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Ideology of Urban Road Transport Chaos and Accident Risk Management for Sustainable Transport Systems

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Abstract: Transport systems are complex systems present in modern cities. The sustainability of all other urban systems depends on the sustainable functioning of urban transport. Various processes occur within transport systems. Road traffic is one of them. At the same time, road traffic is a rather complex process to manage, which is explained by the influence of many different internal and external environmental factors. The unpredictable and chaotic behavior of each vehicle in a traffic flow complicates predicting the transport situation and traffic management. This problem gave rise to several unsolved problems, including traffic congestion and road accident rates. The solution to these problems is connected with sustainably managing transport systems in terms of road traffic. However, numerous regularities between elements within the system should be understood in order to implement the management process. Unfortunately, the results of many previous studies often reflect only partial regularities and have limited functionality. Therefore, a new approach to urban traffic management is needed. As opposed to the existing solutions, the authors of this paper propose to implement management based on the regularities of changes in the chaos of the transport system. In this regard, the purpose of this research is to establish the relationship between road traffic chaos and road accident rates. The general methodological basis of this research is the system approach and its methods: analysis and synthesis. The theoretical studies were mostly based on the theories of chaos, dynamic systems, and traffic flows. The experimental studies were based on the theories of experimental design, probability, and mathematical statistics. To achieve this goal, a profound analysis covered studies on the sustainability of transport and dynamic systems, sociodynamics, and traffic. The authors proposed considering the relative entropy of lane occupancy at signal-controlled intersections as a measure for assessing traffic flow chaos and sustainability. Notably, as the main conclusions, the authors established regularities for the influence of entropy on the kinetic energy of traffic flows and injury risk. It also makes sense to emphasize that the initial data for the experiment were collected via real-time processing of video images using neural network technologies. These technologies will further allow for the implementation of traffic management and real-time forecasting of various events. Ultimately, the authors identified changes in injury risk depending on the level of road chaos. According to the authors, the obtained results can be used to improve the sustainability of urban transport systems. The research identified changes in injury risk depending on the level of road chaos, which could have significant implications for urban traffic management strategies.

Keywords: sustainability of urban transport systems; traffic management; traffic entropy; road accident rate; chaos; risk; neural network technologies

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1. Introduction

Transport is an essential attribute of sustainable existence and development. This thesis is valid for systems of any size and complexity [1]. Historical analysis [2] shows that people tend to live in communities, leading to the emergence of cities and the formation of sustainable urban technologies for life-sustaining activities [3]. According to the World Urban Forum, as of 2023, there are more than 10,000 cities in the world [4], and each of them has long been characterized by certain transport problems [5].

Transport systems are a striking example of complex systems whose functioning is based on the postulates of several theories. H. Sayama believes that these theories can be classified according to seven thematic areas [6] (p. 5), while the degrees of their elaboration differ.

Attempts to model the behavior of transport systems are usually very limited in functionality, and the results of the practical implementation of these models are rarely effective [7]. At the same time, these efforts are extremely necessary since even a slight improvement in the functioning of urban transport systems increases the efficiency and sustainability of almost all life support processes in cities [8] and, ultimately, the efficiency and sustainability of the entire "Urban" system.

This paper considers the possibility of improving the functioning of urban transport systems from the standpoint of assessing the level of chaos in the formation of transport and pedestrian flows and the relationship between road chaos and road accident risks. The paper analyzes the experiences of experts from different countries searching for the dialectical balance between the dual pair of the main attributes pertaining to the "Efficiency–Safety" of urban transport systems. The authors' reasoning is based on the theoretical and experimental modeling of traffic entropy on a local road network section in the large Russian city of Tyumen (as of 2023, its population is about 855 thousand people). An important research aspect is studying the influence of individual disturbances in the form of road accidents (RAs) on the chaotic nature of transport and pedestrian flows. Another research aspect is assessing the relationship between road traffic entropy and road accident risks. An important aspect of this research is the consideration of the studied problem from the standpoint of the energy–information balance of the traffic management system and road safety control. The cumulative study of all these aspects of the functioning of sustainable urban transport systems allows for the development of ideological foundations for managing urban road traffic chaos and accident risks.

In Section 2, we conduct an analysis of studies on the relationship between road conditions, road chaos, and the level of road traffic incidents. In Section 3, we use the entropy of the road traffic flow as the primary indicator for evaluating the organization of road traffic. Section 4 presents the findings from experimental investigations of the dynamic and energy characteristics of the traffic flow. In Section 5, we discuss and analyze the obtained results, examine their connection with previous research, and emphasize their significance and impact on the field of study. We also discussed the limitations of the study and proposed potential directions for further research. Finally, in Section 6, we formulate the main conclusions of our research, highlight its significance, and provide practical recommendations for improving the organization of road traffic based on the obtained results.

2. Literature Review and Basic Research Ideas

2.1. The Place and Role of Chaos in Operation of the Sustainable Urban Transport System (UTS)

Chaos is defined as unstable aperiodic behavior in nonlinear dynamical systems. A distinctive characteristic of chaos is its extreme sensitivity to the initial conditions. A minute perturbation in the boundary conditions of a chaotic dynamic system leads to a finite change in trajectory within the phase space [9].

There are many sources in the literature dealing with complexity and chaos. Starting with A. Poincaré and J. Hadamard, many scholars have been interested in system nonlinearity, including J. Birhoff, A. Kolmogorov, M. Karetnik, J. Leathwood, etc. However, the lack of necessary computing capacities hindered multiple calculation iterations. A breakthrough in chaos research occurred in 1960–1961, when almost simultaneously, E. Lorenz [9] and B. Mandelbrot [10], using different examples, discovered the effects of a significant divergence of dynamically calculated data from the expected ones with a slight deviation in the scale of the initial data.

As already known, chaos and order are interrelated phenomena. Complex chaotic systems are deterministic, i.e., they obey a strict law, and, in a sense, are orderly. Complex systems are extremely dependent on the initial conditions, and minor environmental changes can lead to unpredictable consequences. The main ideas of the theory of complexity and chaos are discussed in detail in [11].

Table 1 presents data on some (out of many) works on system chaos. Some of them consider the chaotic functioning of transport systems. Table 1 contains works on chaos [9–23], assessing the characteristics of the influence of chaos on the functioning of transport systems [17,24–28], and the influence of chaos on human behavioral processes and sociodynamics [29–31], studying the properties of dynamic systems [32–38].

Table 1. Studies of the place and role of chaos in the operation of sustainable urban transport systems (UTSs).

Authors	**Methodology**								
	General Chaos Theory	**Mathematical Foundations of the Chaos Theory**	**Chaotic Data Analysis Methods. Properties of Chaotic Systems**	**Traffic Modeling**	**Study of the Influence of Chaos on Urban Planning Processes**	**Study of the Influence of Chaos on Human Behavioral Processes**	**Study of Traffic Flow Patterns**	**Works on Applied Sociodynamics**	**Modeling of Nonlinear System Performance Dynamics**
Lorenz, E.N [9]	√	√							
Mandelbrot, B. [10]	√	√	√						
Abraham, N.B. et al. [11], Muhmoudabadi, A. [22]	√	√							√
Prigogine, I. [12], Casdagli, M. et al. [13], Hilborn, R.C. [14], Cvitanovic, P. et al. [18], Kiel, D. et al. [19], Zhang, X. et al. [20], Oestreicher, C. [23]	√								√
Argyris, J. et al. [15]		√							
Abarbanel, H.D.I. [16], Kolmogorov, A.N. [32], Murray, R.M. [33], Leok, M. et al. [34], Goertzel, B. [35], Xue, J. [36], Clement, S.J. et al. [37], Frazier et al. [38]			√						
Prigogine, I. et al. [24], Gazis, D.C. et al. [25]				√			√		
Disbro, J.E. et al. [17]			√	√			√		
Van Zuylen et al. [26]					√		√		
Safanov, L.A. et al. [27], Attoor, S.N. et al. [28]						√	√		
Weidlich, W. et al. [29], Bannester, E.M. [30], Koshland, E.D. [31]						√		√	
Dendrinos D.S. [21]	√			√	√				√

Skeptics of applying chaos theory to the study of traffic processes formulate the following common question: "in what way are the chaos and complexity theories specifically applied to urban transport systems?" The authors of [38] answer this question as follows: "The difficulty with hypothesis that transportation systems are often chaotic is that chaos theory presumes system determinism. Since transportation systems involve humans, weather, and other possibly (probably?) random agents, such an assumption is not easy to justify. Thus, chaos theory may not well apply. However, if human behavior is controlled and directed through system laws and restrictions, then outcomes may be determined by system dynamics. Additionally, chaos theory may well apply".

2.2. Road Traffic Management as a Way to Suppress Traffic Chaos and Transform It into Traffic Order

Before considering the declared subject, let us recall the classics of the theory of road traffic management. These are I. Prigogine and R. Herman [24], F.A. Haight [39], W.D. Ashton [40], D.R. Drew [41], D.L. Gerlough and J.H. Huber [42], D.C. Gazis [43], and W. Leutzbach [44], who made essential contributions to traffic theory. However, their followers have further advanced their research, and the modern understanding of road traffic can be interpreted a little differently.

Chaotic behavior is almost universal. This is an integral property of many natural and artificial systems. Very often, it seems that the behavior of these systems is a set of random events and there are no regularities in their functioning. However, everything depends on the scale of the problem considered [45]. The characteristics of traffic behavior can often change within a few seconds in a small space of the road network. Data with sufficiently high spatial and temporal resolution are needed to detect these changes. Only then can we understand the prevailing dynamic state and predict the evolution of the resulting congestion state in the near and short-term future.

Contemporary traffic signal systems incorporate detectors that continuously monitor real-time traffic flows throughout the network. These detectors dynamically adjust the green splits, offsets, and cycle times to optimize system operations, mitigating delays [46]. This enables control of the traffic situation and management of several traffic lights (usually 6–12 adjacent intersections). The efficiency of such systems that respond to changes in traffic demand is much higher than that of systems with a fixed operating time (according to [47]). The effectiveness of optimization procedures is limited to network regions experiencing undersaturated or nearly saturated traffic conditions. In these scenarios, queues form during the red phase and disperse during the green phase, or they can be stored on longer links through precise adjustments of offsets, cycle time, or splits. However, under oversaturated traffic conditions, these procedures prove inadequate in managing sudden surges and perturbations in traffic flow or capacity, often going undetected. This is a complex problem, which is still one of the most pressing for traffic managers. Modern traffic management practices are based on the development and implementation of management solutions that eliminate unfavorable network conditions only after they occur instead of preventing road network congestion in advance [48].

Table 2 presents information on some studies and models of vehicle and pedestrian traffic patterns.

Table 2. Studies of vehicle and pedestrian traffic patterns.

Authors	Goal of Research	Obtained Results
Cheslow, M. et al. [49]	Search for options for improving the adequacy of road traffic management modes lining up with reality.	The essential prerequisite for implementing sustainable dynamic traffic control lies in the capability to formulate and consistently revise forecasts regarding traffic flows and link times, extending several minutes into the future, utilizing real-time data.
Vlahogianni, E.I. et al. [50] Kesting, A. et al. [51] Huang, S. and Sadek, A.W. [52] Qi, Y. and Ishak, S. [53]	Search for ways to understand the laws of traffic flow dynamics	The authors established regularities in the dynamics of the traffic flow.
Zhang, G. et al. [54] Vlahogianni, E.I. et al. [50] Zheng, P. and Mcdonald, M. [55] Guo, J. et al. [56]	Formation of traffic state models, encompassing time series, nonparametric, filtering, and their various hybrids.	The authors established that the applicability of these models to congested traffic situations is limited due to their low adequacy for real processes.
Jianming, H. et al. [57]	Development of a phase state model based on the Chaos Theory concepts.	The authors established that this model has major potential for analyzing the complexities in a disturbed traffic flow.

2.3. Energy–Information System Balance and Entropy

According to M. Tribus and E.C. McIrvine [58], we can conclude that information predominates over all other energy conversion incentives in control systems. The quality of information used for decision making affects system efficiency. In this regard, the energy–information system balance is extremely important and forms the basis for building automatic process control systems. During the 1970s and 1980s, the criteria for information in control system synthesis gained significant popularity within the realm of applied automatic control and measurement systems. It is worth acknowledging the contributions of researchers affiliated with Academician Petrov's academic lineage in this context [59–62]. An informational approach to optimality criteria for control system synthesis was suggested by Bukanov [63].

One of the main ideas of the works [58–63] is the need to consider information in close connection with the concept of entropy. This concept has a variety of meanings [64–66]. The generally accepted classification of entropies implies three classes of meanings in terms of these phenomena: thermodynamic, information, and structural. In this case, we will talk about the information aspect of entropy, i.e., the measure of uncertainty associated with a certain random value.

It has already been known for a century that information and entropy are two sides of one phenomenon. The correlation between entropy and information was initially identified in foundational research by L. Szilard [64]. Subsequently, L. Brillouin [65] formulated the principle of information negentropy, extending the scope of the second law of thermodynamics. As per this principle, entropy and information must be collectively regarded and cannot be independently interpreted. The information negentropy principle serves as a thermodynamic generalization akin to Carnot's principle, as articulated by L. Brillouin, wherein the quantity of information within a physical system is deemed a negative component within the overall entropy of that system. Entropy can serve as a quality meter for energy–information system balance. In this regard, entropy can be considered as a means of assessing the quality of road chaos suppression. Entropy can essentially be presented as a quantification of the traffic order level. At the same time, entropy cannot be interpreted as an unambiguous characteristic of traffic order. I. Prigogine affirmed on that score that "today we know that an increase in entropy is in no way reduced to an increase in disorder since order and disorder arise and exist simultaneously" [66]. In this regard, it is extremely interesting to look at the subject of discussions about chaos, order, and energy–information system balance in urban transport systems from the perspective of road accident rates. Accident rates are a striking example of the negative manifestation of an information gap and an excess of entropy in such a transport system functioning form as road traffic.

2.4. Road Accident Rate and Its Relationship with Road Traffic Conditions and Traffic Chaos

The concept of traffic accident rates is closely related to the concept of "road accident". It is distinguished from any other road incident by the death (rarely) and (or) injuries (often) of road users. In Russia, all road accidents are usually classified into ten types: collision of vehicles (44.1% of the total in 2022), collision with a pedestrian (27.3% of the total in 2022), driving off the road (10.9%), hitting an obstacle (4.9%), collision with a cyclist (3.7%), collision with a stationary vehicle (3.0%), fall of a passenger in public transport (2.5%), rollover of a vehicle (2.4%), collision with an animal (0.6%), and unidentified types of road accidents (0.6%). It is easy to observe that the total share of the two most common types of road accidents in Russia—vehicle collisions and pedestrian collisions—is 71.4%. These road accidents often result from special road traffic conditions associated with traffic chaos.

Road chaos is typical of urban transport systems, especially major metropolises and large cities. Urbanization processes are characteristic of all countries of the world, and in some countries, urbanization has exceeded 90% [4]. In Russia, the level of urbanization is 76% [4], i.e., studying road traffic patterns in cities and their connection with the specifics of road accidents is an essential task both for Russia and most nations of the globe.

There are relatively few studies on the relationship between road and transport conditions and traffic chaos as an extreme of these conditions with road accident rates. A fairly thorough analysis allowed for the identification of the following works on this subject (Table 3). The analyzed works are differentiated into three groups, taking into account their subject.

Table 3. Studies on the relationship between road accident rates and traffic chaos.

Authors	Goal of Research	Obtained Results
General works on the regularities of road traffic formation		
Kűhne R.D. [67]	The paper studies the traffic flow model and control strategy.	The determination of traffic flow stability hinges upon traffic density. Stability conditions can be deduced from the traffic flow model.
Kumari S. and Chugh R. [68]	This paper examined the complete dynamical behavior of the logistic map through the application of diverse dynamical techniques.	A modified chaos-based model for managing chaotic and unpredictable discrete traffic was presented in this paper. Additionally, a physical interpretation was provided to validate the outcomes of this model.
Studies on traffic flow instability		
Martinovič T. [69]	This paper describes the procedure of extracting information on the dynamics of highway traffic speed.	The paper established the regularities of changes in Shannon entropy results on daily highway data
Jiang R. et al. [70]	This paper reports the experimental and empirical studies on traffic flow instability.	The paper established the regularities in the formation of traffic jams.
Works directly or indirectly studying the influence of road traffic (with an emphasis on traffic chaos) on road accident rates		
Schuster H.G. [71]	The author studies the nature of chaos as a phenomenon.	Chaos manifests as a bounded and unstable dynamic phenomenon characterized by sensitive dependence on initial conditions, encompassing infinite unstable periodic motions within nonlinear systems. Despite its seemingly stochastic nature, chaos emerges in a deterministic nonlinear system under deterministic conditions

Table 3. *Cont.*

Authors	Goal of Research	Obtained Results
Quek, W.L. et al. [72]	The authors studied the maximum vehicular flow rate of traffic processing bottlenecks.	The authors concluded that bottlenecks influence changes in the chaotic nature of traffic flow.
Kennedy J. et al. [73]	The goal of the research is to study chaos and order in the social behaviors of birds flocking or fish schooling.	Particle swarm optimization represents a highly straightforward algorithm. Social optimization transpires within the realm of commonplace experiences.
Pang M.-bao et al. [74]	The authors studied the patterns of the origin of chaotic processes in traffic.	The authors developed a model for recognizing chaos in road traffic.
Alatas B. et al. [75]	New methods for particle swarm optimization (PSO) are introduced in this paper. The authors use chaotic maps for the purpose of parameter adaptation	The authors proposed several new methods to improve the convergence of the PSO algorithm.
Zheng Z. [76]	The investigation in this paper delves into the correlation between traffic conditions and crash occurrence likelihood (COL).	The crash occurrence likelihood (COL) is notably influenced by the prevailing traffic conditions. In summary, COL during congested conditions is approximately six times higher than that during free conditions. COL in transitional conditions is approximately 1.6 times higher than that in free conditions.
Gharehchopogh F.S. [77]	The paper studies the possibilities of predicting road accident rates using a hybrid of particle swarm optimization (PSO) algorithm and chaos optimization algorithms (COAs).	The author established that taking into account the contribution of the chaotic traffic flow to the formation of the road situation somewhat increased the accuracy of the accident rate forecasting model.
Narh A.T., Thorpe N., Bell M. C., Hill G.A. [48]	The goal of the research is to study the possibilities of the new applications of chaos theory in road traffic analysis	Chaos theory's capacity to analyze and predict dynamic systems has been examined, with indications that its potential can be harnessed for strategic network-wide control. This complements the functioning of current UTC systems, thereby enhancing the efficacy of demand management within the urban road network.
Senkerik R. et al. [78]	This paper explores the application of complex chaotic dynamics derived from chosen time-continuous chaotic systems and discrete chaotic maps. These serve as chaotic pseudo-random number generators and driving maps for chaos-based optimization	This paper illustrated three sets of complex chaotic dynamics originating from chaotic flows, oscillators, and discrete chaotic maps.
Akgùn-Tanbay N. et al. [79]	This study seeks to examine the effects of road usage frequency on safety, comfort, and chaos within the context of shared spaces.	In the course of sociological research, the authors established the peculiarities of the impact of gender and age differences on the qualitative perception of the traffic chaos level and road accident risks.

Is there evidence to suggest that managing chaos in traffic systems can lead to a reduction in road accidents? In [48,71–79], the authors do not answer this question directly. However, when studying these works, we felt that this particular question was the main one. This thesis had the following reasons, which ultimately contributed to putting forward the research hypothesis.

Perhaps the main conclusion drawn after the analysis of these works is that an increase in traffic chaos increases the number of road accidents (about 1.5–1.6 times). However, the severity of the consequences of these accidents has not been discussed. In this case, we are talking about recording the fact of vehicle collisions when driving in normal conditions on routes familiar to the driver, ignoring the severity of their consequences. The above studies were carried out at the established level of risk homeostasis [80,81]. At the same time, there are many empirical examples when the severity of accident consequences significantly decreases with an increase in the frequency of road accidents (i.e., the likelihood of emergencies and their actualization at the physical level). The most famous of them is the so-called H-Day (3 September 1967) [82], when Sweden announced the transition from left-hand traffic (as in the UK, Japan, and 51 other countries of the world) to right-hand traffic (used in 140 countries of the world) [83]. The increase in traffic chaos in Sweden during the days when traffic rules changed (autumn 1967) led to many ambiguities but simultaneously decreased the level of risk homeostasis [80,81,84,85], which reduced the number of fatal road accidents. This fact ultimately served as the basis for the development of H. Monderman's concept of shared space [84,85], which uses no special technical traffic regulation means (traffic lights, road markings, etc.) to organize traffic in small towns.

Thus, the hypothesis that we would like to test as part of our research is formulated as follows: "an increase in road traffic chaos increases the frequency of road accidents but decreases the severity of their consequences." This thesis, though in a slightly different form, can be presented as: "The road injury risk decreases with an increase in the Relative Entropy of Lane Occupancy $H_n(\theta)$".

To give reasoning for the objectivity of this hypothesis, let us present a diagram of the relationship between road accidents with road and transport conditions and road chaos. We will use the ideas and results of the previous works to construct this diagram.

In [76], the author presents how free traffic transits through the bounded traffic state into transport congestion during the period from 7:25 to 8:45. At the same time, the traffic speed drops, and lane occupancy increases (Figure 1).

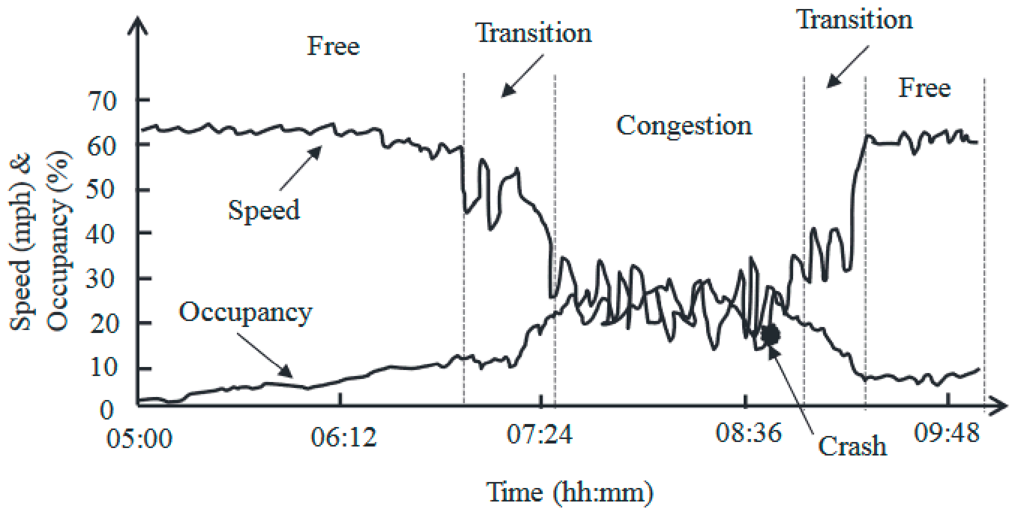


Figure 1. The speed and the occupancy time series [76].

At this moment, the drivers' chaotic actions and the likelihood of their inappropriate actions in a traffic situation increase. The frequency of accident-prone situations increases with an increase in the probability of their errors [76]. Binary logistic models proposed for modeling this situation by Z. Zheng [76] perfectly illustrate the transition of the transport process from the "Free flow" state to the "Congestion" state and back to the "Free flow" state. Traffic chaos exhibits a close connection with speed, speed variance, and flow. To assess the influence of traffic chaos on traffic safety, relying solely on speed variance is insufficient. Consequently, there is a requirement for a new variable, termed the chaos index [76].

The chaos index is defined according to (1):

$$\text{Chaos index} = [\text{Speed variance}/\text{Average speed}] \times \text{Flow}. \tag{1}$$

In [76], Z. Zheng summarizes that compelling evidence suggests that the chaos index exerts a detrimental influence on crash occurrence likelihood (COL). However, this author considers only the very fact of the formation of accident-prone situations and road accidents as their consequences but ignores the severity of road accident consequences for the parties involved. If we take into account the influence of the flow rate on the severity of the road accident outcome, the situation is completely opposite [86].

These results have been more or less confirmed many times [87].

According to the authors, the research results presented in Figure 1 clearly illustrate not only the relationship between vehicle speed and lane occupancy but also the formation of the congestion mode. The congestion mode results in road accidents with damage but no casualties. This is a good visual example of the formation and destruction of chaotic traffic patterns and the relationship between the increase in the likelihood of minor road accidents and the growing chaos.

To summarize these considerations, let us present a hypothetical diagram of the relationship of the probability and severity of the road accident outcome with road and transport conditions and road chaos (Figure 2).

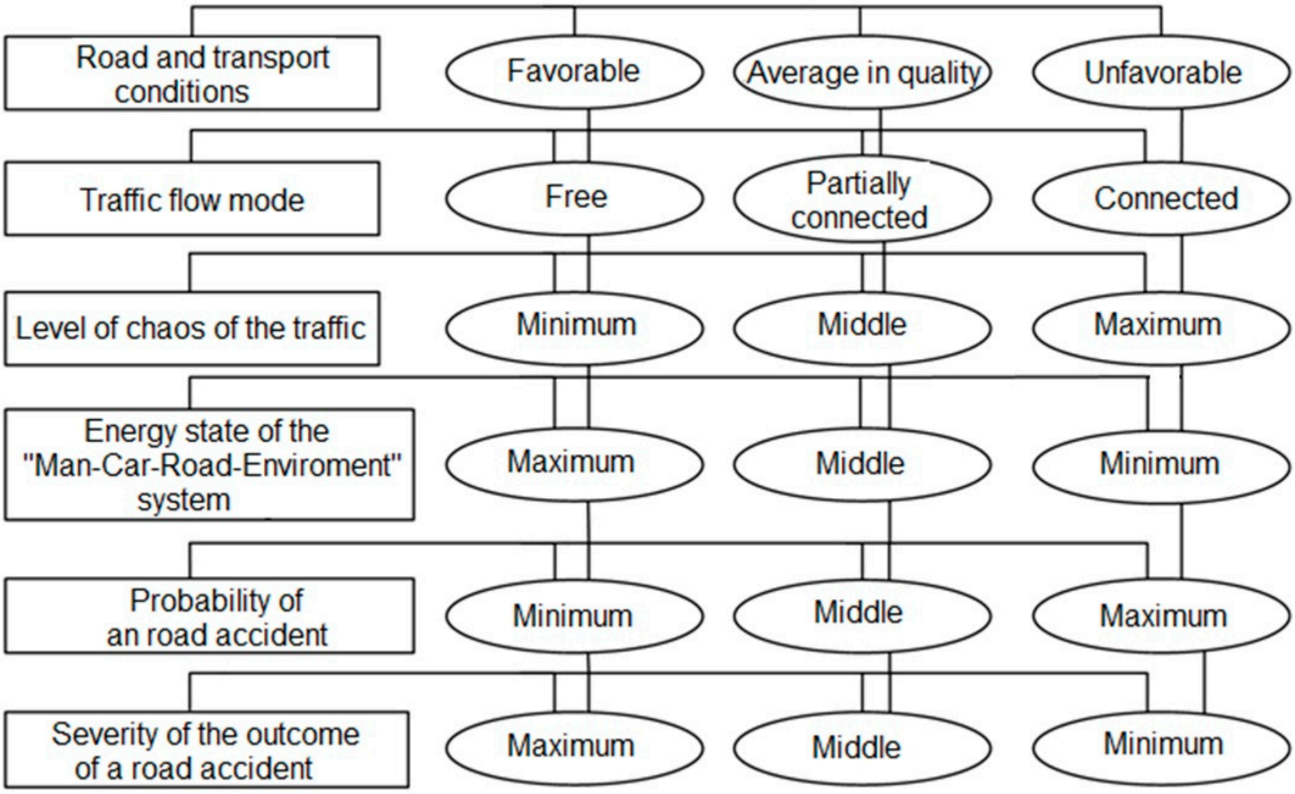


Figure 2. The influence of road and transport conditions on the formation of chaotic traffic flow modes and, as a result, on the two essential characteristics of road accident rates—the probability and severity of the road accident outcome (original development).

Thus, the statistical relationship between road and transport conditions (level 1 of Figure 2), traffic flow modes (level 2 of Figure 2), and the probability of road accidents (level 5 of Figure 2) correlates with the results of the studies carried out by A. Dickerson et al. [88].

The statistical relationship between the probability of road accidents (level 5 of Figure 2) and the severity of their outcome (level 6 of Figure 2) has been studied many times and described by a very simple proportional scheme given in the classic work of H.W. Heinrich [89]: every single fatal road accident counts for about ten road accidents with serious injuries, up to 25–30 road accidents with minor injuries, and up to 250–300 road incidents with property damage, but without human injuries. In the 2020s, these relationships are quantified differently. Nonetheless, current experts [90] continue to endorse the core idea of the Heinrich (1931) and Bird (Bird and Germain, 1986) framework. This model suggests a negative correlation between the severity and frequency of accidents. It also posits that by addressing minor accidents or their factors, such as hazardous behaviors, the probability of more serious but infrequent accidents can be reduced.

So, the severity of the outcome of a road accident is determined by the probability and frequency of a road accident, which in turn depend on the energy state of the "Man–Car–Road–Environment" system.

2.5. Previous Studies on the Impact of Traffic Flow Entropy on Road Accident Rates

The search for previous works on this subject was relatively unsuccessful. Nevertheless, we managed to find several works [91–97], the results of which may be useful to us.

First, let us consider the works that address the impact of traffic congestion on accident rates. In congestion conditions, the flow speed is significantly reduced; the free movement of vehicles becomes impossible and is replaced by a bounded one. This happens when the "Volume over capacity ratio (V/C)" ratio exceeds >0.77 [91].

In [92], D. Shefer hypothesized that there is an inverse relationship between traffic congestion and road fatalities. In a further study [93], D. Shefer and colleagues studied the dynamics of road fatalities during the day. They found that during peak hours, the rate of road fatalities is clearly lower than at other times of the day.

A more recent (2005) study of the impact of traffic congestion on road safety was carried out by R.B. Noland and M.A. Quddus [94], who investigated the nature of traffic congestion in London. According to their data, traffic congestion has a negligible impact on road safety. Based on this result, we conclude that the very low mortality in London is primarily explained by the peculiar policy of the urban speed limit, which prevents even the formation of hypothetical conditions for fatalities.

Quite a long time ago [95–100], studies covered the relationship between road accidents and traffic volume. So, D.J. Turner and R. Thomas [99] observed that in the early morning, when road traffic is light, both the number and proportion of fatal traffic accidents and accidents with serious injuries increase significantly. T.F. Golob and W.W. Recker [100] showed that the severity of road accidents is generally inversely proportional to the traffic volume.

The studies carried out in [101,102] concluded that the probability of both general accidents and fatal accidents is in a U-shaped dependence on the "Volume over capacity ratio (V/C)".

D. Shinar and R. Compton [103] studied road accident rates from the perspective of driver behavior and found that there is a linear relationship between the frequency of aggressive driver behavior and the formation of traffic congestion. In their opinion, this is the root cause that significantly affects road safety.

Perhaps, only the works of Ukrainian authors [104,105] highlight the relationship between the entropy characteristics of the environment and road accident rates. The authors [104,105] presented the results of studying the impact of the driver's perception field entropy on road accident rates. N. Kulbashna et al. have observed, drawing on findings from [88], that an increase in the differential of maximum entropy between neighboring areas correlates with a decline in the accident rate, albeit up to a specific threshold [104]. This correlation is attributed to the fact that accidents predominantly occur in zones where drivers are adjusting and the road conditions are perceived as comfortable. However, they also noted that further escalation in entropy disparity in adjacent sections [88] results in a rise in the relative accident rate on these roads. That is, the increase in the volume and variety of traffic information significantly affects the driver's ability to process this information. If information exposure is high, the driver stops coping with it and begins to make errors, which increases the likelihood of a road accident.

Therefore, the analysis of the state of the art resulted in the following main theses:

1. The urban transport system and its traffic control and traffic safety subsystems are rather complicated, and their operation is often accompanied by chaotic processes.

2. An essential purpose of traffic control is to suppress road chaos and transform it into road order. This work levels the energy–information system balance. Entropy can be used to quantify the level of road order. Entropy is a characteristic of assessing the quality of road chaos suppression.
3. When analyzing the previous works on the relationship between road and transport conditions, road chaos, and road accident rates, we developed a scheme of the influence of road and transport conditions on the formation of chaotic traffic flow modes and, as a result, on the two essential characteristics of road accident rates—probability and severity of the outcome—and formulated a research hypothesis.
4. We analyzed the existing works studying the influence of specific (congestion and free) traffic flow modes on road accident rates. We established that the form of accident manifestation (the ratio of the probability of a road accident and the severity of its consequences) largely depends on the speed characteristics of the traffic flow. Under conditions of traffic congestion, the severity of road accidents decreases while the frequency of road accidents increases. Under the conditions of high speeds (free movement), drivers are not always successfully exposed to large information volumes and the proportion of errors in their actions increases, which adversely affects road safety.

3. Materials and Methods

3.1. Theoretical Studies on the Specifics of the Traffic Flow

We proposed considering the entropy of road traffic flows as the main criterion for assessing traffic organization. Entropy is a very ambiguous concept. In thermodynamics, entropy is understood as the inevitable loss of some energy when a thermal process is implemented [106]. Such a process can be, for example, the operation of an internal combustion engine. In this case, entropy is not associated with internal losses caused by friction forces and other similar phenomena. Entropy will exist even if humanity is able to create ideal technical systems without any internal energy losses during operation. The complete dissipation of energy in a conventional technical system will stop only when the operation of this system stops completely. Thus, entropy can be interpreted as an indicator of vital system activity. Consequently, a decrease in entropy may indicate that the system operation begins to cease.

The original concept of entropy is related to the transfer of heat and energy [107]. Therefore, when adapting this indicator to assess road traffic, it makes sense to turn to gas dynamic and gas kinetic models analogous to traffic flows [41,42,108]. The fundamental theory of traffic flows notes that the total energy of a traffic flow can be described using the law of conservation of energy. At the same time, D. Drew determines that, in reality, energy is not lost but rather transforms from kinetic energy into internal energy [41]. D. Drew explains that according to the second law of thermodynamics, kinetic energy is more useful than an equivalent amount of internal energy, a concept that is particularly applicable to traffic flow. Thus, D. Drew suggests that frictional forces, such as poor geometric characteristics and interactions between vehicles, convert more desirable forms of energy, like vehicle movement, into less useful forms, such as the interaction between vehicles. Additionally, D. Drew notes that in the context of traffic flow, both kinetic energy and internal energy are characterized by the dimension of acceleration [41]:

$$T = E + I, \tag{2}$$

where E is the kinetic energy of the traffic flow, m/s^2, and I is the internal energy of the traffic flow, m/s^2.

D. Drew explains that if a traffic stream possesses internal energy or lost energy, it would be evident through either lost or erratic motion, which can be attributed to the unsatisfactory geometric characteristics of the road or unfavorable interactions between vehicles in the flow [41]. D. Drew clarifies that uneven motion is a manifestation of internal energy, which he describes as acceleration noise [41]:

$$I \approx \delta, \tag{3}$$

$$\delta = \sqrt{\frac{1}{n}(\sum_{i=1}^{n}(x_i - \overline{x})^2}, \tag{4}$$

where δ is acceleration noise, m/s^2, x_i is acceleration on the studied road network section at the moment of time, m/s^2, and $\overline{x}$ is average acceleration, m/s^2.

Acceleration noise (4) represents non-uniform movement due to poor road geometry or unfavorable interactions between vehicles in a traffic flow [41]. Therefore, this indicator can be interpreted as internal energy losses in the system.

Thus, the efficiency of the traffic flow η can be expressed as follows [41]:

$$\eta = \frac{T - I}{T} = \frac{E}{T}. \tag{5}$$

Therefore, to increase the efficiency of a traffic flow, the process should be aimed at maximizing its kinetic energy, E. In turn, the kinetic energy of a traffic flow is determined by the following formula [41]:

$$E = \alpha k u^2, \tag{6}$$

where k is the traffic flow density, cars/m, u is the traffic flow speed, m/s, and α is the dimensionless coefficient.

The introduction of the coefficient α is determined by the following. In practice, traffic density and speed are most often measured in vehicle/km and km/h. Accordingly, the values should be converted to the necessary units of measurement: vehicle/m and m/s. Therefore, α = (3.6^2·1000)$^{-1}$. In the future, the necessary research data will be reduced to vehicle/m and m/s. Therefore, the coefficient α can be eliminated.

Formulas (2)–(6) were developed analogous to the mechanics of gas and liquid molecule motion. However, traffic flow as a control object is compressible. This indicates the risk of possible road accidents. To prevent collisions, road users are forced to vary the vehicle speed [41]. Thus, the idea that kinetic energy will also have a nonlinear dependence on the speed and density of a traffic flow is already formed at this work stage.

Further, Formula (6) can be modified by taking into account the intensity, which is a quantitative indicator of traffic flows. To this end, it is advisable to use the Lighthill–Whitham–Richards hydrodynamic model [42,109]:

$$\begin{cases} u'(p) < 0, \\ Q(p) = pu(p). \end{cases}, \tag{7}$$

where $u(p)$ is a function describing the formation of the speed of a vehicle depending on its density, km/h, and $Q(p)$ is a function describing the formation of traffic intensity depending on its density, vehicles/hour.

Thus, the system of Equations (7) and (6) takes the following form:

$$E = Q(p)pu(p). \tag{8}$$

The results of the studies [110,111] showed that under modern conditions it is more promising to use temporal concentration indicators to assess the traffic flow concentration. This indicator is lane occupancy. The relationship between traffic intensity and lane occupancy has been established and experimentally confirmed. A model of the influence of lane occupancy on the traffic flow intensity has been developed and experimentally confirmed in [110,111]:

$$Q(\theta) = b_1\theta - a_1\theta^2, \tag{9}$$

where a_1 and b_1 are model parameters, vehicle/(h·%).

The lane occupancy itself is the share or percentage of the time, during which vehicles were in the control zone on the lane [42,110,111]:

$$\theta = \frac{\sum_{i=1}^{n} (L_i + d)/u_i}{T}, \tag{10}$$

where θ is lane occupancy; t_i is the time spent by the i-th vehicle in the control measurement zone, s; L_i is the length of the i-th vehicle passing through the control measurement zone, m; d is the length of the control measurement zone, m; u_i is the speed of the i-th vehicle in the flow; and T is the measurement duration, s.

The value of d within a specific traffic lane is constant. The vehicle length will be constant L for a homogeneous traffic flow, while for a heterogeneous flow, the vehicle length in the flow can be considered as the product of its average value $\overline{L}$ and the number of measurements i. The desired expression of speed u should also be considered as the average value of spatial speed $\overline{u}$. Taken together, this allows transforming Formula (10) into (11):

$$\theta = \frac{(\overline{L} + d)i}{T\overline{u}}. \tag{11}$$

Taking a closer look at (10), we can notice that the ratio $\frac{i}{T}$ is nothing more than the traffic flow intensity. Therefore, Formula (11) can be presented as follows:

$$\theta = (\overline{L} + d)\frac{Q}{\overline{u}}. \tag{12}$$

Thus, the traffic flow speed can be determined by the dependence function on lane occupancy:

$$u(\theta) = k_\theta \frac{Q(\theta)}{\theta}, \tag{13}$$

where k_θ is the coefficient of the relationship between the traffic flow speed and lane occupancy.

In practice, lane occupancy is often expressed as a percentage. The speed in this research will be presented in m/s. Therefore, the dimension of the coefficient k_θ will be m·%/vehicle.

Ultimately, the kinetic energy of the traffic flow, taking into account the traffic flow intensity and lane occupancy, has the form:

$$E = k_\theta \frac{Q^2}{\theta}. \tag{14}$$

In turn, the entropy of a traffic flow depending on lane occupancy can be presented as a dependence function [112,113]:

$$H(\theta) = -\sum_{i=1}^{n} w_i \ln(w_i), \tag{15}$$

where w_i is the specific weight of the i-th lane occupancy at the considered signal-controlled intersection; and n is the number of lanes at the signal-controlled intersection.

In this case, the specific weight w of the occupancy of each lane will be determined by the following ratio [112,113]:

$$w_i = \frac{\theta_i}{\sum\limits_{i=1}^{n} \theta_i}. \tag{16}$$

In turn, the relative entropy of the traffic flow depending on lane occupancy at the signal-controlled intersection is determined as follows [112,113]:

$$H_n(\theta) = \frac{H(\theta)}{\ln n}. \tag{17}$$

Model (9) allows for the transformation of Formula (14) through lane occupancy:

$$E = \alpha k_\theta \frac{(b_1\theta - a_1\theta^2)^2}{\theta} = k_\theta \frac{b_1^2\theta^2 - 2a_1b_1\theta^3 + a_1^2\theta^4}{\theta} = a_1^2 k_\theta \theta^3 - 2a_1b_1k_\theta\theta^2 + b_1^2k_\theta\theta. \tag{18}$$

The research sub-hypothesis is based on Formulas (14)–(18): the impact of the relative entropy of lane occupancy $H_n(\theta)$ on the total kinetic energy of traffic flows E at a signal-controlled intersection can be described by a third-degree polynomial:

$$Y = aX^3 + bX^2 + cX + d, \tag{19}$$

where Y is a function describing the impact of the relative entropy of lane occupancy on the kinetic energy of the traffic flow $H_n(\theta)$, $\mathrm{m/s^2}$; X is the relative entropy of lane occupancy $H_n(\theta)$; and a, b, c and d are the parameters characterizing the relationship between the relative entropy of lane occupancy and the kinetic energy of the traffic flow, $\mathrm{m/s^2}$.

3.2. Theoretical Studies on the Specifics of Road Accident Rates

The analysis of the previous studies (Section 2.4) identified the specifics of the "road accident rate" concept. Accident rates cannot be assessed only by the number of road accidents, even taking into account the relative dimension. Concerning the quality of these road accidents, their scale and the severity of their consequences should also be taken into account.

When studying the specifics of road accident rates, both quantitative (number of road accidents per unit of time) and qualitative indicators (scale and severity of their consequences) should be taken into account. The road injury risk R_V (20) can serve as a summarizing accident rate indicator, i.e., an indicator taking into account both the quantity and quality of road accidents.

Here, it is important to clarify the definition of road accident (RA) and traffic incident (TI). A road accident (RA) is a vehicle collision resulting in a human injury (and, less often, death). A traffic incident (TI) is a vehicle collision resulting only in property damage but without injuries or fatalities. For certain sections of the road network and specific intersections, fatal road accidents are quite rare. That is why we will focus on the road injury rate.

Road injury (victim) risk R_V is a combination of the probability and consequences of adverse events resulting from road users' actions. Road injury risk R_V (20) is defined as the product of the probability of a road accident P_{RA} (21) and the road accident damage D_{RA} (22).

$$R_V = P_{RA} \cdot D_{RA}, \tag{20}$$

where P_{RA} is the probability of a road accident probability, and D_{RA} is the road accident damage.

In our case, the probability of a road accident in a specific period of the day $P_{RA\ i\text{-}hour}$ will be determined as the percentage of road accidents that occurred over a certain period of time (hour of the day) of their total number (21):

$$P_{RA\ i\text{-}hour} = N_{RA\,i\text{-}hour} / \sum N_{RA}, \tag{21}$$

where $N_{RA\ i\text{-}hour}$ is the number of road accidents that occurred over a certain period of time (hour of the day), units, and $\sum N_{RA}$ is the total number of road accidents, people.

For example, let us consider a case where 1254 road accidents occurred during the year, and 94 of them occurred between 7:00 and 9:00. The probability of a road accident in a specific period of the day (7:00 to 9:00) is P_{RA} = 94/1254 = 0.0750.

Road accident damage D_{RA} is determined by Formula (22) as the product of two components—the scale of the road accident Sc_{RA} (23) and the severity of its consequences Sev_{RA} (24).

$$D_{RA} = Sc_{RA} \cdot Sev_{RA}, \tag{22}$$

where Sc_{RA} is the scale of the road accident, the number of victims/1 road accident; Sev_{RA} is the severity of the road accident consequences, the proportion of deaths among the victims.

These components are determined by relations (23) and (24).

$$Sc_{RA} = N_V / N_{RA}, \tag{23}$$

where N_V is the number of road accident victims, people; N_{RA} is the number of road accidents with victims, units.

$$Sev_{RA} = N_{RA} / N_{RA\,i\text{-}hour} \tag{24}$$

where N_{RA} is the number of road accidents with victims; N is the number of all traffic incidents.

Let us consider a simple abstract example of calculating the road injury risk R_V for the time period of 7:00–9:00 $R_{V\ 7\text{–}9}$:

Let us assume that during the year there are 1254 conflict cases at a particular urban intersection, including 1215 cases of material damage and 39 accidents involving injuries. Out of them, 94 conflict cases occurred in the morning from 7:00 to 9:00, which included 5 cases with injuries and 89 cases with material damage. There were six victims in these five road accidents.

So,

$$N = 94;\ N_{RA\ 7\text{-}9} = 5;\ Sev_{RA} = N_{RA\ 7\text{-}9}/N = 0.053.$$

$$N_{RA\ 7\text{-}9} = 5;\ N_{V\ 7\text{-}9} = 6;\ Sc_{RA} = N_{V\ 7\text{-}9}/N_{RA\ 7\text{-}9} = 1.20.$$

$$D_{RA\ 7\text{-}9} = Sev_{RA} \cdot Sc_{RA} = 0.053 \cdot 1.20 = 0.0636 \approx 0.064.$$

$$P_{RA\ 7\text{-}9} = N_{\ 7\text{-}9}/\sum N_{RA} = 94/1254 = 0.0750.$$

$$R_{RA\ 7\text{-}9} = P_{RA\ 7\text{-}9} \cdot D_{RA\ 7\text{-}9} = 0.0750 \cdot 0.064 = 0.00478.$$

The calculations are summarized in Table 4 below. We chose the day period from 7:00 to 9:00 because this is the time of morning congestion. Taking into account the research results [76] presented in Figure 1, the authors of this article suggest that in the morning, the urban population moves en masse to their place of work. At the same time, despite the formation of traffic congestion, drivers try to drive as quickly as possible not to be late for the start of the working day. As a result, the number of road accidents may increase. Therefore, the example of calculating the road injury risk *RV* is most representative for this time of the day.

Injury risks at a specific intersection will be determined analogously for each time period.

3.3. Methodology for Planning Experimental Studies

To confirm the hypothesis, we performed planning and carried out experimental studies. The study selected Tyumen, a well-developed socio-economic regional hub with a population exceeding 815,000, situated in Western Siberia, as its object. Tyumen serves as a crucial junction, forming a vital transport corridor facilitating traffic not just from east to west, but also from north to south (and vice versa). This convergence occurs notably in the city's central business district. Similar to numerous urban centers globally, Tyumen's central zones are often plagued by significant traffic congestion, particularly noticeable during weekday peak hours. Increased transport demand also provokes an increase in various types of road accidents and incidents. Consequently, the intersection of Respubliki and M. Toreza streets, which lies at the core of the city's north–south and east–west transport routes (and their reverse directions), was chosen for detailed examination within the road network.

Table 4. An example of calculating the road injury risk R_V for the time period of 7:00–9:00 $R_{V\,7\text{–}9}$.

Hours of the Day	Road Accident (RA) and Traffic Incident (TI).			Number of Victims N_V, People	Scale of the Road Accident Sc_{RA}, Victims/Road Accident	Severity of the Road Accident Sev_{RA}, Share of Road Accidents with Victims	Damage from Road Accident Consequences D_{RA}	Probability of a Road Accident P_{RA}	Injury Risk R_V
	With Victims (RA), N_{RA} Units	With Material Damage (TI), Units	Total N, Units						
7:00–9:00	5	89	94	6	1.20	0.053	0.064	0.075	0.00478

The phenomenon of entropy remains rather ambiguous and unexplored in relation to traffic flows. In addition, this phenomenon has not previously been studied in relation to lane occupancy, which is the concentration of a traffic flow over time. To this end, we introduced some restrictions when planning the experiment. Further experimental studies were carried out in the absence of negative environmental factors. Several requirements were posed for the traffic flow. When carrying out the experimental studies, we considered a homogeneous flow of passenger cars moving in a straight, left turn, right turn, i.e., unmixed travel direction. These restrictions are quite acceptable when studying signal-controlled intersections in the central city zone. These street intersections are the busiest and of greatest interest, especially during working hours and weekdays. At the same time, the movement of freight vehicles is often prohibited there, and special lanes are allocated for public transport. Therefore, the quality of the road surface can also be ignored. In addition, there are often separate lanes and additional traffic light sections for each traffic flow direction. Vehicles move in different directions at different phases of the traffic light cycle.

To collect the data stream, we utilized freely available outdoor surveillance cameras. This choice was straightforward as it allowed us to avoid additional costs for installation and coordination. However, difficulties arose in other aspects, such as a wide field of view, high occlusion levels, object visibility, object counts, and varying scales. For real-time object recognition, we selected the YOLOv5 neural network as it can process 25 frames per second with sufficient accuracy. The YOLOv5 neural network exhibits a higher real-time frame processing speed compared to YOLOv4 and YOLOv7. YOLOv5 operates faster and can handle a greater number of frames per second with minimal loss in accuracy. Testing conducted on a dataset containing multiple types of vehicles, including cars, trucks, motorcycles, and bicycles, resulted in an accuracy rate of 93.23% and an F1 score of 0.93 [114–116]. YOLOv5 differentiates itself from previous versions with its ease of installation and usage, thanks to its utilization of PyTorch 2.2.0 instead of constructing the neural network from source code, as in the case of YOLOv4 [117]. However, one challenge lies in radial distortion caused by imperfections in the camera optics, which affects tasks like determining the vehicle's size, position, and coordinates in the image. To restore the original image, we applied methods based on interpolating the locations of non-integer pixels. To compute the distance between two points on the road network, we employed the classical inverse haversine formula, represented explicitly through arcsine.

$$dist = 2r \cdot arcsin\left(\sqrt{sin^2\left(\frac{\phi_2 - \phi_1}{2}\right) + cos(\phi_2)cos(\phi_1)sin^2\left(\frac{\lambda_1 - \lambda_2}{2}\right)}\right), \quad (25)$$

where *dist* is the measured distance; r is the radius of the Earth (6371 km); $\phi_1, \phi_2, \lambda_1, \lambda_2$ are latitude and longitude of the i-th point.

Adjusting the geographical positions of the observed object is essential for accurately determining a vehicle's speed. The process involves capturing the vehicle's coordinates at every instance of its appearance within the frames. The employment of the SORT tracker has been instrumental in tracking multiple moving objects. The geographic coordinates (latitude and longitude) from both the current and previous frames, coupled with the elapsed time between these frames, are pivotal for calculating the traveled distance. This approach requires dividing the intersection into several distinct, non-overlapping areas, each representing a nearby road or the intersection's center. Assuming that the tracking data for the entire video sequence are available, the vehicle's position in each frame is approximated to the center of the lower edge of its bounding box. With the full trajectory of each vehicle mapped in image coordinates, every point of the path is assigned to one of the intersection regions. The tracker then converts these motion trajectories into a sequence of visited regions. A vehicle's average speeds are calculated by dividing the distance traveled at each i-th step by the time interval between these steps. Due to the inherent error in neural network object detection, frames with a one-second interval were selected instead of consecutive frames, ensuring a more precise calculation of speed and distance traveled. A threshold constant of 1 km/h was established to account for the inability of the neural network to measure a vehicle's speed as precisely zero.

To evaluate the traffic intensity and lane occupancy, the amount of time each vehicle spends in a specific region is measured.

$$\theta' = \frac{\sum_{i=1}^{n}\left(\sum_{j=1}^{m} t_{ij}\right)}{T'}, \quad (26)$$

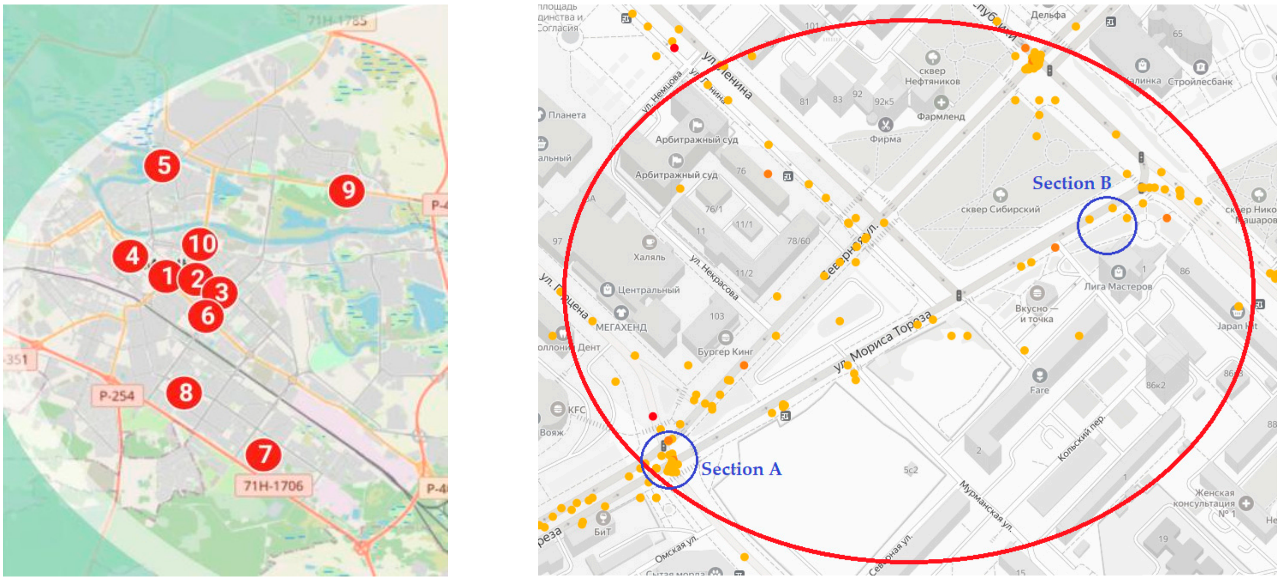
where θ' is traffic intensity along the lanes, n is the number of vehicles, m is the number of time intervals of i-th vehicle during which it was monitored in the j-th time interval was in the control region, s, and T' is the duration of the measurement, s.

Cameras installed in the city center were used to collect images. Vehicles of special_trans, truck, middle_truck, and road_train categories are rarely found at these intersections, leading to insufficient classification and reduced neural network detection of these categories. To overcome this problem, images with the mentioned categories were selected, and the number of such vehicles in the dataset was further increased by data augmentation.

A part of the road is often blocked with poles and wires in the images obtained from the intersection cameras. After training on the initially collected dataset, the neural network showed an unsatisfactory ability to detect vehicles partially blocked by these objects. To solve this problem, we artificially added rectangular objects with a random location in some images during the augmentation process, which allowed the neural network to learn to detect blocked vehicles.

The proposed system makes it possible to count and classify vehicles by driving directions with an average percentage error of less than 6%.

The initial data on accident rates were also collected within the section of M. Toreza Street, in the road network alignment limited by Malygina—Respubliki streets (Figure 3).



(**a**) (**b**)

Figure 3. Localized area for collecting data on road accident rates in Tyumen: (**a**) accident rating in road accident localizations (Research case—Zone 1); (**b**) traffic and road accident monitoring zone in M. Toreza Street section (Research case—Zone 1).

The traffic flow data were collected for this road network section in Tyumen (the intersection of Respubliki Street and M. Toreza Street).

Figure 4 presents some photos of road accidents within this road network section.

(**a**) (**b**)

Figure 4. Selected photos of road accidents within the studied road network section: (**a**) Section A in the scheme of Figure 3 (lateral collision); (**b**) Section B in the scheme of Figure 3 (multiple one-directional collisions).

All of the experimental data were divided into two arrays: data on road accidents with victims (reported in the traffic police statistics) and data on traffic incidents (reported in the statistics of insurance companies making property damage payments).

The information service of the State Traffic Safety Inspectorate of the RF Ministry of Internal Affairs was used to obtain statistical data on road accidents with victims [118]. Aggregated data of insurance companies with the largest customer base were used to obtain data on traffic incidents with property damage.

The results of planning the experimental studies are presented in Table 5.

Table 5. Results of planning the experimental studies.

Experiment Characteristics	Characteristic Description
Experiment type	Passive
Method	Continuous monitoring of traffic flows within the city road network Collection and analysis of experimental data on accident rates within the selected road network section
Conditions	Real traffic conditions within the city road network
Duration	Working days of the week from 07:00 to 23:00 during 2016–2023
Studied values:	
- Target indicator	Kinetic energy of the traffic flow, m/s^2
- Target indicator	Road injury risk R_V
Influencing factors:	
- Relative entropy of the traffic flow depending on its concentration in time	Specific measure of chaos and energy dissipation of the traffic flow.
- Traffic flow concentration in time	Lane occupancy, %
Additional environmental restrictions:	
- Condition of the road surface;	Dry asphalt/asphalt concrete surface, no ice
- Precipitation;	No precipitation
- Fog.	Fair visibility (no fog)
Additional requirements for the traffic flow:	
- Movement direction;	Particular, unmixed direction
- Composition of the traffic flow;	Uniform traffic flow of passenger cars
- Traffic conflict with an oncoming traffic and/or pedestrian flow.	N/a

The total duration of the experimental studies from 2016 to 2023 is explained by the following. Firstly, for the purity of the experiment and to prevent the influence of uncontrolled factors, we decided to introduce several restrictions on environmental conditions and to collect initial data using a natural method, namely, observation. On the one hand, natural data have a higher value and validity. On the other hand, the introduced restrictions did not allow for data collection, for example, during precipitation and/or icing of the road surface. Secondly, we decided to use neural network technologies to collect initial data. The implementation of this approach allowed us to obtain valid data with minimum economic investment. However, the development of the neural network architecture and its training and testing were rather time-consuming.

4. Results

4.1. Results of Experimental Studies on the Dynamic and Energy Characteristics of the Traffic Flow State

The total sample of the actually collected data on the relative entropy and kinetic energy of traffic flows at a signal-controlled intersection was 562 measurements (Figure 5). The relative entropy of lane occupancy $H_n(\theta)$ and the total kinetic energy E of the signal-controlled intersection were determined using Formulas (14)–(18).

The data were processed in the STATISTICA 12 software suite. The initial data were grouped based on Sturges' grouping method by average values [119]. The initial data range was divided by the number of intervals $k = 10$. The value of each interval was $\delta = 0.04$. According to the hypothesis, a third-degree polynomial was used as an approximating function. The results of regression analysis showed that the theoretical curve describes the dispersion of experimental data with the determination coefficient $R^2 \approx 0.93$. This confirms the high reliability of the developed mathematical model of the dependence $E = f[H_n(\theta)]$ (Figure 6).

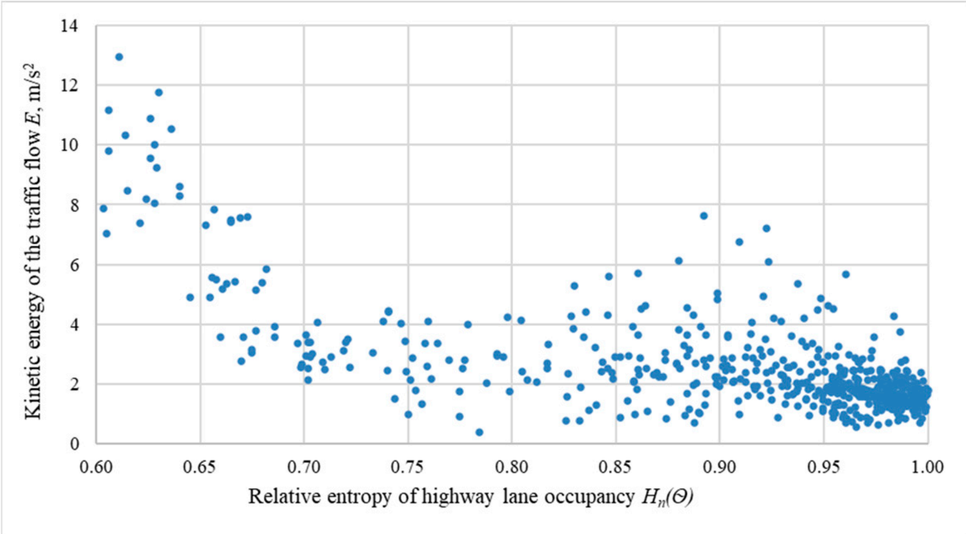


Figure 5. Initial data of the total kinetic energy of the traffic flow depending on the relative entropy of highway lane occupancy $H_n(\theta)$.

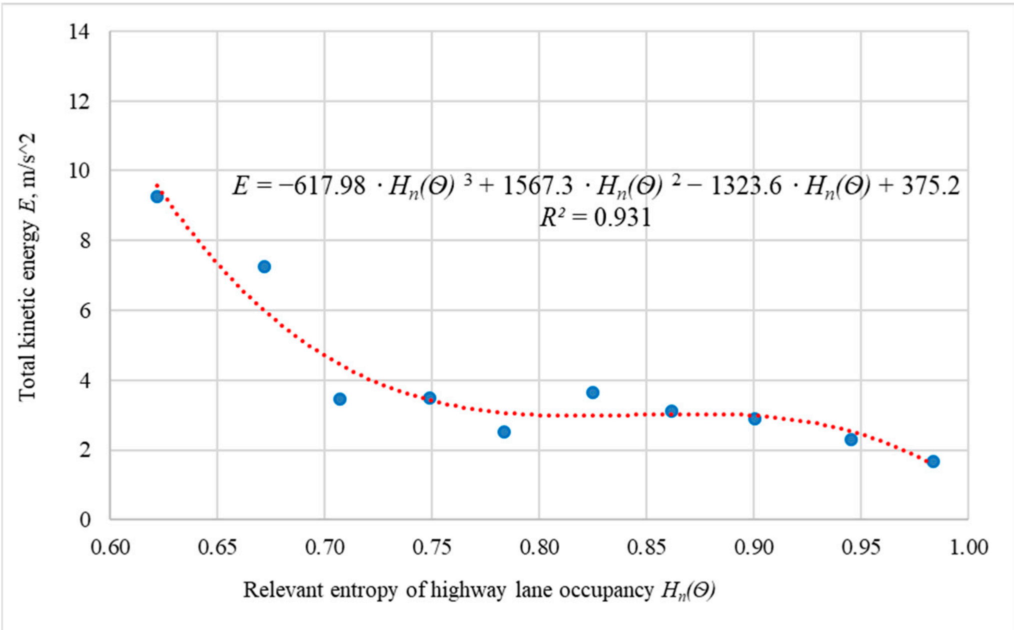


Figure 6. The influence of the relevant entropy of lane occupancy $H_n(\theta)$ on the total kinetic energy of the traffic flow E.

The dependence in Figure 6 shows that the energy state of the traffic flow is significantly higher in the free mode than in the bounded mode.

During the research, we collected information on the dynamics of the changes in highway lane occupancy (in %) at the studied intersection (Figure 7).

The relevant calculations allowed for the determination of the dynamics of the changes in the relative entropy of lane occupancy $H_n(\theta)$ (Figure 8).

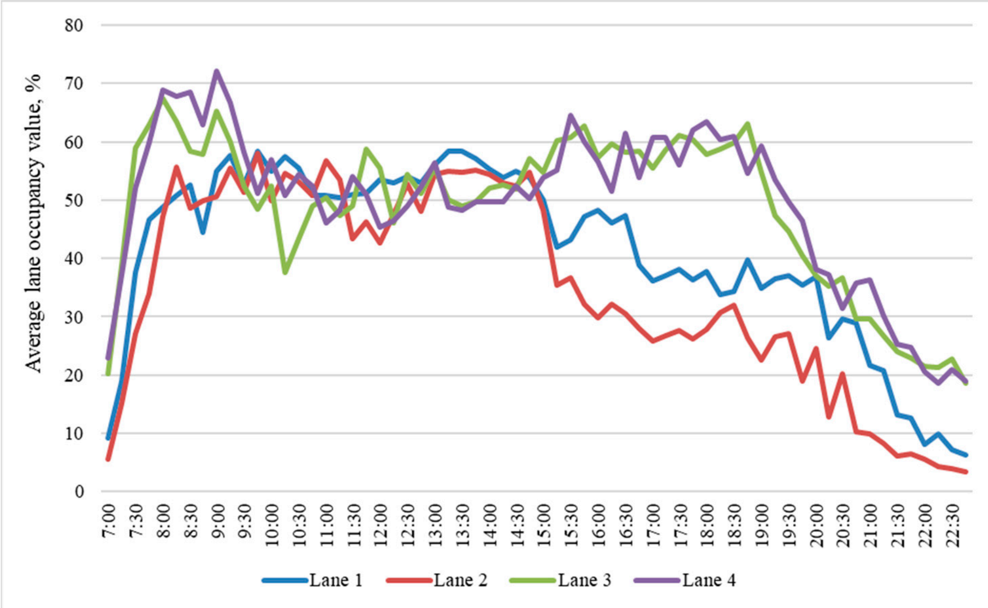


Figure 7. The dynamics of changes in highway lane occupancy at the studied intersection of M. Toreza st.—Respubliki st. in Tyumen during 7:00–23:00.

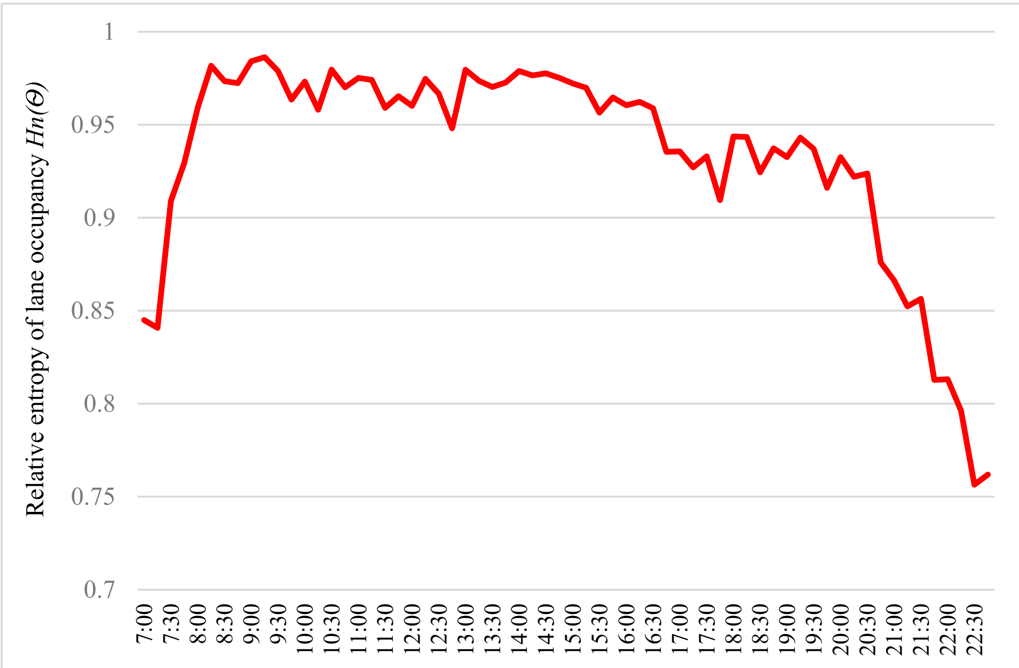


Figure 8. The dynamics of changes in the relative entropy of lane occupancy $H_n(\theta)$ at the studied intersection of M. Toreza st.—Respubliki st. in Tyumen during 7:00–23:00.

It is easy to notice that over the period of 8:00–7:00, the relative entropy of lane occupancy is $H_n(\theta) > 0.9$, and then it begins to decrease, which is especially noticeable after 21:00. Taking into account the dependence shown in Figure 8, we can assume that road accident risks increase in the evening. However, this is not a dogma, as confirmed by the photos in Figure 9.

It is important that road incidents occurred at different levels of the total kinetic energy of the traffic flow E will have very different consequences in terms of the severity of injuries to the persons involved.

(**a**) (**b**)

Figure 9. Visual examples of road accidents in Tyumen at different levels of the total kinetic energy of the traffic flow E: (**a**) road accidents when $E \to min$; (**b**) road accidents when $E \to max$.

4.2. Results of Experimental Studies on the Assessment of the Daily Specifics of Road Accident Rates

Correlation–regression analysis was used to establish the relationship between road chaos and the frequency and severity of road accidents.

The total sample of initial data for 1 January 2016–1 November 2023 amounted to 39 cases for road accidents with victims and 1215 cases for traffic incidents with property damage.

Table 6 shows the distribution of these cases by hours of the day.

Table 6. Distribution of vehicle collisions within the road section of M. Toreza st. in the alignment limited by Malygina—Respubliki streets.

Hours of the Day	**Number (%) of Vehicle Collisions, Taking into Account Their Specifics**			
	Road Accidents with Victims (RA)		**Traffic Incidents with Material Damage (TI)**	
	Number	**%**	**Number**	**%**
23:00–7:00	6	15.4	14	1.2
7:00–9:00	5	12.8	89	7.3
9:00–11:00	3	7.7	128	10.5
11:00–13:00	2	5.1	145	11.9
13:00–15:00	3	7.7	166	13.7
15:00–17:00	4	10.3	182	15.0
17:00–19:00	5	12.8	225	18.5
19:00–21:00	5	12.8	201	16.5
21:00–23:00	6	15.4	65	5.3
Total	39	100.0	1215	100.0

Figure 10 graphically presents the data from Table 6.

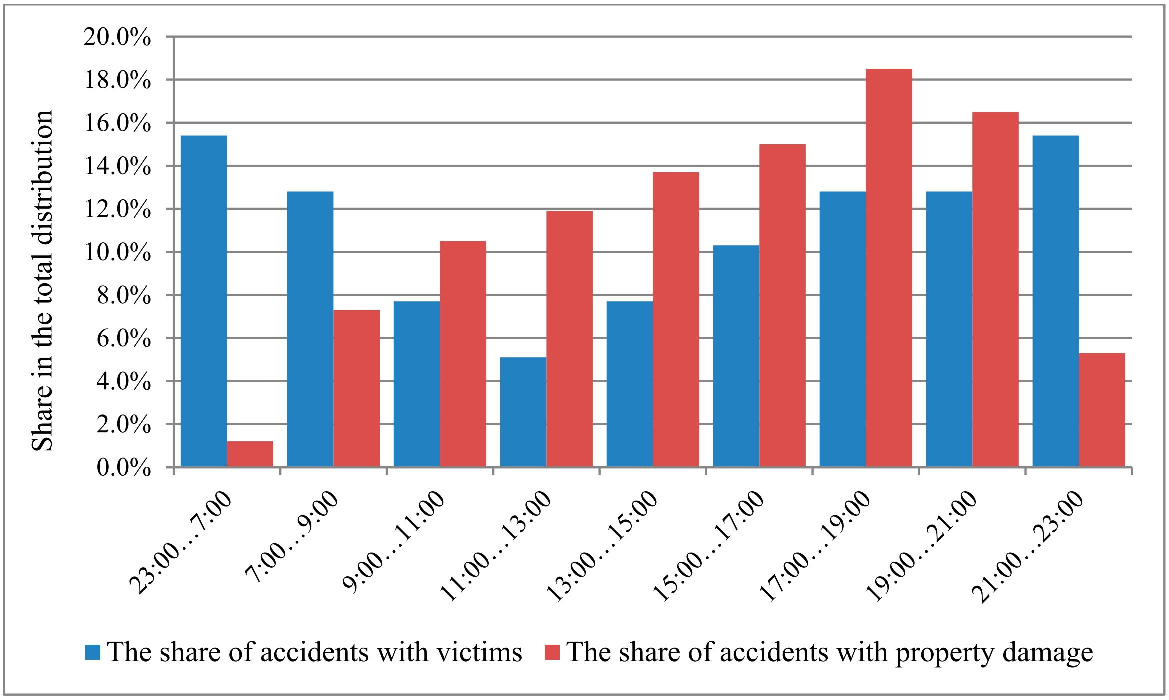


Figure 10. Change in the total kinetic energy of the traffic flow depending on the relative entropy of highway lane occupancy $H_n(\theta)$.

Table 7 presents the distribution of vehicle collisions by severity.

Table 7. Distribution of vehicle collisions by hours of day according to their severity.

Hours of the Day	Number (%) of Vehicle Collisions, Taking into Account Their Specifics		
	Road Accidents with Victims		Traffic Incidents with Material Damage
	Number of Fatalities	Number of Injured, (%)	Amount of Material Damage
23:00–7:00	0	10 (18.2)	No differentiated data are available. As part of the calculation, material damage can be accepted at the level of the average statistical payments by an Insurance Company for one average statistical road accident (118.2 thousand rubles/road accident)
7:00–9:00	0	6 (10.9)	
9:00–11:00	0	4 (7.3)	
11:00–13:00	0	3 (5.4)	
13:00–15:00	0	4 (7.3)	
15:00–17:00	0	5 (9.0)	
17:00–19:00	0	6 (10.9)	
19:00–21:00	0	8 (14.6)	
21:00–23:00	0	9 (16.4)	
Total	0	55 (100)	

Figure 11 graphically presents the data from Table 7.

Therefore, the data from Tables 6 and 7 and Figures 10 and 11 allow us to draw the main conclusion on the daily specifics of road accident rates in Tyumen. During the day, the accident rate quality is transformed: in the daytime, traffic incidents with material damage prevail; at night, the proportion of road accidents with victims increases sharply. Obviously, this is connected with road traffic and its features—connectivity and speed limits.

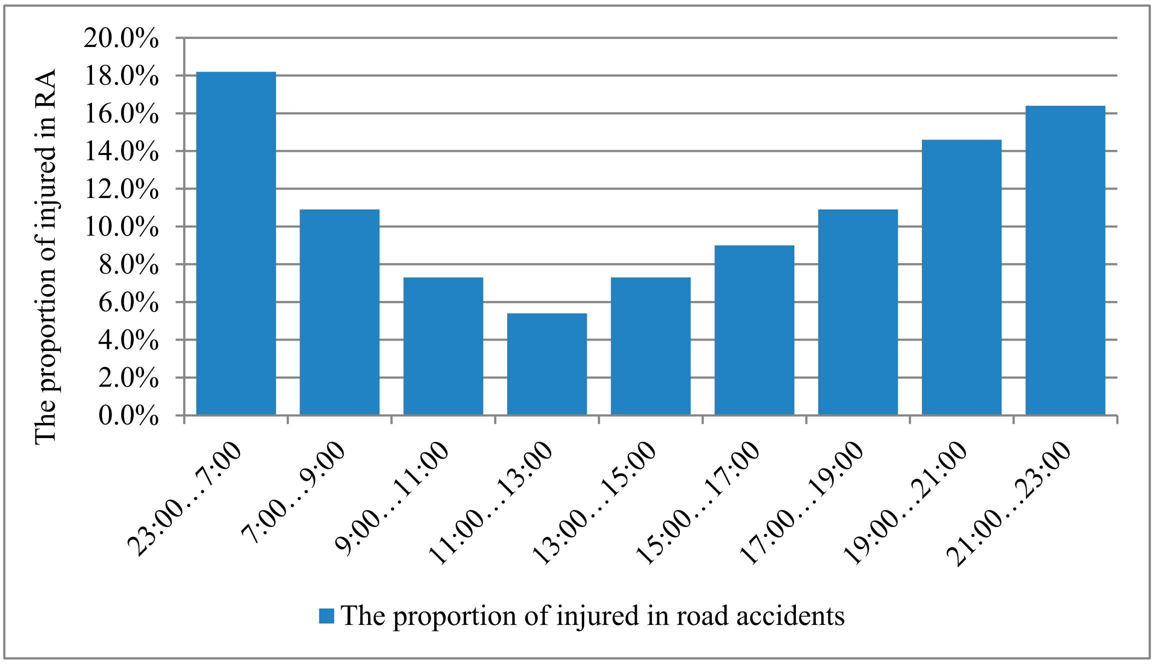


Figure 11. Distribution of the number of people injured in road accidents by hours of the day within the studied road network section.

Table 8 presents all the necessary data and the results of calculating the road injury risk R_V by certain hours of the day.

Table 8. Estimated values of the road injury risk R_V within the road network section by hours of the day.

Hours of the Day	Number of Vehicle Collisions			The Number of Victims N_V, Units	Scale of the Road Accident Sc_{RA}, Victims/Road Accident	Severity of the Road Accident Sev_{ra}, Share of Road Accidents with Victims	Damage from Road Accident Consequences D_{RA}	Probability of the Road Accident P_{RA}	Injury Risk R_V
	With Victims, N_{RA} Units	With Material Damage, Units	Total N, Units						
23:00–7:00	6	14	20	10	1.67	0.300	0.500	0.0159	0.00797
7:00–9:00	5	89	94	6	1.20	0.053	0.064	0.0750	0.00478
9:00–11:00	3	128	131	4	1.33	0.023	0.031	0.1045	0.00319
11:00–13:00	2	145	147	3	1.50	0.014	0.020	0.1172	0.00239
13:00–15:00	3	166	169	4	1.33	0.018	0.024	0.1348	0.00319
15:00–17:00	4	182	186	5	1.25	0.022	0.027	0.1483	0.00399
17:00–19:00	5	225	230	6	1.20	0.022	0.026	0.1834	0.00478
19:00–21:00	5	201	206	8	1.60	0.024	0.039	0.1643	0.00638
21:00–23:00	6	65	71	9	1.50	0.085	0.127	0.0566	0.00718
Total	39	1215	1254	55	-	-	-	-	-

Table 9 presents the values of relative entropy of lane occupancy $H_n(\theta)$ at the studied intersection of M. Toreza—Respubliki streets in Tyumen during 7:00–23:00 averaged according to mathematical statistics rules.

Table 9. Average values of the relative entropy of lane occupancy $H_n(\theta)$ within the road network section by hours of the day.

Hours of the Day							
7:00–9:00	**9:00–11:00**	**11:00–13:00**	**13:00–15:00**	**15:00–17:00**	**17:00–19:00**	**19:00–21:00**	**21:00–23:00**
Average values of the relative entropy of lane occupancy $H_n(\theta)$							
0.920	0.972	0.968	0.972	0.951	0.928	0.903	0.806

Taking into account the data from Tables 8 and 9, we determined the dependence $R_v = f(H_n(\theta))$, as presented in Figure 12.

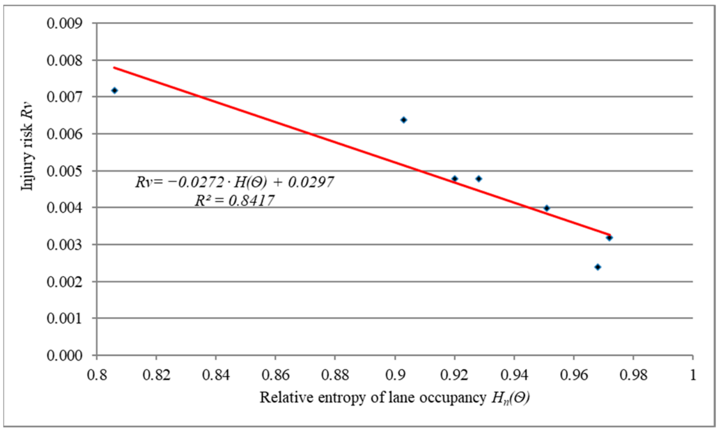


Figure 12. The dependence $R_v = f(H_n(\theta))$.

5. Discussion

Effective transportation systems are essential for sustainable development in modern cities. Like any complex system, transportation systems face various challenges, including traffic congestion and accident rates. Therefore, the aim of this research is to develop ideological foundations for managing urban traffic, focusing on the formation of road chaos and the level of road traffic incidents.

The study indicates that the relationship between traffic conditions, chaos, and accident levels is significant. The analysis draws on more than 70 research papers and suggests that traffic entropy can serve as an indicator of energy–information balance and chaos in the system. The researchers propose and confirm that changes in road chaos directly impact the variability of road traffic incidents.

Furthermore, the study investigates the impact of traffic chaos on the likelihood and severity of road traffic incidents. The results suggest that increased traffic chaos may lead to a higher frequency of incidents but not necessarily increased severity.

To assess traffic chaos, the researchers focus on the entropy of lane occupancy as a suitable indicator. Additionally, a mathematical model is developed to relate the kinetic energy of the traffic flow to the relative entropy of lane occupancy.

The experiments in this study involve dry asphalt conditions without ice, precipitation, or fog. The researchers utilized a neural network to process real-time video streams from street surveillance cameras, gathering data for analysis. This method demonstrates advantages such as obtaining a significant amount of real-time experimental data at a lower cost compared to traditional field monitoring. It also presents opportunities for predictive functions, enabling the forecasting of traffic-related events in the future.

Finally, statistical data on vehicle collisions were collected and analyzed, differentiating cases based on time intervals with corresponding averaged values of relative entropy of lane occupancy. The authors then examined the relationship between the level of road traffic injuries and the characteristic chaotic patterns of traffic flow.

As expected, the hypothesis "*The road injury risk R_v decreases with an increase in the Relative entropy of lane occupancy $H_n(\theta)$*)" was confirmed experimentally (Figure 12). According to the authors, the insight into this relationship will allow for the management of road safety by changing traffic light cycles at urban signal-controlled intersections. The purpose of cycle adjustment is to level out the $H_n(\theta)$ value and maintain it at a certain level. It is expected that the optimal level of $H_n(\theta)$ will be determined by taking traffic management objectives into account.

Notably, the choice of a specific signal-controlled intersection is only an illustrative example for carrying out the research. According to the authors, similar patterns of changes in accident rates over time will be characteristic of other intersections of the urban road network. This does not exclude a slight variability in the percentage distribution of traffic incidents with material damage (TI) and road accidents with victims (RA). It was important for the authors to identify the specifics of the redistribution of the severity of road accidents over time. The authors believe that this goal was achieved, and the obtained results are universal, taking into account the restrictions introduced in the research.

According to the authors, the obtained research results are in line with the fundamental principles of the theories of chaos, dynamic systems, traffic flows, etc. The dependence shown in Figure 6 generally correlates with the results obtained in [40–42,76,110,111]. The convergence of our work with these works lies in the fact that with an increase in lane occupancy to the maximum value, the level of chaos increases, but the productivity of the traffic flow decreases. At the same time, the dependence in Figure 12 shows that with an increase in chaos, the road injury risk $R_{v.}$ decreases.

The developed approach can be integrated with the Internet of Things (IoT) [120–122]. Within the framework of this approach, the collection of initial data on the characteristics of traffic flows can be carried out using the YOLOv5 neural network. In the future, the developed neural network model can be modified to detect and predict traffic accidents in real time. At the same time, the use of cloud sensors [120] can provide storage and high-speed processing of a large amount of source data. The additional use of edge computing technology [122] will reduce the load on computing systems. Together, the proposed measures will be able to support decision making on the choice of the operating mode of signal-controlled intersections in the road networks of cities.

As a possible method of monitoring and evaluating the practical implementation of the developed approach, it is advisable to consider monitoring by means of unmanned aerial vehicles (drones) [123]. From the point of view of the authors, the advantages of this method are as follows: Firstly, drones can also be integrated with the IoT [123]. Secondly, such a decentralized monitoring technology, unlike stationary video cameras and detectors, allows for the rapid collection and analysis of data in any part of the city's road network [123]. Thus, it becomes possible to assess the impact of decisions made not only within the boundaries of signal-controlled intersections but also on stretches.

Another possible development of the proposed approach is the integration of Large Language Models (LLMs), such as GPT-4, into Intelligent Transportation Systems (ITSs). LLMs can play a significant role within Intelligent Transportation Systems (ITSs), especially in managing road traffic [124,125]. Due to the fact that they are capable of processing and interpreting vast amounts of data, including textual information from road reports, social networks, and news feeds, LLMs can be instrumental in enhancing road safety and traffic optimization. An application of LLMs in ITSs could be the analysis of social media posts [124] for rapid detection and response to road traffic incidents or unexpected road situations. For instance, an LLM might analyze drivers' messages about traffic congestions or road accidents and automatically transmit this information to traffic management centers.

This would allow for prompt responses to changes in road conditions, reallocating traffic flows or providing timely information to drivers through mobile applications or road signs.

Ultimately, the proposed integration of the developed approach with IoT, drones and LLMs will make it possible to implement sustainability management of urban transport systems based on patterns of changes in traffic chaos and accidents in real time.

6. Conclusions

The results of the study have significant implications for enhancing the sustainability of transportation systems through the management of urban road traffic chaos and accident risks.

The key finding of this research is the establishment of a negative statistical correlation between the characteristics of road traffic chaos and road injury risk (*Rv*). It is worth noting that road injury risk (*Rv*) closely relates to the widely recognized indicator of human risk (*HR*), an essential measure for evaluating road safety levels at the national, regional, or city levels [126].

The study confirms that HR levels gradually decrease with increasing automobilization (A), primarily due to limitations in urban road networks and traffic capacity. Countries with higher levels of automatization tend to exhibit lower HR levels, indicating a correlation between traffic flow characteristics and the kinetic energy of traffic flows.

The dependence $R_v = f(H_\mathrm{n}(\theta))$ established for the large Russian city of Tyumen (with a population of about 850 thousand people) indicates a twofold increase in the road injury rate with a decrease in the entropy of lane occupancy $H_n(\theta)$ from $H_n(\theta)_1 = 0.97$ to $H_n(\theta)_2 = 0.81$.

This difference in "permitted" vehicle speeds, which has developed in practice in Europe and Russia and reaches 20–25 km/h, determines the differences in the human risk *HR* levels typical of the EU countries and Russia [127].

Thus, the ideology of accident risk management for sustainable transport systems presupposes the need to reduce the permitted traffic flow speeds V in cities. At the same time, the chance of transforming the free unbound vehicle movement mode into a bound mode increases. From the standpoint of energy–information balance, this will reduce the kinetic energy of the traffic flow E, increase the relative entropy of lane occupancy $H_n(\theta)$, and reduce the road injury risk R_v.

Taking into account the restrictions introduced herein, the following areas can be identified as future research. Firstly, this is a study of the influence of environmental conditions on changes in the level of road chaos and accident risks. This primarily concerns the influence of weather conditions (air temperature and precipitation) on the visibility and slipperiness of the road surface. Secondly, this is a study of changes in road chaos and accident risks, taking into account more complex requirements for traffic flows. In this case, the authors imply traffic in mixed directions, traffic conflict with other vehicles and/or pedestrians, and the heterogeneous composition of the traffic flow. Thirdly, taking into account the complexity and nonlinearity of the developed approach, its further elaboration can be continued within the framework of the theory of decision making and analysis. In particular, the obtained research results can be used in conjunction with hybrid multi-criteria decision-making (MCDM) methods to manage the urban transport system [128,129]. Taken together, the identified areas represent further prospects for research.

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