveyed drivers;

– in rest houses at the turnover point, 41% of drivers do not sleep. The rest sleep mainly for about two hours and often wake up;

– drowsiness after rest at the turnover point is manifested 5 times more often than after rest at home.

From the above it is clear that the magnitude of the complexity of external conditions was influenced by many factors that change either gradually in time or instantly. The estimation of the $C_{env}(k)$ value in the first approximation was performed according to the following algorithm. Based on statistics, the complexity of external conditions was calculated as the arithmetic mean value of the complexities caused by individual factors, namely the climatic factor, the factor of the period of the day, etc. Using Min-Max scaling, the following expressions for normalization were derived.

The normalized value of the climatic factor is determined using the following formula

$$C_{climate}(k) = \frac{N^C(k) - N_{min}^C}{N_{max}^C - N_{min}^C}, \tag{8}$$

where $N^C(k)$ is the number of traffic safety violations according to statistics in the current period of time, determined by the current month; $N_{min}^C(N_{max}^C)$ – minimum (maximum) number of traffic safety violations per month according to statistical data (according to Fig. 4 $N_{min}^C = 7, N_{max}^C = 20$).

The normalized value of the day period factor is determined using the following formula

$$C_{time}(k) = \frac{N^t(k) - N_{min}^t}{N_{max}^t - N_{min}^t}, \tag{9}$$

where $N^t(k)$ is the number of traffic safety violations according to statistics in the current period of time, determined by the current hours of the day; $N_{min}^t(N_{max}^t)$ – minimum (maximum) number of traffic safety violations by hours of the day according to statistical data (according to Fig. 5 $N_{min}^t = 7, N_{max}^t = 19$).

In general, $C_{env}(k)$ for any number of factors is calculated using the following expression

$$C_{env}(k) = \sum_{i=1}^m \frac{C(k)_i}{m}, \tag{10}$$

where $C(k)_i$ – i th factor of external influence; m – total number of factors influencing the complexity of external conditions.

5. 4. Assessing the decision-making speed factor

During the train movement, the driver is constantly in operational readiness to make a control decision. In addition to the fact that control decisions must be "correct", they must also be made "in a timely manner".

It is known that with an increase in the time for preparation and analysis of the consequences of a particular decision, the quality of the control decision increases, but up to a certain limit [29, 30].

Fig. 6 shows a conditional curve characterizing the quality of human decision-making in ergatic systems. There are

three zones here: time deficit, optimal time, and excess time. The most attention should be paid to the first zone, where the driver does not have time to obtain and process all the necessary data and is forced to use intuitive strategies. But there is a danger here associated with the driver's experience and his/her psychophysiological state. Both of these factors significantly affect the quality of the decision made under conditions of time deficit.

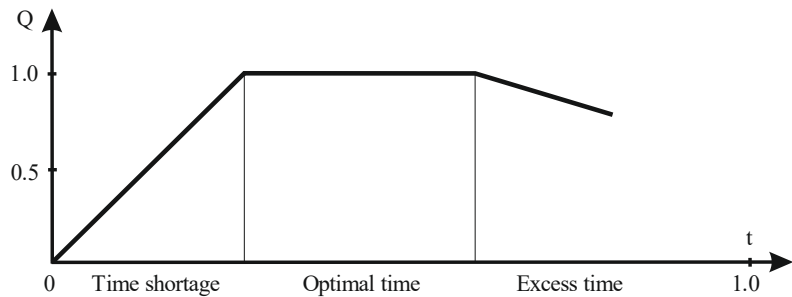


Fig. 6. The nature of changes in the quality of decisions made depending on the time taken to make this decision

Therefore, to estimate the decision speed factor $T_{DS}(k)$, we have derived the following expression

$$T_{DS}(k) = \frac{(v_k + E_x + P_s)}{3}, \tag{11}$$

where v_k is the relative value of the current speed in the time interval k ; E_x is the relative value of the locomotive driver's experience (1 is a novice, 0 is the most experienced employee); P_s is the relative value of the psychological characteristics of a person, which is determined by the results of his/her examination upon employment and periodic control.

All parameters in the numerator of formula (11) are relative dimensionless quantities belonging to the interval from 0 to 1.

5. 5. Experimental justification of the weight of the influence of each factor on the load of the locomotive driver

The next stage of our work was the justification of the weight coefficients w_i used in expression (2). The mode of movement and the type of train movement affect the load on the locomotive driver in different train events. Therefore, based on the analysis of the work of the railroad locomotive service, five main types of activities of the locomotive driver were identified:

1. Passenger traffic (up to 110 km/h).
2. Freight traffic.
3. High-speed traffic (up to 160 km/h).
4. Suburban traffic.
5. Shunting traffic.

For each of these traffic modes, the distribution of the influences of the above factors $N_{info}(k)$, $C_{env}(k)$ and $T_{DS}(k)$ will be different. Specific values of weight coefficients depending on the traffic modes are proposed to determine by using the method of hierarchy analysis. As experts for the implementation of this method, drivers from the Kyiv-Passenger locomotive depot (11 people) were involved, who have 1st and 2nd class and sufficient experience.

A survey of experts for the "Passenger traffic" mode determined that the conditions for it are a stable route and schedule, moderate speed, but high responsibility for passengers. Therefore, the comparison matrix for this mode takes the form given in Table 2.

Table 2

Pairwise comparison matrix of weight coefficients

Value	w_1	w_2	w_3
w_1	1	3	1
w_2	0.(3)	1	0.(3)
w_3	1	3	1
	2.(3)	7.0	2.(3)

The normalized matrix is given in Table 3.

Table 3

Normalized matrix of pairwise comparisons of weight coefficients

Value	w_1	w_2	w_3	Mean
w_1	0.43	0.43	0.43	0.43
w_2	0.14	0.14	0.14	0.14
w_3	0.43	0.43	0.43	0.43

That is, the weight coefficients in formula (2) for passenger traffic were distributed as follows: $w_1 = 0.43$; $w_2 = 0.14$; $w_3 = 0.43$.

In a similar way, the weight coefficients for other traffic modes were obtained (Table 4).

Table 4

Consolidated weighting factors by traffic mode

No.	Traffic mode	w_1	w_2	w_3	Consistency Ratio (CR)
1	Passenger traffic	0.429	0.143	0.429	0.000
2	Freight traffic	0.260	0.634	0.106	0.034
3	High-speed traffic	0.243	0.088	0.668	0.004
4	Suburban traffic	0.633	0.106	0.260	0.034
5	Shunting traffic	0.723	0.083	0.193	0.054

During the survey, the drivers pointed out different characteristic features of each mode. "Passenger traffic" is characterized by the stability of the route and schedule, moderate relatively stable speed, great responsibility for the life and health of passengers. Freight traffic is characterized by low speeds, high weight of trains, braking features, and profile variability. High-speed traffic is characterized by high speed and a large flow of information signals. Suburban traffic is characterized by frequent stops, a large number of signals, and large passenger traffic. Shunting traffic is low speed, a very large number of signals and other information, and contact with the train assembler.

Weight coefficients depending on the type of traffic are visualized in Fig. 7. Here w_1 indicates the weight coefficient of the information flow; w_2 is the weight coefficient of the complexity of external conditions; w_3 is the weight coefficient of the decision-making speed factor.

Based on our analysis of the weight coefficients of various factors, it was found that on average the most dominant factor is the information flow that reaches the driver.

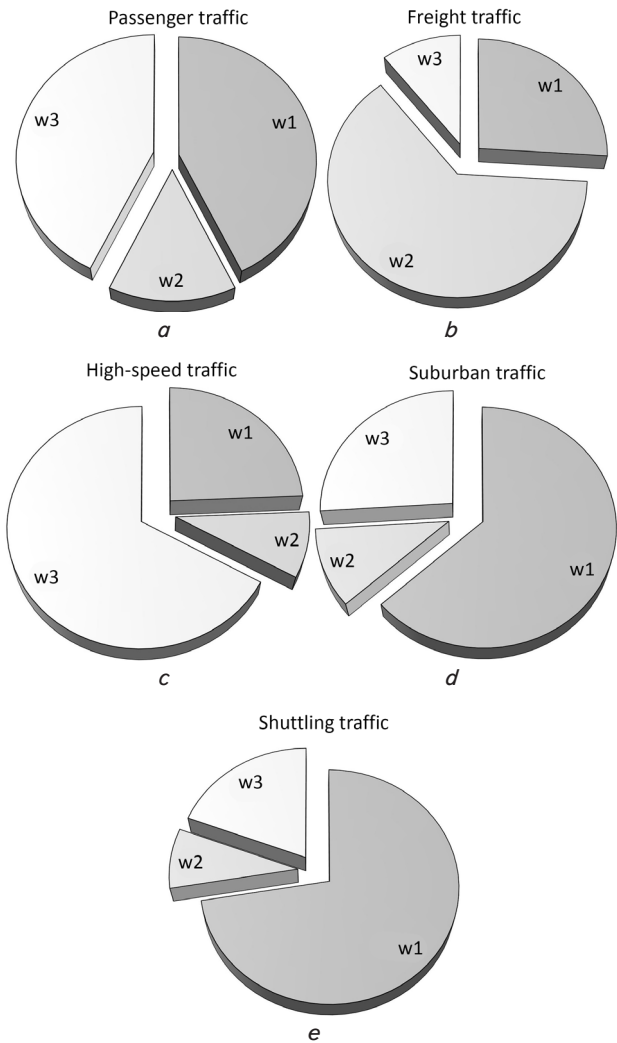


Fig. 7. Distribution of weight coefficients depending on the type of traffic: *a* – passenger traffic; *b* – freight traffic; *c* – high-speed traffic; *d* – suburban traffic; *e* – shunting traffic

6. Discussion of the study results and the prospects for their application

At the current stage of development of the transport industry, the introduction of intelligent agents in the control of vehicles, technological processes, social processes, etc. is becoming quite widespread. In the future, intelligent control systems should be used to control locomotives and to possibly completely eliminate humans and secure the transportation process. But this process will not happen quickly due to a number of obstacles, from technical and theoretical to legal. In addition, it is necessary to take into account that the quality of train control by an intelligent system should not be lower than the quality of train control by a person. This poses an important scientific task: to build a model of the work of a human operator and determine the basic parameters of this work. Our study formalizes one of the key parameters for human work – cognitive load.

The work investigates the parameters of the environment in which the ergatic system "driver-train" operates. The environment affects a person in accordance with the structure of the information load shown in Fig. 1. This indicates that there

are three main channels through which information enters the driver's consciousness and two main systems are also identified that are influenced by the driver, namely the train and, separately, the locomotive.

The results of applying the method for determining the driver's load are due to the specificity of train work and adequately describe the processes during movement. Thus, according to Fig. 3, the most information-laden mode is the movement along station tracks. When studying on a simulator, these results were confirmed; the influence of the time of day (Fig. 5) on the speed and quality of human decisions was also confirmed.

As a result of obtaining an assessment of the complexity of the external conditions of train movement, it was established that drivers encounter a state of drowsiness for both internal and external reasons. Internal ones include illness, insufficiently deep sleep during rest, and food regime. External factors include the season, travel time, as well as the quality of equipment in the rest areas at crew facilities. Our study summarizes and formalizes the climatic factor (8), which was not reported in previous papers.

One of the advantages of studying the cognitive load on the driver is the introduction of the decision-making speed factor into the calculations. All components of this factor are computed in relative units as normalized values in the interval $[0; 1]$. The adequacy of such a model for determining $T_{DS}(k)$ is ensured by the fact that as a result of the normalization of the initial data, the decision-making speed factor decreases with a decrease in the speed of movement, an increase in the person's experience, and an increase in psychological stability. In actual calculations, the values of Ex and Ps for a particular person will change very slowly in time, so their sum can be taken as constant for one trip. Then the changes in the value of the decision-making speed factor during movement will depend only on the current speed.

As a result of our experimental substantiation of the weight of the influence of factors on the load of the locomotive driver, five main types of activities have been identified. For each of them, the weight coefficients are different, which is an advantage in comparison with other similar studies. The predominant role of the information load factor in determining the driver's workload has been established, as evidenced by the data in Table 4. This result indicates that the main reserve for reducing the load on a person in the "driver-train" ergatic system is to reduce the amount of information coming both from the outside and from the internal technical systems of the train. In a separate case, in "high-speed traffic", the factor of decision-making speed needs to be reduced. In both of these cases, it is possible to reduce the driver's workload and fatigue by implementing decision-making support systems (including intelligent ones), which will significantly relieve the person. That is, the driver will be provided with only critically important information and ready-made solutions for controlling the locomotive.

Our method expands the understanding of the influence of human factor on the process of train control and provides a quantitative assessment of the driver's workload. Thanks to this approach, the form of the negative influence of the human factor and its source have been clarified.

When applying the devised method in practice, the following limitations must be taken into account. The amount of information received by the driver can be estimated only using existing technical solutions (sensors, video surveillance, etc.). These means can only record the presence or absence of an information signal. But when calculating the amount of information according to expression (5), the probability of the

appearance of such a signal is used. Under current conditions, it is not possible to estimate such a probability for the full list of existing signals. This is mainly due to the small amount of statistical data on the appearance of certain information signals in real operating conditions. In addition, the limitations of the method include a certain subjectivity in determining the weight coefficients for partial criteria.

The disadvantages of the study include the fact that the load on the driver is estimated only on the basis of external influences in relation to the person. That is, regardless of who is at the helm of the controller, the L_c value will not be variable as it depends on the condition of the track, weather conditions, time of day, track profile, etc. But experience shows that different people tolerate external influences differently (depending on temperament, psychological state, or health status). Therefore, the same external loads on drivers could lead to different consequences, from minor fatigue to loss of control and making wrong decisions when driving a train. Hence the need to establish the relationship between the optimal state of the human operator, his/her psychophysiological characteristics, and the current value of the cognitive load in further studies. It is necessary to verify our results in further studies using medical equipment that directly determines the state of the driver in motion.

7. Conclusions

1. When determining the parameters of environment in which the ergatic system "driver-train" operates, it was found that the volume of stimuli acting on the driver during one trip is 18–20 thousand, of which only 10% are of critical importance (traffic lights, crossings, speed limiters, track profile indicators, etc.). The main channel for perceiving all these parameters is vision. With the help of vision, the driver perceives all the information about the state of the track, signals, space near the track, etc. The volume of this information for the operator is quite large. In accordance with the developed structure of the information load on the locomotive driver, all influences on the driver are distributed into three channels: vision, hearing, touch. The driver influences the train situation by controlling the train and locomotive systems.

2. Modeling of information load was carried out based on the density of the incoming information flow and the probability of the occurrence of an information signal. The information signal with the lowest probability was the information signal "obstacle at the crossing", its probability is $p(x_i) = 0.00072$. The maximum recorded value $\lambda(k)_{\max} = 39$ bits per minute.

3. The assessment of the complexity of external conditions of train movement is based on statistics calculated as the arithmetic mean value of the complexities caused by individual factors. Using Min-Max scaling, expressions were derived for normalizing the parameter of the complexity of external conditions.

4. The factor of decision-making speed is estimated based on the experience of the locomotive driver, the psychological characteristics of a person, and the speed of movement. The quality of the control decision depends on the time for its adoption. Three zones are observed: time deficit, optimal time, and excess time. Most attention should be paid to the first zone, where the driver does not have time to receive and process all the necessary data and is forced to use intuitive strategies.

5. We have substantiated the influence of each factor on the load on the locomotive driver. For this purpose, based on the analysis of the work of the locomotive service of the railroads,

five main types of driver's activities have been identified: passenger traffic; freight traffic; high speed movement; suburban traffic; shunting movement. It was established that the most dominant factor is the information flow coming to the driver.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study and the results reported in this paper.

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Data availability

All data are available in the main text of the manuscript.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Authors' contributions

Oleksandr Gorobchenko: Conceptualization, Methodology, Project administration; **Denys Zaika:** Validation, Formal analysis, Writing – original draft; **Oleksandr Nevedrov:** Visualization; **Halyna Holub:** Software; **Victor Tkachenko:** Investigation, Data curation; **Serhii Kara:** Resources.

References

- Shaffer, F., Ginsberg, J. P. (2017). An Overview of Heart Rate Variability Metrics and Norms. *Frontiers in Public Health*, 5. <https://doi.org/10.3389/fpubh.2017.00258>
- Chen, J., Li, H., Han, L., Wu, J., Azam, A., Zhang, Z. (2022). Driver vigilance detection for high-speed rail using fusion of multiple physiological signals and deep learning. *Applied Soft Computing*, 123, 108982. <https://doi.org/10.1016/j.asoc.2022.108982>
- Abe, T. (2023). PERCLOS-based technologies for detecting drowsiness: current evidence and future directions. *SLEEP Advances*, 4 (1). <https://doi.org/10.1093/sleepadvances/zpad006>
- Dankovich, L. J., Joyner, J. S., He, W., Sesay, A., Vaughn-Cooke, M. (2024). CogWatch: An open-source platform to monitor physiological indicators for cognitive workload and stress. *HardwareX*, 19, e00538. <https://doi.org/10.1016/j.ohx.2024.e00538>
- Hassanzadeh-Rangi, N., Jalilian, H., Farshad, A.-A., Khosravi, Y. (2023). Correlation of Work Fatigue and Mental Workload in Train Drivers: A Cross-sectional Study. *Journal of Research in Health Sciences*, 23 (4), e00600. <https://doi.org/10.34172/jrhrs.2023.135>
- Wang, P., Fang, W., Guo, B. (2019). Mental workload evaluation and its application in train driving multitasking scheduling: a Timed Petri Net-based model. *Cognition, Technology & Work*, 23 (2), 299–313. <https://doi.org/10.1007/s10111-019-00608-w>
- Wang, H., Chen, D., Huang, Y., Zhang, Y., Qiao, Y., Xiao, J., Xie, N., Fan, H. (2023). Assessment of Vigilance Level during Work: Fitting a Hidden Markov Model to Heart Rate Variability. *Brain Sciences*, 13 (4), 638. <https://doi.org/10.3390/brainsci13040638>
- Gorobchenko, O., Matsiuk, V., Holub, H., Gritsuk, I., Nevedrov, O. (2024). Increasing the efficiency of operation and management of railroad transport infrastructure based on maximum levels of fault tolerance. *Eastern-European Journal of Enterprise Technologies*, 5 (3 (131)), 55–65. <https://doi.org/10.15587/1729-4061.2024.311829>
- Catelani, M., Ciani, L., Guidi, G., Patrizi, G. (2021). An enhanced SHERPA (E-SHERPA) method for human reliability analysis in railway engineering. *Reliability Engineering & System Safety*, 215, 107866. <https://doi.org/10.1016/j.res.2021.107866>
- Chen, Z., Guo, Z., Feng, G., Shi, L., Zhang, J. (2021). A Qualitative Study on the Workload of High-Speed Railway Dispatchers. *Engineering Psychology and Cognitive Ergonomics*, 251–260. https://doi.org/10.1007/978-3-030-77932-0_21
- Zoer, I., Sluiter, J. K., Frings-Dresen, M. H. W. (2014). Psychological work characteristics, psychological workload and associated psychological and cognitive requirements of train drivers. *Ergonomics*, 57 (10), 1473–1487. <https://doi.org/10.1080/00140139.2014.938130>
- Gorobchenko, O., Holub, H., Zaika, D. (2024). Theoretical basics of the self-learning system of intelligent locomotive decision support systems. *Archives of Transport*, 71 (3), 169–186. <https://doi.org/10.61089/aot2024.gaevsp41>
- Goolak, S., Liubarskyi, B., Riabov, I., Chepurina, N., Pohosov, O. (2023). Simulation of a direct torque control system in the presence of winding asymmetry in induction motor. *Engineering Research Express*, 5 (2), 25070. <https://doi.org/10.1088/2631-8695/acde46>
- Tverdome, V., Dmytro, Z., Kokriatska, N., Lukoševičius, V. (2024). The Detection of Railheads: An Innovative Direct Image Processing Method. *Sustainability*, 16 (12), 5109. <https://doi.org/10.3390/su16125109>
- Hwang, C.-L., Yoon, K. (1981). *Multiple Attribute Decision Making*. Springer Berlin Heidelberg. <https://doi.org/10.1007/978-3-642-48318-9>
- Belton, V., Stewart, T. J. (2002). *Multiple Criteria Decision Analysis*. Springer US. <https://doi.org/10.1007/978-1-4615-1495-4>
- Jahan, A., Edwards, K. L. (2016). *Multi-criteria decision analysis for supporting the selection of engineering materials in product design*. Butterworth-Heinemann. <https://doi.org/10.1016/c2012-0-02834-7>

18. Ishizaka, A., Nemery, P. (2013). Multi-Criteria Decision Analysis. <https://doi.org/10.1002/9781118644898>
19. Gorobchenko, O. (2021). Theoretical fundamentals of estimatability assessment of train situation signs for work of intellectual locomotive control systems. Collection of Scientific Works of the State University of Infrastructure and Technologies Series "Transport Systems and Technologies", 1 (38), 223–231. <https://doi.org/10.32703/2617-9040-2021-38-220-21>
20. Wickens, C. D., Hollands, J. G., Banbury, S., Parasuraman, R. (2015). Engineering Psychology and Human Performance. Psychology Press. <https://doi.org/10.4324/9781315665177>
21. Naweed, A. (2020). Getting mixed signals: Connotations of teamwork as performance shaping factors in network controller and rail driver relationship dynamics. Applied Ergonomics, 82, 102976. <https://doi.org/10.1016/j.apergo.2019.102976>
22. Gorobchenko, O., Nevedrov, O. (2020). Development of the structure of an intelligent locomotive DSS and as-sessment of its effectiveness. Archives of Transport, 56 (4), 47–58. <https://doi.org/10.5604/01.3001.0014.5517>
23. Chambon, T., Guillaume, J.-L., Lallement, J. (2023). Information Complexity Ranking: A New Method of Ranking Images by Algorithmic Complexity. Entropy, 25 (3), 439. <https://doi.org/10.3390/e25030439>
24. Zenil, H., Marshall, J. A. R., Tegnér, J. (2023). Approximations of algorithmic and structural complexity validate cognitive-behavioral experimental results. Frontiers in Computational Neuroscience, 16. <https://doi.org/10.3389/fncom.2022.956074>
25. Lange, C., Ahrens, A. (2025). Digital Transmission Engineering. Springer Fachmedien Wiesbaden. <https://doi.org/10.1007/978-3-658-46789-0>
26. Gibson, J. D. (2023). Digital Communications. Springer International Publishing. <https://doi.org/10.1007/978-3-031-19588-4>
27. Renzo, M. D., Migliore, M. D. (2024). Electromagnetic Signal and Information Theory. IEEE BITS the Information Theory Magazine, 4 (1), 25–39. <https://doi.org/10.1109/mbits.2024.3359523>
28. Kustov, V. (2025). Fundamental limitations of basic dangerous failure models for functional safety assessment in train control systems. Collection of Scientific Works of the Ukrainian State University of Railway Transport, 212, 301–314. <https://doi.org/10.18664/1994-7852.212.2025.336537>
29. Rieger, T., Manzey, D. (2020). Human Performance Consequences of Automated Decision Aids: The Impact of Time Pressure. Human Factors: The Journal of the Human Factors and Ergonomics Society, 64 (4), 617–634. <https://doi.org/10.1177/0018720820965019>
30. Laxar, D., Eitenberger, M., Maleczek, M., Kaider, A., Hammerle, F. P., Kimberger, O. (2023). The influence of explainable vs non-explainable clinical decision support systems on rapid triage decisions: a mixed methods study. BMC Medicine, 21 (1). <https://doi.org/10.1186/s12916-023-03068-2>