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Review on Intelligent Active Control Technology for Safety Distance of Heavy-duty Vehicles

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Abstract: Road freight plays a key role in national economy, but heavy vehicles have high risk of rear-end collision accident on complex road sections due to their inherent physical characteristics, and traditional static safety distance standards are difficult to cope with dynamic and complex driving environment. Firstly, the paper analyzes the different demands of safe distance on five typical risk road sections such as curve, long downhill, ramp, tunnel and special weather, and then classifies the existing safe distance models into three paradigms based on vehicle kinematics, driving behavior mechanism and data driving, and compares their advantages and disadvantages and applicability. On this basis, an intelligent active management and control technology system covering perception layer, decision layer and execution layer is constructed, and it is pointed out that the research is undergoing a fundamental transformation from single point technology breakthrough to "vehicle-road-cloud-edge" ecological synergy. Finally, the limitations of the current research on the disjunction between the model and the complex scene, and the lack of understanding of human-vehicle-road interaction mechanism are analyzed, and the future research directions are prospected, including the construction of special dynamic vehicle distance model, the development of driver digital twins, and the breakthrough of key technologies of formation control, in order to provide systematic theoretical reference and technical guidance for improving the driving safety of heavy vehicles.

1. Introduction

Highway transportation plays an important role in the development of national economy by virtue of its flexible, efficient and convenient characteristics. In China, highway freight especially occupies a dominant position. According to the statistics of the Ministry of Transport, the annual freight volume of the national highway has reached 41.88 billion tons in 2024, accounting for about 75% of the logistics volume, which strongly supports the economic and social operation. However, the inherent physical characteristics of heavy vehicles, such as high mass, high inertia and slow braking response, couple with road geometry conditions in complex sections such as steep curves, resulting in significantly increased safety risks. Accident data further highlight the seriousness of this problem. The National Highway Traffic Safety Administration (NHTSA) analyzed 233,000 large trucks before the accident, showing that rear-end collisions are the most common accident type, accounting for 23.5%. At the same time, the analysis of the warning data of more than 30,000 freight vehicles by the active safety cloud platform of China Pacific Insurance Company also shows that heavy vehicles face higher risk of rear-end collision and fatigue driving during driving [1].

The traditional static safety distance standard is difficult to adapt to the dynamic changing traffic environment, individual driving behavior differences and the unique compound risks of steep road sections. Therefore, it has become an urgent need to develop an intelligent, adaptive and accurate response to specific scenarios active control technology system. In recent years, the rapid development of key technologies such as vehicle-road collaboration (V2X), artificial intelligence, high-precision perception and digital twinning is pushing forward the fundamental transformation of research in this field. Its methodology shifts from relying on empirical rules to data-driven, and its technical path evolves from focusing on single-vehicle intelligence to focusing on system collaboration.

In order to systematically sort out the research progress in this field, this study adopts bibliometric methods to screen evidence: firstly, SCOPUS database is ("car-following model"OR"safe distance model")AND ("heavy vehicle" OR truck) was used as the search mode, 86 English literatures were initially searched; 50 Chinese literatures were searched simultaneously in China Knowledge Network with the key words "truck + vehicle distance". According to the abstract contents of the literatures, correlation assessment and quality screening were conducted around four core dimensions of "heavy vehicles," "steep curved road sections," "safe vehicle spacing" and "intelligent active control technology," and 30 high-quality core literatures (20 English literatures and 10 Chinese literatures) were finally determined as the analysis basis of this review.

Based on the systematic review of 30 core literatures, this study constructs an overall analysis framework covering four dimensions: road characteristics, safety distance model, active control technology, limitations and prospects.

2. Road types mainly involved in the study of safe distance between heavy duty vehicles

Based on the analysis of 30 core literatures, the road environments affecting the study of safe distance between heavy vehicles can be classified into five typical scenarios: curve section, long downhill section, ramp/junction section, tunnel section and special weather section. This classification not only reflects the differences in physical attributes of different scenarios, but also closely relates to the driver's perception and cognitive load, the vehicle's dynamic response characteristics and the fundamental changes in traffic flow interaction patterns, providing a clear theoretical basis for constructing differentiated safe vehicle distance control strategies.

2.1. Curve Road Section

The core of the study on safe distance between vehicles on curved road sections lies in the coupling effect between centrifugal force caused by curvature radius and vehicle dynamics characteristics. Existing studies mainly focus on accident cause analysis, safe sight distance modeling and safe distance calculation. Mouyid Islam et al.[2]pointed out that speeding and driving negligence are the key human factors inducing truck accidents based on the curve accident data in rural North Carolina from 2010 to 2017; Alfredo Garcia et al.[3] pointed out that the radius of curve should be more than 2500 meters to realize truck formation driving from the perspective of fleet coordination, and found that the automatic driving system can effectively compress the safe distance. In terms of model construction, Zhang et al.[4]introduced the slope acceleration parameter to establish a safe distance calculation model suitable for steep curve sections, which provided theoretical support for the sign layout in practical engineering. On the whole, the safe distance between vehicles in curves is not only restricted by geometric line shape, but also affected by multiple factors of people, vehicles and roads, which should be comprehensively considered in the control strategy.

2.2. Long Downhill Section

Long downhill section (slope≥1%, length≥3km), the core contradiction lies in the dynamic balance between the thermal degradation effect caused by continuous braking and the speed control demand. The existing research mainly focuses on risk threshold identification, braking strategy optimization and engineering intervention measures[5]. Zou Haiyun et al.[6]based on the accident data of western expressway, constructed collision deceleration rate model through speed difference and headway, and proposed 0.4916m/s2 as risk warning threshold, which provided quantitative basis for active warning system. QuanJ et al.[7]proposed an intelligent auxiliary system based on GIS and vehicle dynamics from the perspective of active intervention, which can effectively reduce the thermal load of the main brake and prolong the safe downhill distance through strategies such as slope top speed pre-control and engine auxiliary braking coordination. At the engineering practice level, Zhang Tao[8]put forward systematic transformation scheme from warning sign setting, traffic management measures and sight distance improvement for long downhill sections of Kunchu Expressway, reflecting the transformation path from theory to application. Generally speaking, safety vehicle spacing control of long downhill sections needs to break through traditional static standards and establish a multi-level dynamic response system including slope front warning, braking coordination and engineering intervention.

2.3. Ramp/junction

The research of safe vehicle spacing on ramp/junction mainly focuses on the speed difference between main and junction traffic, trajectory conflict and dynamic risk caused by space resource competition. Hussain et al.[9] analyzed the adjustment behavior of vehicle spacing in confluence area through nonlinear regression model, and found that when the speed difference exceeds 30km/h, the vehicle spacing decreases exponentially, and the spacing compression effect of heavy vehicles is more significant, revealing the nonlinear erosion effect of speed difference on safe buffer space. Li et al.[10]studied the influence of trucks on traffic flow in bottleneck sections from the system level and established a mixed traffic flow model. The results show that the increase of truck proportion will aggravate traffic congestion at ramp sections, reduce traffic efficiency and capacity, and reflect the disturbance effect of heavy vehicles on the overall traffic flow during the merging process. Comprehensively speaking, the safe vehicle distance of ramp/junction section is not only affected by micro-vehicle interaction behavior, but also closely coupled with macro-traffic flow state, so it is necessary to construct collaborative management and control strategy from micro-behavior to meso-bottleneck and macro-network multi-scale perspective.

2.4. Tunnel Section

The core challenge of the research on safe distance between vehicles in tunnel sections lies in the significant interference of environmental characteristics such as enclosed space, light mutation and lack of reference objects on driver's distance perception and speed judgment. Xie Yidan [11]comprehensively considered road service level, speed difference, linear parameters and driver's cardio physiological parameters to establish a mountain highway safety evaluation model, and proposed the calculation of tunnel entrance brightness, speed limit sign setting position and safe distance between bridge and tunnel transition sections. method provides systematic theoretical support for engineering practice. Qiu Tianfu [12]established a driving model based on truck braking performance and driver characteristics from the coupling angle of vehicle dynamics and driving behavior. Through parameter definition and TruckSim simulation verification, the recommended value of minimum safe driving distance in tunnel section was given, and the closed-loop research from theoretical modeling to numerical verification was realized. Generally speaking, the safety distance control of tunnel sections needs to break through the research paradigm of traditional open sections, focus on solving special problems such as perception bias, psychological load and Incident Response Service in closed environment, and establish a collaborative mechanism from environment perception to behavior response and finally to distance control.

2.5. Special Weather Conditions

The core of the research on safe vehicle distance in special weather conditions (rain, fog, etc.) lies in the compound compression effect of visibility reduction and road adhesion coefficient reduction on safe buffer space. Xu Mengjie[13]established a safe distance calculation model under different driving conditions by analyzing the coupling effect of water film thickness, circular curve radius, vehicle type and vehicle speed, and developed a rainy day expressway driving safety warning system based on QT platform, realizing the transformation from theoretical model to engineering application. Li Xuan[14]established a simplified braking distance model under different fog levels and traffic volumes for fog area environment, verified the braking performance under different initial vehicle speeds and braking pressures through Carsim/Trucksim simulation, and finally established a calculation model for safe vehicle distance in fog area and proposed control standards. In general, the safety distance control of heavy vehicles under special weather conditions needs to break through the research limitation of single environmental variable, establish the analysis framework of visibility, adhesion coefficient and vehicle dynamics multi-factor coupling, and pay attention to the technical transformation path from offline modeling to online warning system.

3. A Safe Distance Model for Heavy-Duty Vehicles

3.1. Safe Distance Model Based on Vehicle Kinematics

Based on the vehicle kinematics model, the safe distance model is mainly constructed from the perspective of vehicle physical motion characteristics, focusing on the kinematic parameters such as acceleration, deceleration and speed change of the vehicle, as well as the dynamic characteristics such as vehicle mass and braking force.[15][16] Such models are usually based on Newton's law of motion and describe the relative motion relationship between the front and rear vehicles by establishing vehicle motion equations, such as the classical IDM model[17]and FVD model[18].Yang et al.[19]analyze four different car-following combinations based on heterogeneous optimal velocity model (passenger car-passenger car, passenger car-heavy vehicle, heavy vehicle-passenger car, heavy vehicle-heavy vehicle) on traffic flow stability; Quan et al.[7] proposed a safe speed/distance control strategy based on vehicle dynamics and brake temperature rise models. The advantage of vehicle kinematics model lies in its clear physical meaning and relatively stable parameters, which can better reflect the motion law of vehicle in emergency braking and car-following scenes, but it simplifies driver behavior factors relatively, and its adaptability in complex traffic environment has certain limitations.

3.2. Safe Distance Model Based on Driving Behavior Mechanism

The driver behavior model regards the safe distance as the comprehensive result of the driver cognition-decision-reaction process, focusing on the psychological and behavioral characteristics of the driver such as perception threshold, reaction time, risk perception and decision preference.

Durrani et al.[20] use the accumulator model Liu et al.[21]developed a new car-following model based on cognitive risk dynamic equilibrium. Zhang et al.[22]introduced the concept of pressure effect and used potential field theory to quantify the impact of large trucks on the psychology and behavior of surrounding passenger car drivers, thus establishing a new car-following model. The distance model based on driving behavior simulates actual driving behavior by introducing expected spacing, reaction delay and other parameters. The advantage is that it is closer to the real driving scene and can explain the distance difference between different drivers and different driving states. However, the calibration of model parameters is complex, which challenges the quantification of individual differences of drivers.

3.3. A Data-driven Model for Safe Distance between Vehicles

Data-driven method provides a new technical path for safe distance modeling by mining potential rules in vehicle operation data. The model does not rely on traditional physical or behavioral assumptions, but establishes a nonlinear mapping relationship between input and output in a data-driven manner. Mantouka et al.[23]developed a self-supervised model using LSTM-Transformer self-encoder to realize fine reproduction of car-following behavior of heavy-duty vehicles; Jin Chengqian[24]optimizes the vehicle spacing and speed coordination strategy of formation vehicles from the perspective of formation control through particle swarm optimization combined with double-loop PID control algorithm; Xu Yueru[25]adopts GA optimization BP neural network to construct active safety warning response prediction model under different drivers and road environment, providing support for system personalized design. In general, data-driven methods break through the parameter dependence limitations of traditional theoretical models and can better capture the complexity and heterogeneity of driving behavior, but pay attention to engineering application challenges such as data quality, model generalization ability and real-time performance.

3.4. Model Comparison and Applicability Analysis

The three main types of safe distance models have their own emphases on theoretical basis, modeling objects, parameter characteristics and application scenarios, and together constitute a complete research spectrum from physical mechanism to behavior cognition, and then to data intelligence. The model comparisons are shown in Table 1.

Table 1 Comparison of main model characteristics of safe distance between heavy duty vehicles

Model type	Advantages	Limitations	Applicable scenarios
vehicle kinematic	The physical mechanism is clear, the calculation is efficient, the parameter stability and interpretability are strong.	The driver behavior, psychological state and dynamic changes of complex traffic environment are not considered enough, and the model is relatively simplified.	Theoretical analysis and simulation of foundation safety threshold calculation, emergency braking and car-following stability.
Driver behavior mechanism	Effectively depict the cognitive decision-making process of drivers, capture individual differences, and accurately warn.	Parameter calibration is complex, quantification of individual differences is challenging, computational efficiency and generalization ability are limited.	Driver behavior analysis and prediction, human-computer interaction system design, risk assessment in complex traffic environments.
data-driven	No strong assumptions, good at mining complex nonlinear relationships and potential patterns from data, strong model fitting ability.	Dependence on data quality and size, poor interpretability.	Large-scale natural driving data analysis, intelligent network connection and formation driving and other complex interactive scene modeling, performance optimization of existing systems.

4. Intelligent Active Control Technology for Safety Distance of Heavy-duty Vehicles

4.1. Perception layer: Multi-source heterogeneous data fusion

The perception layer is the information foundation of the system. It is responsible for achieving comprehensive perception of the driving environment and vehicle status by fusing heterogeneous data from different sources and formats. Typical data sources include five categories:

One is high-precision space-time trajectory data, which is obtained by UAV aerial photography or fixed overhead camera combined with computer vision technology[22][23]. It is an important data source for studying car-following behavior and traffic flow characteristics, especially for analyzing the interaction between heavy vehicles and small vehicles;

The second is natural driving data, which is obtained through continuous recording by data collection equipment installed on the vehicle[17][21][26].The data can reflect driving behavior under real and non-interference conditions, especially the analysis of different preceding vehicle types and drivers. The impact of characteristics on the safe distance to follow.

Third, road and environmental state data, including static road attributes such as road alignment (curvature, slope), lane number, tunnel bridge position, etc., as well as dynamic environmental information such as real-time weather (rainfall, snow, fog), road condition (water film thickness, icing, snow accumulation) and visibility collected by meteorological and road state sensors[13], which are key inputs for correcting safe vehicle distance model.

The fourth is on-board active safety monitoring data, mainly from the advanced driver assistance system (ADAS) and driver monitoring system (DMS)[1] that have been assembled on a large scale in commercial vehicle fleets, which can record the trigger records of forward collision warning, vehicle proximity warning, lane departure warning and other events, as well as driver status monitoring (such as fatigue and distraction) data.

Fifthly, vehicle network data, vehicles obtain real-time traffic information from surrounding vehicles, roadside units and clouds through V2X communication, expand the perception range of single vehicles, realize "over-the-horizon" perception, and are the basis for supporting collaborative formation and high-level warning[24].

4.2. Decision layer: risk prediction and adaptive early warning

As the brain of intelligent active control system, the core task of decision-making layer is to carry out real-time risk judgment based on multi-source information provided by perception layer, and generate corresponding warning or control instructions. Heavy vehicle research mainly focuses on the following directions:

One is to improve the classic car-following model. In order to reflect the complexity of interaction between heavy vehicles and small vehicles in mixed traffic flow more accurately, scholars focus on improving the traditional car-following model[16] [18] [19] [27] .By introducing vehicle type, compression effect, traffic flow heterogeneity and other factors, the model decision is more consistent with the real risk of mixed traffic flow.

The second is driving behavior identification and personalized risk assessment. The accuracy of decision-making is inseparable from a deep understanding of the behavior subject. The study identifies and classifies drivers 'following styles (such as aggressive, common, and conservative)[20][28]. On this basis, personalized risk prediction models are constructed to achieve differentiated customization of warning thresholds and strategies.

The third is to introduce multi-dimensional dynamic risk assessment indicators. In order to overcome the limitations of single indicators, research efforts are devoted to developing and integrating more refined risk quantification indicators. In addition to traditional collision time, dynamic indicators such as reverse collision time, collision deceleration rate and brake thermal decay risk index are introduced [6][7][21] [29]. These indicators can quantify the urgency and severity of conflicts in real time from different dimensions, providing more accurate decision-making basis for triggering graded early warning.

The fourth is human-computer interaction and strategy optimization of early warning system. Part of the research focuses on the effectiveness optimization of early warning system itself.[13][25] By analyzing the physiological reaction of drivers and vehicle operation data before and after warning trigger, the effect of different warning modes (vision, hearing, touch) and warning timing is evaluated, and adaptive optimization algorithm is used to realize the virtuous circle of human-computer collaborative decision-making.

4.3. Executive level: collaborative control and formation optimization

The executive layer is the "hands and feet" of the intelligent active management and control system, responsible for transforming the instructions of the decision-making layer into the actual control actions of the vehicle. The core goal is to achieve accurate, stable and efficient automatic adjustment of the safe distance between vehicles. The research on heavy-duty vehicles mainly revolves around the following key technical paths:

The first is the coordinated vehicle formation control strategy, which is the core embodiment of the executive layer. Research focuses on designing distributed coordinated control algorithms for multi-vehicle formations.[15][24] The control algorithms not only ensure that the fleet maintains a stable desired separation, but also achieve significant optimization of overall fuel economy by exploiting the aerodynamic drag effect of the preceding vehicle. The research focuses on balancing car-following safety, queue stability, and overall energy saving.

The second is dedicated models and methods for autonomous vehicle formation. Due to the characteristics of heavy trucks with large mass and slow braking response, autonomous vehicle formation control faces special challenges. The study develops robust car-following models and hierarchical control architectures specifically for truck formation[3][29]. The upper layer performs trajectory planning and collaborative decision-making, while the lower layer performs precise longitudinal (throttle/brake) and lateral control, focusing on solving the control delay and stability problems caused by large inertia systems.

The third is the modeling and parameterization of the safety distance under specific working conditions. In order to ensure the safety of the control algorithm, accurate input of the underlying parameters is required. For specific high-risk scenarios such as long downhill, curve, wet road, etc., a refined minimum safety distance calculation model is established through dynamic simulation or theoretical derivation.[10][12][30]The model considers variables such as load, slope, and road adhesion coefficient, and provides a crucial theoretical basis and parameter benchmark for setting safety thresholds in the executive layer controller.

4.4. System Integration: From Single Point Technology to Ecological Synergy

At present, the research paradigm of intelligent active control technology for safety distance of heavy-duty vehicles is undergoing profound transformation, and its evolution track clearly shows the overall trend from closed loop technology to open ecological collaborative development. The core characteristics of this trend can be condensed into the following two key dimensions:

First of all, the research realizes the leap from isolated vehicles to vehicle-road environment collaborative systems. The research focus has gone beyond the traditional single-vehicle intelligent category, and the heavy-duty vehicles are placed in the complex real scene of people, vehicles, roads and environments for systematic consideration. Specifically, it is deeply integrated with the dynamic driving environment, such as adaptive adjustment for severe weather conditions such as rain, fog, ice and snow, and complex traffic flow conditions[13][14]; The second is collaborative integration with static road infrastructure, such as precise control in combination with geometric and structural features such as road alignment, gradient, tunnel, bridge, etc.[3].This study fundamentally addresses the core issue of how to achieve safe, efficient, and reliable collaboration between intelligent vehicles and the external multi-dimensional environment.

Second, technology development has moved from algorithm innovation to holistic engineering solutions. Research is no longer limited to proposing a single improved algorithm or verifying a specific model, but is committed to building a technology chain that runs through the entire process, from environment and state awareness to risk assessment and intelligent decision-making, and finally to precise control and execution. Its effectiveness often depends on system-level validation in simulation platforms such as SUMO or CarSim, or field-level functional validation through integrated prototype systems such as advanced warning systems and driver assistance systems.[7][13][14][24]It marks a critical transition from theoretical exploration and technological breakthroughs to engineering practice and industrial implementation.

5. Research Limitations and Future Research Directions

5.1. Deep analysis of existing limitations

(1) Model and scene disconnection problem outstanding

The existing safe distance models are mostly constructed based on single road features, while the actual traffic sections usually contain "curve-slope-tunnel" compound scenarios. The driver load in the compound scenarios presents nonlinear superposition effect, which leads to significant decline in the prediction accuracy of the models. The safe distance demand of tunnel connecting downhill sections is not a simple sum of all factors, and the coupling mechanism of visual adaptation process, braking heat accumulation effect and psychological load should be comprehensively considered. Existing research lacks systematic description of this.

(2) The cognitive fragmentation of Human-Vehicle-Road interaction mechanism

The study on the interaction of vehicle type, driver behavior and road geometry shows fragmentation characteristics. The influence of lane type on risk indicators has significant heterogeneity, but there is no unified quantitative framework. The design of early warning system focuses on single vehicle distance judgment, ignoring driver cumulative behavior characteristics and long-term habits, which is easy to cause early warning fatigue and trust decline. It is urgent to establish a database covering the interaction of vehicle type, driving style, road type and other factors to deepen the understanding of human factors mechanism.

(3) Technology landing adaptability faces multiple challenges

The vehicle distance detection system significantly increases the false alarm rate under severe weather conditions such as rain and fog; the forward collision warning system lacks the ability to warn the risks such as sideslip and brake failure that are unique to steep road sections; the stability of formation technology faces severe challenges when the road geometry changes (such as sharp turns and sudden changes in gradient). The existing systems focus on after-action response and lack feedforward prediction and active intervention capabilities for the risk evolution process, so it is difficult to achieve "prevention before it occurs".

5.2. Future research direction

(1) Construction of special safety distance model for heavy duty vehicles under different road geometry

By integrating multi-source information such as road geometry parameters, real-time vehicle dynamics, and driver health indicators, this study develops lightweight, high-precision dynamic calculation models. This enables customized control strategies tailored to specific curves and slopes, ultimately overcoming the bottleneck of compound scene modeling.

(2) Developing Driver Behavior Digital Twin and Personalized Warning

Based on DMS, physiological sensors, historical trajectories and other multi-modal perception data, the digital twin of driver behavior is constructed to realize accurate portrait and dynamic evolution prediction of risk behavior. Differentiated warning strategies are customized for different driving styles to improve warning acceptance and intervention effectiveness, and promote the transition of early warning system from universality to individualization.

(3) Breakthrough of Key Technologies for Heavy Duty Vehicle Formation Control

Develop predictive formation control algorithm, deeply integrate high-precision map, real-time perception and vehicle dynamics model, predict curve curvature and slope change trend, dynamically optimize formation shape, vehicle spacing and speed profile. This study focuses on addressing formation stability issues in complex scenarios such as ramp convergence and sharp curve transitions, thereby enhancing cooperative driving safety and comfort.

(4) Promote the ecological construction of "vehicle-road-cloud-edge" collaborative control

Deploy roadside intelligent units such as millimeter wave radar, meteorological sensors, video analysis, etc. to build high-fidelity digital twins. By leveraging 5G-V2X, this study enables sub-second risk information sharing and collaborative decision-making. Furthermore, deploying lightweight early warning models at edge computing nodes reduces cloud dependence and communication latency, ultimately forming a closed-loop ‘perception-decision-control-feedback’ system to achieve feedforward risk prediction and active intervention.

6. Conclusion

The results show that road type is the decisive external variable of safe distance, and different modeling should be implemented for curve, long downhill, ramp, tunnel and special weather sections; Intelligent management and control technology has formed a three-layer system of "perception-decision-execution". Vehicle distance detection and reminder, forward collision warning and automatic driving formation have become the three technical pillars; the existing core bottlenecks focus on the disconnection between model and compound scene, insufficient cognition of human-vehicle-road interaction mechanism, and limited adaptability of technology landing.

Future breakthroughs need to focus on five directions: building a special dynamic safety vehicle distance model for steep curved sections, developing digital twins and personalized early warning of driver behavior, overcoming key technologies for formation control of steep curved sections, promoting the collaborative ecological construction of "vehicle-road-cloud-edge", and strengthening interdisciplinary integration and standard system construction. Through multi-disciplinary intersection and industry-university-research collaboration, we can systematically solve the safety problems of heavy-duty vehicles in steep and curved sections, provide solid scientific and technological support for the construction of a powerful traffic country, and help China's road traffic safety management to move towards a new stage of intelligence, precision and humanization.

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