Machine learning-based study of fire evacuation parameters in inclusive secondary schools*

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Abstract

The work is dedicated to the application of machine learning methods in fire safety. Inclusive education is developing very rapidly. At the same time, existing models for calculating the evacuation duration do not make it possible to perform such calculations for secondary schools with inclusive classes. To solve this problem experimental studies have been conducted. Based on the experimental results, a dataset of speed measurements has been formed. The obtained dataset has been divided into training and test samples and a regression analysis of evacuation parameters from the buildings of secondary education institutions with inclusive classes has been carried out. The dependence of flow speed on density, the percentage of flow participants using wheelchairs and the average age of evacuation participants has been established using a linear regression model. The regression problem was also solved using a neural network. To test the obtained models, they were used to calculate the evacuation duration. The obtained results have been compared with the results of computer modeling using the Pathfinder software complex. It has been established that the use of the obtained models makes it possible to adapt the existing models for calculating the evacuation duration to their application for school education institutions with inclusive classes.

Keywords

linear regression, neural network, machine learning, evacuation, inclusive education, wheelchairs [1]

1. Introduction

1.1. Problem statement

As of December 1, 2023, there were 29,321 inclusive classes and 807 special classes in general secondary education institutions of Ukraine, in which 40,354 and 7,044 pupils with special educational needs studied, respectively. Statistics provided by the Ministry of Education and Science of Ukraine indicate that over the past 5 years, the number of pupils with special educational needs in inclusive classes has more than doubled, and over the past 10 years - almost tenfold [1].

As we can see, inclusive education in Ukraine is at a stage of rapid development, and its implementation, like every innovative process, faces a number of problems. Ensuring the required level of fire safety is one of the most essential.

The value of the individual fire risk is an important indicator of the fire prevention condition at each object. To determine this indicator, it is necessary to calculate the duration of evacuation from the building in case of fire. In general, the methods used to make such calculations are based on 2 types of models: individual and flow. Individual models provide for the possibility to take into account the change in the movement speed of each evacuation participant depending on external

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factors. Their advantage is the ability to take into account the presence of evacuation participants with different mobility. It is on such model types that the majority of modern software and modeling complexes are based on. Flow models are simpler and do not require significant computing power, although they are considered less accurate, compared to individual models. In these models, the evacuation flow is assumed to be a homogeneous (homogeneous) structure, where all participants move according to a single established law of movement.

It would seem that individual models are best suited for calculating the evacuation duration from schools with inclusive education. But studies of evacuation processes [2] have shown interesting results. In case of a fire, each class moves to a safe zone under the supervision of a teacher (and/or an assistant), who are personally responsible for the children. Therefore, a scenario in which some pupils move faster or slower than others and are separated from the general flow is, as a rule, unlikely. At the same time, the use of individual models to reproduce such processes gives significant deviations from the evacuation duration in real conditions. Observation of evacuation in educational institutions with inclusive classes showed that effective duration calculation entails the use of flow models.

1.2. Literature review

Normative document that regulate the methods of calculating the evacuation duration in case of fire describe the influence of the crowd density on the speed of homogeneous flows. These flows consist of adults and children of different ages. At the same time, the initial data for the calculation are only partial cases, which do not make it possible to model the parameters of the movement of flows, which include participants with different mobility. Thus, guided by this document, it is possible to perform calculations for ordinary schools. As for educational institutions with inclusive classes, there is not enough data for calculation in this document. The requirements for structural and planning solutions of school buildings include the provision of a barrier-free environment. However, the mere presence of barrier-free access (ramps, wide doorways, elevators, etc.) does not automatically guarantee the timely and safe evacuation of all pupils in the event of fire. Current regulations explicitly state that in one inclusive class the number of pupils using wheelchairs must not exceed two, while the total number of pupils in such a class is limited to 20.

The analysis of scientific literature also showed that the results of experimental and analytical studies devoted to evacuation from buildings and structures do not allow applying the obtained results to modeling evacuation processes from inclusive classes. Thus, in [3], the dynamics of participants moving in wheelchairs was modeled. But the paper considers the movement of a mixed flow, in which all participants are not obliged to move as part of a defined group. Therefore, the proposed models do not work in the conditions of a school with inclusive education. In [4], not only participants in wheelchairs, but also those using crutches were considered. At the same time, as in the previous case, the organized movement under the control of pedagogical workers was not taken into account. The work [5] is also devoted to the movement of participants in wheelchairs. The dynamic characteristics of movement on turns and bottlenecks and their influence on the overall speed of movement have been established. At the same time, children were not considered as participants in the evacuation. Works [6] and [7] are devoted to evacuation from educational institutions in case of fire, but they pay attention to organizational issues of evacuation from schools, in particular, training drills and psychological preparation of pupils. In [8] and [9], the dependencies of speed on flow density during evacuation from preschool and school education institutions are presented. However, in both works homogeneous flows of children were considered. The issue of evacuation of pupils with reduced mobility was not considered. In [10], a partial case of evacuation from a school building with inclusive education is considered. At the same time, the percentage of evacuation participants in wheelchairs in the stream was 10% and the influence of the evacuation participants' age on the flow speed was not taken into account. In [2], the authors justify the need to improve existing models for calculating evacuation from preschool and school education institutions, in particular, to introduce changes to regulatory documents that would allow taking into account the presence of students of different ages and mobility.

In recent years, machine learning techniques have been increasingly and successfully applied to a wide range of fire safety problems, including the prediction of fire and smoke propagation, occupant behaviour modelling, and evacuation dynamics [18,19]. Specifically in the field of human evacuation during fire, data-driven approaches such as regression models, decision trees, and neural networks have demonstrated superior accuracy compared to traditional parametric formulas when dealing with heterogeneous or reduced-mobility populations [20]. These studies confirm that relatively compact experimental datasets, similar to the one collected in the present work, are sufficient to train reliable predictive models that can be seamlessly integrated into existing regulatory calculation frameworks [15].

It can be concluded that in most works the movement speed of evacuation participants V is presented as a function of one variable, which is the flow density D (the number of evacuation participants per square meter of the evacuation route at a certain point in time). In secondary education institutions with inclusive classes, in addition to density, such indicators as the percentage of participants with reduced mobility in the flow and the average age of the pupils will affect the speed. Therefore, establishing a regression relationship between these indicators is an urgent task.

1.3. Purpose and research tasks

Given that regression [11-13] is one of the machine learning tasks, the purpose of this work is applying regression algorithms to establish the dependence between the movement parameters of evacuation flows in secondary education institutions with inclusive classes. To achieve the purpose, the following tasks must be solved:

- conducting experimental observations and forming an empirical database of evacuation parameters to prepare data for regression model;
- applying regression algorithms to the obtained data, and establishing the regression coefficients using the algorithm with the best accuracy metrics;
- calculating the evacuation duration from the building of a secondary education institution with inclusive classes and comparing the results with similar data obtained both experimentally and with the help of other calculation methods for practical evaluation of the proposed regression model.

2. Preparation of data for the model

Data collection for the regression model was carried out in several ways.

The first method involved conducting real-life experiments with secondary education pupils of various ages with dynamic video recording. The experiments were conducted in Lviv School #30. For ethical reasons, the movement of the evacuation participants in wheelchairs was recreated by the volunteering higher education graduates of Lviv State University of Life Safety. Movement of mixed human flows with different percentage of participants in wheelchairs has been conducted. According to standard regulations, no more than 2 pupils using wheelchairs are allowed in each inclusive class, and the total number of pupils in such classes does not exceed 20 people. At the same time, in addition to the teacher, an assistant is involved in the organization of the educational process. So both the teacher and the assistant are able to help participants with reduced mobility in the evacuation process.

Due to the method of dynamic video recording several evacuation participants have simultaneously used action cameras with a coverage angle of up to 170°, dimensions 6×4×2.5 cm and a weight of 40 g (Figure 1).

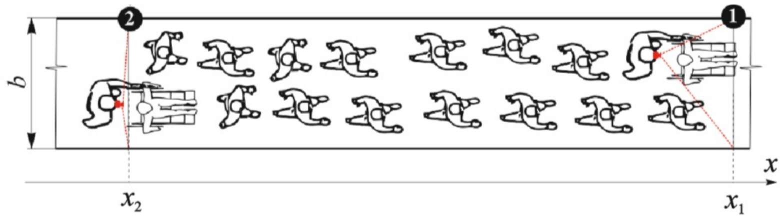

Figure 1: Dynamic video recording of the experiment.

All experiments were conducted on a straight horizontal corridor section 40 m long and 3 m wide. The entire path was marked with painter's tape every 2 m for precise distance reference. The behaviour of children with reduced mobility was realistically simulated by trained adult volunteers. Dynamic video recording was performed using action cameras (170° field of view) worn by the first and last participants in each group. The static overhead surveillance cameras were installed at the start and end of the section at a height of 3 m to provide complementary trajectory data.

Due to the floor plans and marks on the evacuation route, the synchronization of the cameras made it possible to accurately determine the x_1 and x_2 coordinates of the participants at different moments of time and determine the corresponding values of speed V (1) and density D (2):

$$V=\frac{[x_1(t_{n+1})-x_1(t_n)]+[x_2(t_{n+1})-x_2(t_n)]}{2\cdot(t_{n+1}-t_n)}, \tag{1}$$

where x_1, x_2 are the coordinates of participants performing video registration; $t_{(n+1)}$ and t_n –time of two consecutive measurements.

$$D=\frac{D(t_{n+1})-D(t_n)}{2}, \tag{2}$$

This average density value represents the mean flow density over the time interval between two consecutive measurements and is a standard approach when instantaneous density values are available from synchronized video recordings.

The second method involved obtaining data by analyzing the video stream of surveillance cameras using OpenCV tools to recognize evacuation participants of different mobility groups and the SORT (Simple Online and Real-time Tracking) algorithm in combination with a Kalman filter to determine their movement speed [15-17]. In general, the number of measurements for each of the scenarios is presented in Table 1. Thus, the database obtained due to results of experimental studies consisted of 449 measurements.

Table 1
The number of measurements at different values of the predictors

Percentage of participants using wheelchairs	Average age of evacuation participants		
	7,5 years	11,5 years	15 years
0% (total number of agents – 20, on wheelchairs – 0)	50	49	50
5% (total number of agents – 20, on wheelchairs – 1)	45	48	45
10% (total number of agents – 20, on wheelchairs – 2)	70	45	47

3. Analysis and results

In the dataset of 449 measurements, obtained after conducting experimental studies, the movement speed V is the predicted indicator and the flow density D, the percentage of participants using wheelchairs W(M4), and the average age A (AgeAvg) of the participants are the predictors.

Regression analysis was performed in Google Collaboratory using Python language and Scikit-learn, MathPlotLib, NumPy, Pandas, Seaborn libraries.

Figure 2 shows Speed V and density D scatterplots.

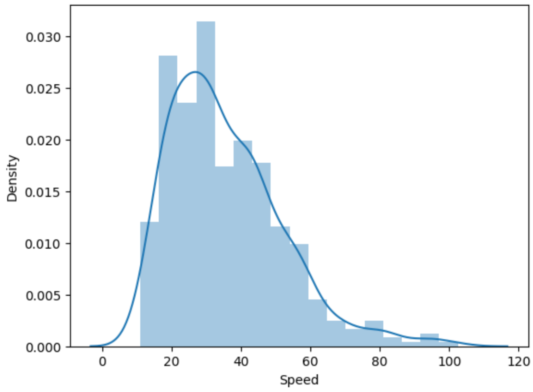

Figure 2: Speed and density scatterplots.

The correlation between the predictors has been calculated and the correlation heat map has been built (Figure 3). It shows that the flow density has the greatest influence on the speed change. At the same time, an increase in density naturally leads to a decrease in speed. Increasing the percentage of evacuees using wheelchairs also slows traffic. An increase in the average age of evacuation participants leads to an increase in speed indicators. The figure indicates a very low correlation of predictors among themselves, which indicates the absence of multicollinearity.

Based on the above, regression analysis has been performed in two ways.

3.1. Analysis using linear regression model

The first way has involved the use of a linear regression model. To train this model, the dataset has been divided into training and test samples in the ratio of 80% to 20%, respectively. Thus, the training set consisted of 359, and the testing set – of 90 measurements.

The coefficient of determination R^2 and mean absolute error (MAE) have been used as accuracy metrics. The value of the dependent variable under the condition that all predictors acquire zero (intercept), has been also calculated.

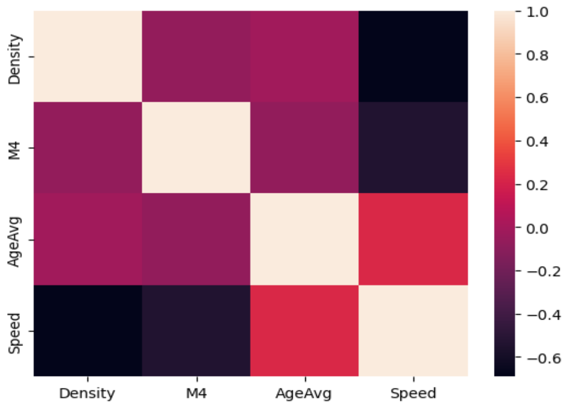

Figure 3: Correlation heat map.

The results of linear regression model training are as follows:

- Training data R^2=0,8517974766661927.
- Test data R^2=0.87147496081119.
- Intercept: 62.90300495036077
- Mean absolute error (MAE): 4.1254266643612423

Figure 4 shows a scatter plot of the test sample values prediction results.

Regression coefficients, established based on the results of model training, are given in dependence (3):

$$V = 62{,}9 - 6{,}98 \cdot D - 300{,}188 \cdot W + 1{,}184 \cdot A\,, \qquad (3)$$

where: D – flow density, person/m^2; W – percentage of participants using wheelchairs; A – average age of evacuation participants, years.

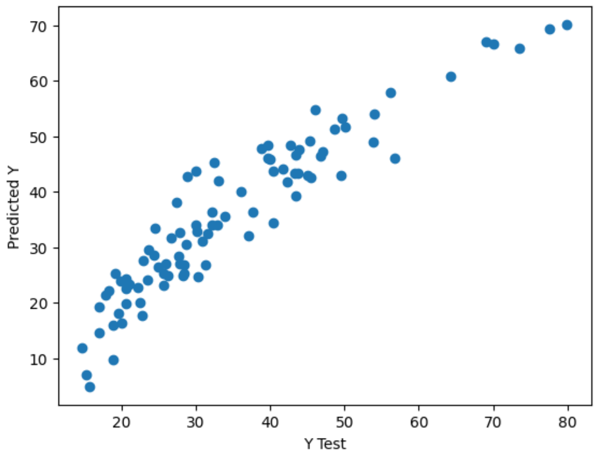

Figure 4: Test sample values prediction results.

The normality of the error distribution (Figure 5) indicates the satisfactory quality of the model.

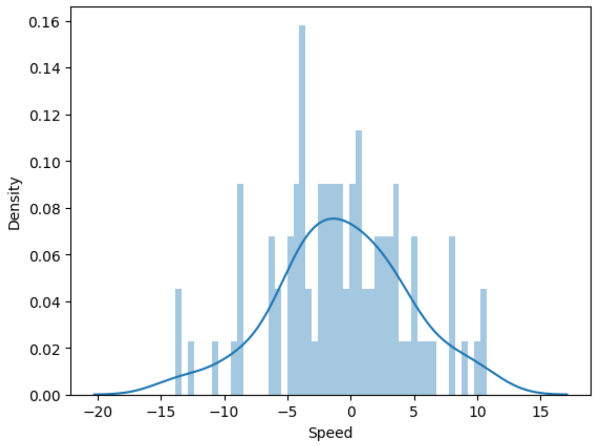

Figure 5: Error distribution.

3.2. Neural network analysis

The second method involved the use of a fully connected neural network. Initially, data normalization was performed using the .mean() and .std() methods.

The model is a fully connected feed-forward neural network with 3 input neurons (density, percentage of wheelchair users, average age), one hidden layer of 128 neurons with ReLU activation, and a single output neuron with linear activation for regression. Total trainable parameters: 641. As in the previous case, the distribution of the dataset into the training and test samples was predicted in the ratio of 80 to 20. Adam was chosen as the optimizer, and the mean square error (MSE) was chosen as the quality criterion. The MAE accuracy metric was also chosen.

After 100 training epochs, the MSE reached a value of 26,95 on the training and 17,2 on the test samples (Figure 6). MAE reached a value of 4,04 on the training and 3,28 on the test samples (Figure 7).

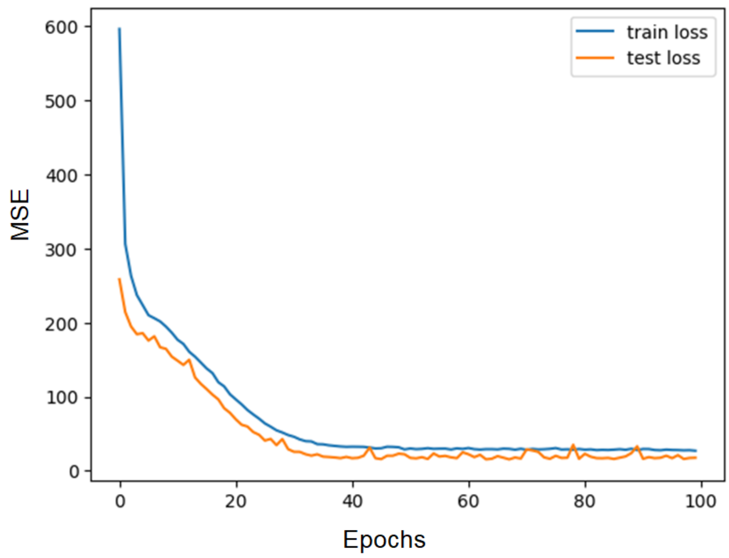

Figure 6: Reducing the MSE value during model training.

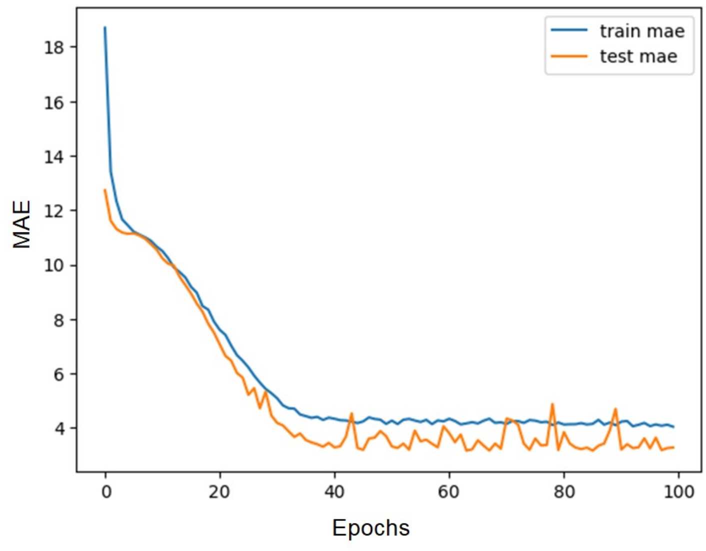

Figure 7: Reducing the MAE value during model training.

4. Computer simulation

To test the practical applicability of the proposed models, evacuation duration was calculated using three independent approaches. The first approach relied on detailed computer simulation in the Pathfinder software, which implements a fine-grained individual movement model and explicitly accounts for differences in mobility among participants (Figure 8).
The second approach employed a simplified analytical technique based on the traditional flow (group) model. While the tabular data provided in current national standards do not contain coefficients for mixed flows that include wheelchair users, incorporating the regression equation (3) obtained in this study or predicting instantaneous speed with the trained neural network

eliminates this limitation and enables fast hand calculations for inclusive-school scenarios. The third approach used direct experimental measurements conducted under real-school conditions as the reference (ground truth).

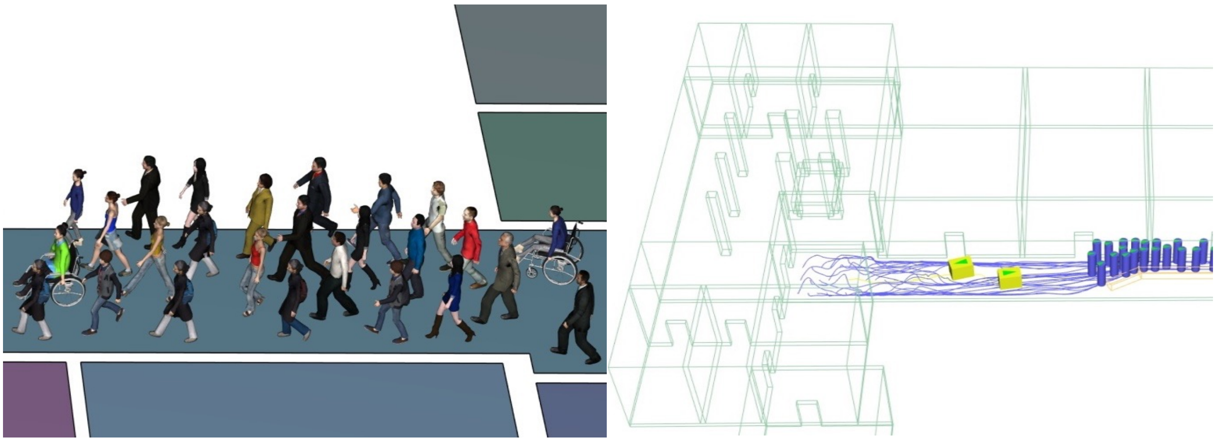

Figure 8: Evacuation process simulation in Pathfinder.

As already mentioned, the total number of people who participated in the experiment was 22 (20 pupils, the teacher and the teacher's assistant). The experiment has been conducted on a horizontal section of the corridor 40 m long and 3 m wide.

The results are summarized in comparative table 2.

Table 2
Comparison of evacuation duration values determined by different methods (in seconds)

Percentage of participants using wheelchairs	Experiment results	Pathfinder simulation	Calculation due to Eq.(3)	Calculation using neural network
		7,5 years		
0%	44	48	52	50
5%	63	76	71	69
10%	71	83	77	75
		11,5 years		
0%	39	43	49	47
5%	59	71	68	67
10%	65	77	73	72
		15 years		
0%	34	37	43	42
5%	55	67	64	63
10%	61	72	69	69

The regression analysis carried out in this work shows that the movement speed during evacuation from secondary education institutions with inclusive classes depends to a large extent not only on the density of the flow, but also on the number of pupils with reduced mobility, as well as the average age of the evacuation participants. A characteristic feature of evacuation from schools with inclusive education is the need to move as part of a class under the teacher's control. Therefore, pupils using wheelchairs significantly reduce the entire class movement speed, and therefore, increase the total evacuation duration.

The machine learning models presented in the work make it possible to improve the methodology for calculating the evacuation duration from educational institutions with inclusive classes regulated by state standards [3]. This is confirmed by the results shown in Table 2, where both linear regression and the neural network allow obtaining significantly smaller discrepancies with the results obtained in real conditions than using an individual model.

5. Conclusions

The article presents the results of applying machine learning methods to study fire evacuation processes from secondary education institutions with inclusive classes. Particular attention has been paid to mixed flows that include pupils using wheelchairs, with the goal of determining reliable movement parameters for accurate evacuation duration calculation.

The research objectives have been achieved through the following key outcomes:

1. 1.Based on full-scale on-site observations in a real secondary school with inclusive education, an empirical dataset of 449 speed measurements was created from evacuation flows of pupils with different ages and mobility groups on horizontal sections. Data preprocessing enabled the use of linear regression and a neural network to establish relationships between flow density, percentage of wheelchair users, average age, and movement speed.
2. 2.The models were validated by three methods: experimental measurements (ground truth), Pathfinder simulation, and analytical calculations using traditional flow theory with the obtained regression. The neural network showed the highest accuracy, with deviations not exceeding 15 %. The linear regression equation (3), integrated into a simplified analytical model, reduced the maximum error from 23 % to 17 % compared to conventional individual-movement models.

The results can be directly applied in fire-safety practice for schools with inclusive classes containing pupils in wheelchairs. The methodology is transferable to other reduced-mobility groups (e.g., pupils on crutches or with visual impairments), requiring only an experimental training dataset. The proposed models provide a flexible, data-driven way to adapt regulatory methods to modern inclusive education without costly standard changes.

In summary, this work bridges the gap between inclusive education and fire-safety requirements, showing that simple, interpretable machine learning models trained on real-school data significantly improve evacuation time predictions for mixed-ability populations.

Declaration on Generative AI

During the preparation of this work, the authors used X-GPT-4 in order to grammar and spelling check. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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