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Vitalii Samoilyk[1], Valerii Samsonkin[2], Oleksii Vynohradov[3], Oleksandra Soloviova [4], Iryna Biziuk[5]

[1]Master of Transport Technologies, train driver at Municipal enterprise “Kyiv Metro”, 35, Beresteyskyi Avenue, Kyiv, 03056. ORCID: http://orcid.org/0009-0005-6626-1275.
[2]Doctor of science, professor at the Department of Transport Technologies and Transportation Process Management, 1 Mykhailo Omelianovych-Pavlenko Str., Kyiv, 01010, Ukraine. ORCID: http://orcid.org/0000-0002-1521-2263.
[3]Postgraduate student at the Department of Transport Technologies and Transportation Process Management, 1 Mykhailo Omelianovych-Pavlenko Str., Kyiv, 01010, Ukraine. ORCID: https://orcid.org/0009-0001-9096-9020.
[4] PhD, senior lecturer at the Department of Transport Technologies and Transportation Process Management, 1 Mykhailo Omelianovych-Pavlenko Str., Kyiv, 01010, Ukraine. ORCID: http://orcid.org/0000-0002-7933-3929.
[5] Senior Lecturer at computer and control systems department, Ukrainian State University of Railway Transport, 7 Feuerbach Square, Kharkiv, 61050, Ukraine, ORCID: http://orcid.org/0000-0002-6458-5701.

*Corresponding author: legals44@yahoo.com.

The Human Factor in Metro Operations: Determining the Driver's Condition During Pre-Departure Procedures

The article analyzes the influence of the human factor on the reliability and safety of metro operations, focusing on the methods for assessing the psychophysiological state of train drivers before the start of a work shift. The study examines the current system of human factor monitoring implemented in the Kyiv Metro and emphasizes the need for objective diagnostic tools in daily safety control. Experimental research based on Schulte-Gorbov tables was conducted to evaluate attention stability, perception speed, and cognitive response of metro drivers. A month-long self-testing experiment performed before and after shifts revealed statistically significant differences depending on the driver’s condition - normal, drowsy, or fatigued. The analysis demonstrated that fatigue and reduced alertness lead to slower reaction time and lower concentration, negatively affecting driving safety. The results confirm the effectiveness of the Schulte test as a practical tool for monitoring the psychophysiological readiness of metro drivers and for preventing human-factor-related errors during transport operations.

Keywords*: rail transport, human operator, automated control, ergatic system, psychophysiological state of the driver, testing.*

The automation of metro operations under global digitalization is one of the key directions in the development of passenger transportation systems in urban rail transit. Metro trains with automated train operation (ATO) are classified by levels of automation, ranging from fully manual control to complete autonomy governed by an onboard computer. Currently, four levels of automation are defined (commonly referred to as Grades of Automation or GoA):

1. GoA 1 (Grade of Automation 1): trains require continuous presence of a driver who is responsible for acceleration, braking, and door operations.
2. GoA 2: partially automated trains, where acceleration and braking are performed automatically, but the driver remains responsible for stopping at stations and door control.

3. GoA 3: there is no driver in the cab, but a staff member is onboard to monitor door operations and respond to emergencies, while all other functions are automated.

4. GoA 4 (Unattended Train Operation – UTO): fully autonomous trains operated entirely by the onboard computer system without any human presence, including door operations.

Experts in the field of ATO design and implementation emphasize that major technological disasters typically result not from a single cause, but from a chain of multiple contributing factors forming a fatal sequence. While the causes of such incidents may vary, they are almost always united by a common element: the human factor.

From a technological standpoint, full automation of metro train operations is simpler than developing self-driving cars. However, the potential consequences of safety violations in rail transport are significantly more severe. This may explain why the global transition to driverless metro systems is occurring more slowly than expected.

Nevertheless, the number of metro lines operating under automated control continues to grow. Some systems have already eliminated human drivers entirely or are gradually reducing their number. The primary reason why the Kyiv Metro is not yet prepared for driverless trains is the intensity of train traffic. For safe operation without drivers, the headway between trains must be at least 2.5 minutes, while in Kyiv it is often significantly shorter. Additional challenges include the inability to remotely resolve technical malfunctions. Another obstacle is the high financial cost of implementing ATO, which may not be offset by simply replacing the driver with automation, as this requires extensive upgrades to trains, stations, track infrastructure, and signalling systems. Therefore, ensuring the reliability of the human driver will remain a relevant and critical issue for the foreseeable future. The article explores the issue of diagnosing the driver's condition at various stages of the work shift.

Analysis of recent research and problem statements. Research on the human factor in railway transport is a cornerstone of traffic safety. Contemporary approaches are shifting from reactive analysis of consequences to proactive risk management, which implies the identification of latent failures, psychophysiological limitations of operators, and organizational shortcomings.

Study [1] presents the REVIEW methodology for proactive assessment of organizational safety, which enables the identification of hidden risk factors at the managerial level. It distinguishes three groups of determinants: policy and management decisions, workplace culture, and operational conditions. The method has proven effective in detecting systemic causes of accidents and engaging personnel in safety management. However, this approach focuses on organizational aspects and does not account for the individual psychophysiological characteristics of the driver prior to departure.

In [2], it is emphasized that the human factor remains central at all stages of the system life cycle. The authors criticize the excessive reliance on standards EN 50126–EN 50129, proposing to integrate ergonomic and cognitive analysis into system design to reduce the likelihood of human error. Nevertheless, their focus lies on standardized procedures and quantitative risk assessment without real-time diagnostics of the driver's condition, which prevents capturing short-term fluctuations in attention and performance.

Article [3] justifies the application of the Model-Based Systems Engineering (MBSE) methodology for integrating safety requirements into the design process, ensuring traceability of risks and consistency between technical and "human" aspects. Yet, this model-oriented approach does not encompass individual psychophysiological factors of personnel during actual operation; there remains a need for real-time assessment tools for drivers' states to complement engineering methods.

Study [4] investigates the relationship between neuroticism, occupational stress, and psychological symptoms in metro drivers: high neuroticism amplifies stress and fatigue, impairing work quality. Work demonstrates the role of safety culture (employee participation, communication, training) in reducing accident rates and enhancing collective psychological resilience. However, these studies rely mainly on subjective questionnaires without objective, real-time measurements of operator state.

Paper [5] classifies types of fatigue (physical, mental, central) and distractions (visual, auditory, cognitive, biomechanical); major risk factors include monotony, circadian rhythm disruption, and sleep deprivation. Research [6] develops the concept of objective monitoring, proposing an algorithmic model for detecting cognitive distractions using ECG and HRV data, achieving high classification accuracy - confirming the potential of automated real-time driver monitoring. Nevertheless, these works emphasize signal processing without demonstrating implementation in actual metro conditions (short runs, high traffic frequency, compact cabins) or integration into pre-departure procedures.

Study [7] analyzes SIL allocation practices in EU countries and proposes unifying risk acceptance approaches for interoperability. Article [8] stresses the integration of functional safety and cybersecurity into a single risk management framework, as cyber threats can compromise safety. However, these works maintain a regulatory–technical focus, neglecting the human factor as a source of hazard and lacking mechanisms for operational monitoring of operators' psychophysiological states.

Article [9] proposes an integrated methodology for assessing metro drivers' fatigue risk based on the AHP–FCE model, which covers physiological, psychological, managerial, and environmental factors, confirming the effectiveness of quantitative fatigue assessment (case study result - "medium" risk). However, it still depends on expert judgments and lacks continuous, objective real-time monitoring before and during operation.

Study [10] surveyed 1,194 Tehran Metro drivers using Samn–Perelli, FAS, and NASA-TLX scales: fatigue significantly increased by the end of the shift, and cognitive workload positively correlated with exhaustion (greatest contributors — time pressure and cognitive demands). The limitation lies in the exclusive use of self-assessment tools without biometric data, making it impossible to detect the exact onset of dangerous fatigue.

Work [11] compares automation levels GoA1-GoA4: at lower automation levels (GoA1-GoA2), cognitive workload and fatigue are higher; at higher levels (GoA4), workload decreases, but the risk of losing situational awareness grows. The driver remains a critical control and response element. However, this study provides only comparative analysis without instruments for objective real-time assessment of individual driver states.

Article [12] analyzes behavioural risk models in the railway sector, considering individual psychophysiological characteristics, safety culture, and technical aspects of interaction with automated systems. It recommends continuous personnel monitoring and the use of biometric sensors. Yet, the study remains largely conceptual, lacking validated measurement protocols and practical implementation tools.

Organizational and regulatory tools (REVIEW, SIL, MBSE) are necessary but insufficient without considering the individual operator's condition. Safety culture and psychological factors (stress, neuroticism) substantially affect reliability but are still assessed mostly through subjective measures. Biometric and machine-learning approaches demonstrate potential for objective monitoring; however, they require adaptation to metro-specific constraints and integration into pre-operation procedures.

Despite the increasing levels of automation (GoA2–GoA4), the driver remains the critical link in the human-machine (ergatic) system: vigilance, reaction speed, fatigue, and concentration directly determine traffic safety. Existing methods - from organizational frameworks (REVIEW, SIL, MBSE) to safety-culture programs - do not provide fast, objective evaluation of a specific driver's functional readiness immediately before a trip. Medical-psychological examinations are largely formal and fail to reflect the driver's current psychophysiological state at the moment of duty clearance. Subjective questionnaires cannot capture short-term critical changes, while biometric monitoring technologies have not yet been fully integrated into real metro operations.

Therefore, it is essential to ensure the reliability of the human factor in metro driver activity by developing an objective, rapid, and operationally applicable system for assessing their psychophysiological condition prior to a trip. Such a system should combine validated biometric indicators (e.g., HRV, attention and reaction tests), algorithms for detecting risk states, and clear threshold criteria for work clearance; it must be compatible with cabin and schedule constraints and seamlessly embedded into safety processes - complementing existing regulatory and organizational mechanisms.

The purpose and tasks of the study. The purpose of the study is to analyze the use of Schulte tables for diagnosing the functional state of a metro train driver.

The task of the study:

1. To identify the existing system for ensuring human reliability in the Kyiv Metro.
2. To conduct an experiment aimed at assessing the functional state of a train driver using the Schulte table test.
3. To process the experimental results and determine relevant patterns and regularities.

Materials and methods of research.

1. Identification of the Existing Human Reliability Assurance System in the Kyiv Metro

The impact of human factors on violations of traffic safety in transportation systems is highly significant. Therefore, there is a pressing need to develop a comprehensive set of tools for monitoring the human condition, designing safety systems in vehicles involved in passenger and freight transportation, implementing hygienic measures, reducing working hours, and more [13, 14]. The "human factor" in this context is considered from two perspectives: (1) the objective determination of the degree of human involvement in safety violations; and (2) the creation of systems and technical means for monitoring, training, and duplicating human activities.

Additionally, attention should be paid to the three-level manifestation of the human factor's influence:

1. Individual human factor – actions of train drivers, dispatchers, and other personnel who's direct behaviour led to safety violations;
2. Work organization – incorrect decisions made by supervisors, maintenance crews, outdated operational instructions, which indirectly contributed to violations;
3. Design and engineering level - errors or shortcomings made by developers of technical equipment, documentation, and technological solutions, including manufacturers, research institutions, design, and engineering organizations.

Human activity within the railway transport system can be characterized by its final result RR, which is determined by the following function:

$$KP = f\left(C \cdot H \cdot 3\right), \tag{1}$$

where *CC* – predisposition to perform a specific type of work;
LL – level of training;
HH – current health condition.

Thus, the final result represents an integrated expression of these three components. However, a tangible outcome can only be achieved when each component has a non-zero value. If any of the components equals zero, the overall effectiveness of a person's activity within the railway transportation system will also equal zero.

Let us consider the implementation of the three components from equation (1) [15] within transport systems.

(1) *Predisposition.*

An individual's predisposition to perform a specific job is assessed through a professional selection system. The main objective of professional selection is to identify and recruit individuals who are most capable of efficiently performing the required tasks. Depending on the level of responsibility and the impact of a given profession, various types of professional selection are applied in the transportation sector, including:

1. Socio-educational selection, which determines the level of education, living conditions, age, professional skills, and a range of social and psychological characteristics (e.g., predisposition to disciplinary violations, personality traits, etc.);
2. Medical selection, which aims to assess an individual's state of health and its suitability for the chosen profession;
3. Psychophysiological selection, aimed at identifying professionally important qualities necessary for acquiring knowledge, skills, and abilities, and which influence the success of training and effectiveness in professional activity;
4. Psychological selection, which focuses on identifying psychological traits that are critical for successfully performing the given job.

(2) *Level of Training*

This component reflects the amount of knowledge and expertise possessed by a given specialist. It includes:

1. Basic education received in accredited institutions of levels II–IV;
2. Secondary education or retraining obtained at institutions of levels III–IV;
3. Advanced professional training;
4. Experience exchange through participation in seminars, conferences, workshops, and other scientific or technical forums as an attendee or speaker;
5. Self-education, including engagement with professional literature and relevant media (libraries, mass media, internet) to enhance subject knowledge or broaden professional outlook.

(3) *Health Status or Functional Psychophysiological State*

This component is maintained in four key areas, as regulated by the company or employer:

a) periodic medical and psychological examinations;
b) pre-shift health screening to assess the worker's fitness to perform duties;
c) intra-shift monitoring of the current condition to evaluate ability to continue working;
d) post-shift evaluation aimed at determining the need for recovery measures after duty completion.

Additionally, individual responsibility for maintaining one's own health plays a role, which depends on both the personal cultural level and the corporate culture of the organization.

A study was conducted under the conditions of the Kyiv Metro to evaluate the real-time condition of train operators. It is well known that the train operator plays a key role in ensuring the safety of passenger train movement.

To assess the functional state of the train driver, a psychophysiological method — the Schulte Tables Test - was proposed [16].

The essence of working with Schulte tables lies in the rapid and sequential identification of all numbers or other objects arranged within the grid. The table size may vary, but most commonly it is 5×5 or 7×7. The tables can be either colored (most often red and black) or non-colored. During testing, the primary emphasis is placed on the speed of number recognition. Typically, Schulte tables are used to develop the pace of information perception, as well as to assess the current state of this cognitive function. Continuous practice with Schulte tables enhances peripheral vision. A wide visual field reduces the time required to locate relevant information segments. Furthermore, the use of such tables improves the speed of visual scanning movements.

Additionally, Schulte tables are frequently employed in neuro-linguistic programming (NLP) training to achieve a so-called "high-performance state." This state is characterized by a shift in consciousness from critical perception to a certain level of detachment, allowing individuals to perform logical and sequential tasks more efficiently. In essence, this effect is also important for speed reading.

Schulte tables are well-known among psychologists, psychophysiologists, educators, and human factors specialists under alternative names such as Schulte–Gorbov Tables or Schulte–Platonov Tables.

In the current experiment, red-and-black Schulte–Gorbov Tables [17] were used, as illustrated in Figure 1.

12	21	23	21	15	19	9
2	11	12	14	5	10	19
3	25	6	8	13	17	16
10	3	9	17	1	18	18
6	8	22	7	4	24	14
20	4	23	24	20	2	22
1	7	15	16	13	5	11

Fig. 1. ***Appearance of red-and-black Schulte–Gorbov tables***

The tasks assigned to the subject primarily involve: (a) the sequential search for numbers of a single color in ascending or descending order, and (b) a mixed search pattern: black numbers in ascending order and red numbers in descending order, i.e., 1 black, 25 red, 2 black, 24 red, ... 24 black, 1 red. The test completion time is recorded for each session. The researcher conducting the experiment in 2023 was V. O. Samoylyk, then a graduating student and now a co-author of this article, who at the time worked as a train operator for the Kyiv Metro.

Experimental Design

The researcher was instructed to perform self-testing using the Schulte–Gorbov tables before and after each work shift. The duration of the study was one month.

Each self-test session included the following steps:

1. Accessing the red-and-black Schulte–Gorbov table online via the website: https://cepia.ru/speedreading/schulte/gorbov
2. Completing a single test using the mixed number search method (variant (b) described under Figure 2), with precise measurement of test completion time;
3. Recording the completion time in the experiment log.

Research Hypothesis

The hypothesis of the experiment was to confirm the statistical significance of the difference in test results before and after the work shift.

Results of the Research

Identification of the Human Reliability Assurance System in the Kyiv Metro.

A study was conducted within the operational environment of the Kyiv Metro to examine the key aspects of human factor integration. Based on this research, a structured model for ensuring human reliability was developed, as illustrated in Figure 2.

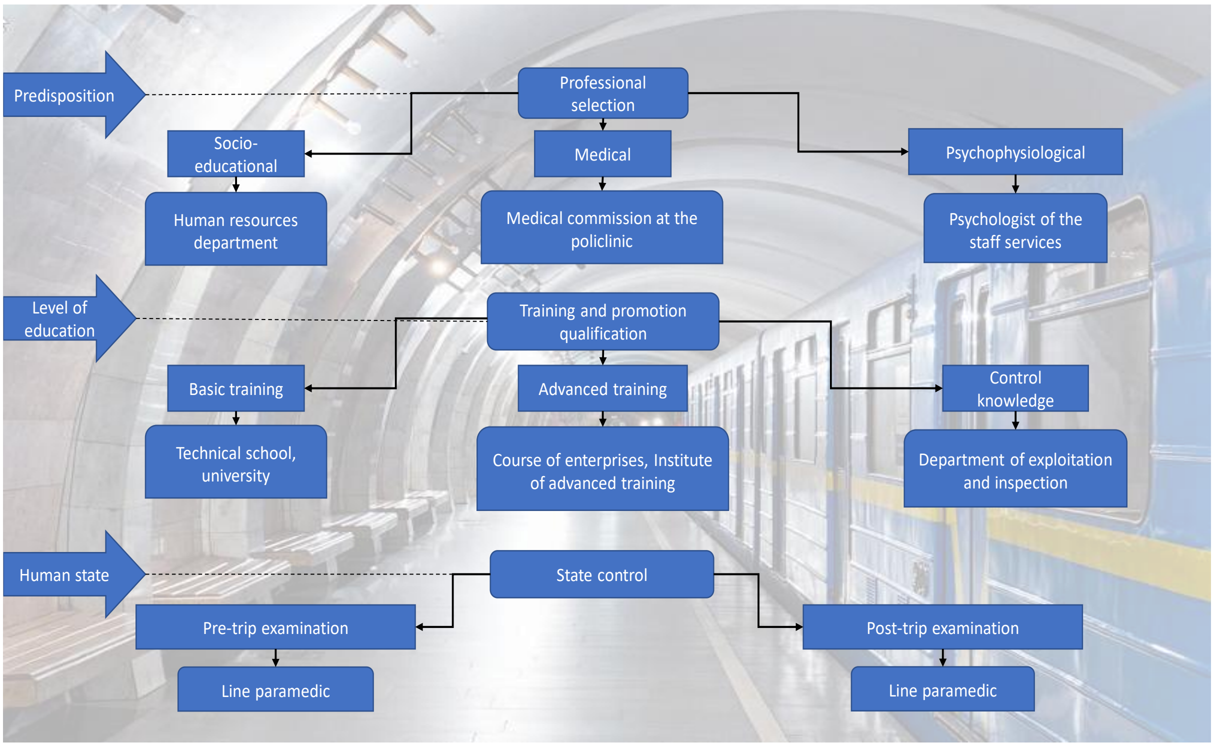

Fig. 2. ***Human Reliability Assurance System in the Kyiv Metro***

2. Conducting an Experiment to Determine the Condition of a Metro Train Operator Using the Schulte Method

The results of the experiment are presented in Table 1.

Table 1. ***Experimental Results for Determining the Functional State of the Train Operator***

№	Date	Day of the week	Before the shift		After the shift	
			Test time/Well-being	Result	Test time / Well-being	Result
1	2	3	4	5	6	7
1	29.09	Fri	14:02/N	1:44	21:32/N	2:31
2	30.09	Sat	07:09/D	1:50	14:39/N	2:32
3	01.10	Sun	16:45/N	1:29	-	-
4	02.10	Mon	-	-	09:05/F	2:42
5	03.10	Tue	10:00	1:18	16:00	1:33
6	04.10	Wed	07:04/D	1:34	14:31/N	1:23
7	05.10	Thu	12:35/N	1:26	16:35/N	1:52
8	06.10	Fri	07:25/N	1:55	15:11/N	2:40
9	07.10	Sat	09:00/N	1:33	15:39/N	1:59

Continuation of *Table* 1

1	2	3	4	5	6	7
10	08.10	Sun	07:20/N	2:00	13:31/N	2:21
11	09.10	Mon	07:01/D	2:05	13:16/N	2:26
12	10.10	Tue	13:39/N	1:45	20:31/N	2:01
13	11.10	Wed	17:26/N	1:49	-	-
14	12.10	Thu	-	-	09:01/F	3:01
15	13.10	Fri	06:30/D	2:01	13:31/N	1:41
16	14.10	Sat	09:03/N	1:18	16:51/N	3:15
17	15.10	Sun	10:00/N	1:19	16:00/N	1:01
18	16.10	Mon	10:00/N	1:23	16:00/N	1:17
19	17.10	Tue	10:00/N	1:21	16:00/N	1:20
20	18.10	Wed	16:41/N	1:33	-	-
21	19.10	Thu	-	-	09:01/F	4:00
22	20.10	Fri	06:30/F	1:59	13:30/N	1:25
23	21.10	Sat	16:41/N	1:40	-	-
24	22.10	Sun	-	-	09:01/F	4:05
25	23.10	Mon	06:35/D	2:30	13:30/N	1:30
26	24.10	Tue	10:00/N	1:00	16:00/N	1:22
27	25.10	Wed	17:00/N	1:42	-	-
28	26.10	Thu	-	-	09:06/F	4:55
29	27.10	Fri	06:30/D	2:00	13:30/N	1:49
30	28.10	Sat	13:02/N	0:59	19:57/N	1:31
31	29.10	Sun	10:23/N	1:17	17:00/N	1:39
32	30.10	Mon	13:34/N	1:15	19:34/N	1:52

Days off are highlighted with a yellow background. The letter *N* indicates a normal state of well-being, *D* (Drowsy) indicates a drowsy condition, and *F* (Fatigued) indicates fatigue.

3. Processing of Experimental Results and Identification of Patterns

The processing of the experimental results was carried out under the assumption that the statistics of the outcomes follow a normal probability density distribution of test completion time (x), described by formula (2)

$$f(x)=\frac{1}{\sqrt{2\cdot\pi}\cdot\sigma}\cdot e^{\frac{(x-m)^2}{2\cdot\sigma}}, \tag{1}$$

where *m* is the mathematical expectation (mean) of the continuous random variable *x*, representing the time to complete the Schulte-Gorbov test;
σ is the standard deviation, or the root mean square deviation of the random variable *x* from its mean value *m*, which serves as an analogue of variance - that is, the dispersion of *x* around the distribution center *m*.

The relation (2) is well known. However, the inclusion of this formula in the article is explained by the need for a clear understanding of the parameters given below.

In a normal distribution (2) about 70% (68.27%) of all possible values of x lie within the interval m ± σ [18].

Interval:

$$[m-\sigma, m+\sigma]=norm. \tag{3}$$

We will refer to this as the **norm** of a random process described by the random variable *x*. Thus, in order to determine the norm for V. Samoilyk's condition, two parameters must be known: *m*, σ.

It is well known that determining these parameters requires an infinite number of experiments, which is unrealistic. Therefore, in practical mathematical statistics, analogues of these values are used the arithmetic mean

$$\overline{x}\sim m=\frac{\sum_{i=1}^{n}x_i}{n}, \tag{4}$$

and the standard deviation

$$s\sim\sigma=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\overline{x})^2}{n-1}}. \tag{5}$$

Now, let us determine the values of m and σ according to formulas (4) and (5) for the various states of well-being of the test subject.

a) First, for general information (Table 1)

We calculate the arithmetic mean using the formula for the overall result of the experiment:

$$\overline{x}\sim m=\frac{\sum_{i=1}^{n}x_i}{n}=1{,}9min.=1min.54sec.(114sec.).$$

We calculate the standard deviation using the formula for the overall result of the experiment:

$$s\sim\sigma=\sqrt{\frac{\sum_{i=1}^{n}(x_i-\overline{x})^2}{n-1}}=0.8min.(48sec).$$

Then, according to equation (3), we determine the overall norm:

$$Norm1\ (gen) = [66, 162].$$

b) For the normal functional state (Table 2 derived from Table 1)

Table 2. ***Experimental Results for Determining Functional State During Morning Shifts (State N Highlighted with Yellow Background)***

№	Date	Day of the week	Before the shift		After the shift	
			Test time/ Well-being	Result	Test time / Well-being	Result
1	2	3	4	5	6	7
1	30.09	Sat	07:09/D	1:50	14:39/N	2:32
2	03.10	Tue	10:00/N	1:18	16:00	1:33
3	04.10	Mon	07:04/D	1:34	14:31/N	1:23
4	06.10	Fri	07:25/N	1:55	15:11/N	2:40
5	07.10	Sat	09:00/N	1:33	15:39/N	1:59
6	08.10	Sun	07:20/N	2:00	13:31/N	2:21
7	09.10	Mon	07:01/D	2:05	13:16/N	2:26
8	12.10	Thu	-	-	09:01/F	3:01
9	13.10	Fri	06:30/D	2:01	13:31/N	1:41
10	14.10	Sat	09:03/N	1:18	16:51/N	3:15
11	15.10	Sun	10:00/N	1:19	16:00/N	1:01
12	16.10	Mon	10:00/N	1:23	16:00/N	1:17
13	17.10	Tue	10:00/N	1:21	16:00/N	1:20
14	19.10	Thu	-	-	09:01/F	4:00
15	20.10	Fri	06:30/D	1:59	13:30/N	1:25
16	22.10	Sun	-	-	09:01/F	4:05
17	23.10	Mon	06:35/D	2:30	13:30/N	1:30
18	24.10	Tue	10:00/N	1:00	16:00/N	1:22
19	26.10	Thu	-	-	09:06/F	4:55
20	27.10	Fri	06:30/D	2:00	13:30/N	1:49
21	29.10	Sun	10:23/N	1:17	17:00/N	1:39

Using formulas (4) and (5), the following results were obtained:

m=2.03 min.=2 min. 1 sec. (121 sec.);
σ=0.93 min. (56 sec).

Table 3. ***Experimental Results for Determining Functional State During Evening Shifts (State N)***

№	Date	Day of the week	Before the shift		After the shift	
			Test time/ Well-being	Result	Test time / Well-being	Result
1	29.09	Fri	14:02/N	1:44	21:32/N	2:31
2	01.10	Sun	16:45/N	1:29	-	-
3	05.10	Thu	12:35/N	1:26	16:35/N	1:52
4	10.10	Tue	13:39/N	1:45	20:31/N	2:01
5	11.10	Wed	17:26/N	1:49	-	-
6	18.10	Wed	16:41/N	1:33	-	-
7	21.10	Sat	16:41/N	1:40	-	-
8	25.10	Wed	17:00/N	1:42	-	-
9	26.10	Thu	-	-	09:06/F	4:55
10	28.10	Sat	13:02/N	0:59	19:57/N	1:31

Using formulas (4) and (5), the following results were obtained:
m=1.92 mim.=1 min. 55 sec. (115 sec.);
σ=0.94 min. (56 sec).

Table 4. ***Experimental Results for Determining Functional State Under Normal (N) Condition***

№	Date	Day of the week	Before the shift		After the shift	
			Test time/ Well-being	Result	Test time / Well-being	Result
1	2	3	4	5	6	7
1	29.09	Fri	14:02/N	1:44	21:32/N	2:31
2	30.09	Sat	-	-	14:39/N	2:32
3	01.10	Sun	16:45/N	1:29	-	-
4	03.10	Tue	10:00/N	1:18	16:00/N	1:33
5	04.10	Wed	-	-	14:31/N	1:23
6	05.10	Thu	12:35/N	1:26	16:35/N	1:52

Continuation of *Table* 4

1	2	3	4	5	6	7
7	06.10	Fri	07:25/N	1:55	15:11/N	2:40
8	07.10	Sat	09:00/N	1:33	15:39/N	1:59
9	08.10	Sun	07:20/N	2:00	13:31/N	2:21
10	09.10	Mon	-	-	13:16/N	2:26
11	10.10	Tue	13:39/N	1:45	20:31/N	2:01
12	11.10	Wed	17:26/N	1:49	-	-
13	12.10	Thu	-	-		3:01
14	13.10	Fri	-	-	13:31/N	1:41
15	14.10	Sat	09:03/N	1:18	16:51/N	3:15
16	15.10	Sun	10:00/N	1:19	16:00/N	1:01
17	16.10	Пн	10:00/N	1:23	16:00/N	1:17
18	17.10	Tue	10:00/N	1:21	16:00/N	1:20
19	18.10	Wed	16:41/N	1:33	-	-
20	20.10	Fri	-	1:59	13:30/N	1:25
21	21.10	Sat	16:41/N	1:40	-	-
22	23.10	Mon	-	-	13:30/N	1:30
23	24.10	Tue	10:00/N	1:00	16:00/N	1:22
24	25.10	Wed	17:00/N	1:42	-	-
25	27.10	Fri	-	-	13:30/N	1:49
26	28.10	Sat	13:02/N	0:59	19:57/N	1:31

Overall, for the normal condition, the following results were obtained:

m=1.7 mim.=1 min. 42 sec. (102 sec.);

σ=0.29 min. (32 sec).

The norm in the normal state is:

$$Norm2(H)=[70,134]. \quad (6)$$

c) For the fatigued functional state (Table 5 derived from Table 1)

Table 5. ***Experimental Results for Determining Functional State Under Fatigued (FG) Condition***

№	Date	Day of the week	Before the shift		After the shift	
			Test time/ Well-being	Result	Test time/Well-being	Result
1	02.10	Mon	-	-	09:05/F	2:42
2	12.10	Thu	-	-	09:01/F	3:01
3	19.10	Thu	-	-	09:01/F	4:00
4	22.10	Sun	-	-	09:01/F	4:05
5	26.10	Thu	-	-	09:06/F	4:55

Using formulas (4) and (5), the following results were obtained:

m=3.74 mim.=3 min. 44 sec. (244 sec.);

σ=0.88 min. (53 sec).

In the fatigued state, the calculated norm is:

$$Norm3(F)=[171,277]. \tag{7}$$

For the drowsy functional state (Table 6 derived from Table 1).

Table 6. ***Experimental Results for Determining Functional State Under Drowsy (DR) Condition***

№	Date	Day of the week	Before the shift		After the shift	
			Test time/ Well-being	Result	Test time / Well-being	Result
1	30.09	Sat	07:09/D	1:50	-	-
2	04.10	Wed	07.04/D	1:34	-	-
3	09.10	Mon	07.01/D	2:05		
4	13.10	Fri	06:30/D	2:01	-	-
5	23.10	Mon	06:35/D	2:30	-	-
6	27.10	Fri	06:30/D	2:00	-	-

Using formulas (4) and (5), the following results were obtained:

m=1.99 mim.=1 min. 59 sec. (119 sec.);

σ=0.2 min. (12 sec).

In the drowsy state, the norm is:

$$Norm(D)=[107,131]. \tag{8}$$

Now, the calculated data are summarized in the consolidated Table 7.

Table 7. ***Operator's Norm in Three Functional States***

State	Value, sec		
	m	***σ***	***norm***
Normal (N)	102	32	[70, 134]
Fatigued (F)	224	53	[171, 277]
Drowsy (D)	119	12	[107, 131]

The norm reflects the quality of test performance, i.e., the readiness for work. For clarity, the results of the norm presented in Table 7 are visualized graphically (see Figure 3).

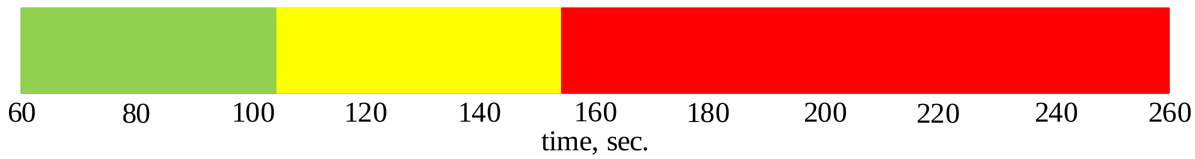

Figure 3. ***Norm Positions for Performing the Schulte Psychophysiological Test for Three Operator States: Normal (green), Drowsy (yellow), and Fatigued (red)***

Conclusions. Based on the analysis of Table 7 and Figure 3, the following conclusions can be drawn:

1. The normative performance on the Schulte test varies across different functional states;
2. It has been demonstrated that as the operator's condition deteriorates, the normative value shifts to the right, indicating an increase in test completion time, which in turn reflects a decline in attention-switching readiness and driver reaction speed;
3. The hypothesis regarding differences in driver behaviour norms under various conditions, as measured by the Schulte test, has been confirmed;
4. The Schulte psychophysiological test can be effectively used to assess a driver's readiness for duty.

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Віталій Самойлик[1], Валерій Самсонкін[2], Олексій Виноградов[3], Олександра Соловйова[4], Ірина Бізюк[5]

[1]Магістр транспортних технологій, машиніст метро Комунального підприємства "Київський метрополітен", 03056, Україна, м. Київ, просп. Берестейський, буд. 35. ORCID: http://orcid.org/0009-0005-6626-1275.

[2]Доктор наук, професор кафедри технологій транспорту та управління процесами перевезень Національного Транспортного Університету, 03115, Україна, м. Київ, вул. Котельникова, буд. 29/18. ORCID: http://orcid.org/0000-0002-1521-2263.

[3]Аспірант кафедри технологій транспорту та управління процесами перевезень Національного Транспортного Університету, 03115, Україна, м. Київ, вул. Котельникова, буд. 29/18. ORCID: https://orcid.org/0009-0001-9096-9020.

[4]Доктор філософії, старший викладач кафедри технологій транспорту та управління процесами перевезень Національного Транспортного Університету, 03115, Україна, м. Київ, вул. Котельникова, буд. 29/18. ORCID: http://orcid.org/0000-0002-7933-3929.

[5]Старший викладач кафедри обчислювальної техніки та систем управління Українського Державного Університету Залізничного Транспорту, 61050, Україна, м. Харків, майдан Фейєрбаха, 7. ORCID: http://orcid.org/0000-0002-6458-5701.

Людський фактор в експлуатації метро: визначення стану водія під час передрейсових процедур

Анотація. *У статті досліджено вплив людського чинника на надійність та безпеку роботи* *метрополітену, зосереджено увагу на методах оцінювання психофізіологічного стану машиністів перед початком зміни. Проаналізовано діючу систему контролю людського чинника в Київському метрополітені та підкреслено необхідність упровадження об'єктивних діагностичних засобів у щоденну практику безпеки руху. Експериментальні дослідження із застосуванням таблиць Шульте–Горбова дали змогу оцінити стійкість уваги, швидкість сприйняття та когнітивну реакцію машиніста. Протягом місяця самотестування до і після зміни виявлено статистично значущі відмінності у результатах залежно від функціонального стану працівника - нормального, сонливого чи втомленого. Аналіз показав, що втома та зниження бадьорості спричиняють уповільнення реакції, погіршення концентрації та уваги, що негативно впливає на безпеку керування. Отримані результати підтверджують ефективність тесту Шульте як дієвого інструменту для моніторингу психофізіологічної готовності машиністів і попередження помилок, пов'язаних із людським чинником.*

Ключові слова: *залізничний транспорт, людина-оператор, автоматизоване керування, ергатична система, психофізіологічний стан водія, тестування.*

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