Future Technology
Open Access Journal
ISSN 2832-0379

November 2025| Volume 04 | Issue 04 | Pages 311-317
Journal homepage: https://fupubco.com/futech
https://doi.org/10.55670/fpll.futech.4.4.25

Future Publishing LLC

Review

Innovative applications of big data and simulation technologies in the optimization design of crash safety for autonomous vehicles: a systematic review from a biomechanical aspect

Lingxiao Sun*

School of Information Engineering, Chang'an University, Xian, 710018, China

ARTICLE INFO

Article history:
Received 10 July 2025
Received in revised form
29 August 2025
Accepted 18 September 2025

Keywords:
Autonomous vehicles, Collision safety, Biomechanics, Big data, Simulation technology, Optimization design, Machine learning

*Corresponding author
Email address:
lingxiaosunedu@163.com

DOI: 10.55670/fpll.futech.4.4.25

ABSTRACT

The rapid development of autonomous vehicles (AVs) has intensified the demand for advanced strategies to guarantee crash safety in increasingly complex traffic environments. Traditional design methods, reliant on physical crash tests and limited empirical data, are insufficient to capture the full spectrum of biomechanical responses during collisions. This systematic review synthesizes recent advances in the integration of big data analytics and simulation technologies for optimizing collision safety, with a particular focus on biomechanical modeling. Big data enables the large-scale collection and analysis of heterogeneous data sources- including vehicle sensors, physiological signals, and traffic dynamics- supporting the construction of high-fidelity injury prediction models. Simulation methods, such as finite element analysis (FEA), multi-body dynamics (MBD), and parametric optimization, facilitate precise evaluation of occupant kinematics, stress distributions, and tissue-level injury mechanisms. Furthermore, emerging applications of machine learning, digital twin systems, and biomimetic design demonstrate substantial potential for improving active and passive safety. This review highlights the synergistic role of biomechanics, data science, and simulation technologies in shaping the next generation of collision protection systems. Finally, it identifies key challenges–including data privacy, model accuracy, and computational efficiency – and proposes future directions toward multi-scale biomechanical modeling, AI-driven optimization, and cross-disciplinary integration for safer and more adaptive autonomous driving systems.

1. Introduction

Since the 1990s, pioneering projects such as ALVINN at Carnegie Mellon University demonstrated the feasibility of neural networks for lane-keeping in autonomous vehicles (AVs) [1]. The subsequent DARPA Grand Challenge further catalyzed advancements in perception, decision-making, and control technologies, driving global progress in AV development [2]. Today, AVs promise safer and more efficient transportation systems; however, ensuring crash safety in unpredictable real-world conditions remains a fundamental challenge. Traditional vehicle safety design has relied heavily on physical crash tests and restraint system evaluations. While effective in conventional contexts, these methods struggle to address the complex dynamic responses of the human body and the variability of AV operating environments. As a result, novel approaches that combine biomechanics, big data analytics, and advanced simulations are increasingly essential [3]. Biomechanics offers critical insights into the kinematic and physiological responses of occupants during collisions, including joint motion, tissue deformation, and energy transfer pathways. When integrated with vehicle dynamics models, biomechanics enables a deeper understanding of injury mechanisms and supports the design of more adaptive safety systems [4]. At the same time, big data provides the foundation for capturing multi-source information–from in-vehicle sensors and traffic networks to physiological and behavioral parameters–allowing for more personalized and context-aware safety solutions [5]. Simulation technologies, such as finite element analysis (FEA) and multi-body dynamics (MBD), further expand the design space by enabling detailed modeling of structural deformation, occupant kinematics, and tissue-level stresses [6]. When coupled with machine learning, digital twin platforms, and biomimetic design strategies, these methods present unprecedented opportunities to optimize both active and passive safety performance [7]. This review systematically examines the innovative applications of big data and simulation technologies in collision safety design, with a particular emphasis on their contributions from a biomechanical perspective. By analyzing recent progress in data-driven injury modeling, advanced simulation methodologies, and optimization frameworks, this study aims to establish a comprehensive roadmap for future research. Unlike earlier reviews that considered big data, simulation, or biomechanics in isolation, this paper provides an integrative perspective that explicitly connects large-scale data analytics, machine learning models, simulation technologies, and biomechanical validation into a unified framework. This novelty ensures a more complete understanding of collision safety and distinguishes this work from existing literature.

1.1 Research objectives

- To identify how big-data analytics contribute to crash risk assessment and severity prediction.
- To examine the role of machine learning models in perception, prediction, and decision-making for safety-critical scenarios.
- To evaluate simulation technologies for traffic-level and occupant-level safety analysis.
- To integrate biomechanics and human factors into system-level evaluations of crash safety.
- To propose future directions for digital twins, AI-driven optimization, and regulatory applications in AV safety.

2. Related works

Research on autonomous vehicle safety has developed rapidly in recent years, with efforts spanning sensing technologies, big-data analytics, machine learning, simulation, and occupant biomechanics. Early breakthroughs in perception and control established the foundations of AV research. For example, Carnegie Mellon's ALVINN system demonstrated lane-keeping with neural networks [1], while the DARPA Grand Challenge stimulated advances in autonomous navigation and decision-making [2]. Subsequent work has expanded toward robustness in localization, communication, and safety assurance, each of which contributes to collision prevention and mitigation.

2.1 Sensing, localization, and communication

Accurate perception and positioning are indispensable for collision safety. Robust localization under GNSS-denied conditions has been achieved using LiDAR and visual sensing in high-dynamics environments [6]. Fusion of multiple sensors, including inertial and visual inputs, has improved real-time loop closure performance in SLAM-based navigation [7-9]. On the communication side, the development of 5G network slicing has been proposed to support ultra-low-latency vehicular services, which are critical for collision avoidance and cooperative safety applications. At the same time, resilience against adversarial interference has been explored, with approaches designed to maintain safety even when sensor attacks compromise normal operation. These studies highlight that perception and communication layers form the essential substrate for reliable safety functions.

2.2 Big-data analytics for crash risk

The growth of large-scale traffic datasets has enabled new approaches to crash risk modeling. Data-mining techniques have been applied to discover unrecorded highway incidents and improve accident databases [10]. Urban-scale analyses have used spatial grid modeling to identify pedestrian collision hotspots and the factors contributing to them [11]. More advanced statistical techniques, such as spatio-temporal kernel density estimation, have been employed to analyze accident distributions, including those involving electric vehicles [12]. Machine learning has also been introduced into crash data analysis. For instance, comparative studies of classifiers demonstrated that random forests achieved superior accuracy in predicting collision severity, outperforming Bayesian and k-nearest neighbor models [13]. Time-series based models have further been proposed to capture spatio-temporal features of traffic flow for dynamic risk prediction [14]. Together, these studies illustrate how big data can serve as a basis for more proactive and context-aware collision safety assessment.

2.3 Machine learning for prediction and decision-making

Beyond data mining, machine learning techniques have been widely applied to prediction and decision-making in safety-critical AV tasks. Vehicle-pedestrian interaction has been modeled using spatio-temporal learning frameworks, enabling more accurate risk assessment in urban settings [14]. VR-based simulation environments have been combined with decision-tree models to predict pedestrian collision risks under different scenarios [15]. Advances in pedestrian detection and classification have also been reported, including the use of multispectral sensing to improve detection accuracy under challenging conditions [16]. Behavior classification frameworks have been developed to predict pedestrian intent and interaction with vehicles [17-19]. At the decision-making level, frameworks based on partially observable Markov decision processes (POMDPs) have been designed to reduce unnecessary braking while maintaining safety in occluded environments [20]. Related applications in other transport domains demonstrate the potential of AI-based optimization for collision avoidance [21]. Emerging approaches, such as transformer-based sequence models, graph neural networks (GNNs), and reinforcement learning (RL), are increasingly applied to trajectory prediction, complex interaction modeling, and adaptive decision-making. While still in early stages, these techniques show potential to enhance the robustness of AV safety systems and merit further exploration in biomechanical contexts.

2.4 Simulation and traffic dynamics

Simulation studies provide an essential complement to empirical data in assessing collision risks and safety measures. DSRC-based cooperative braking systems have been evaluated in simulation environments, demonstrating measurable improvements in rear-end collision avoidance [19]. Connected and automated vehicles (CAVs) have been shown to reduce traffic oscillations in microscopic simulations, indirectly contributing to improved safety [22, 23]. Near-miss incidents have been integrated into Monte Carlo simulations, reducing error rates in crash frequency prediction compared to traditional methods [24]. Reviews of blackspot identification methods and transportation safety analytics also underline the need for rigorous evaluation frameworks [25, 26]. Driving simulators have been widely used to study human factors, though limitations remain in terms of fidelity and transferability to real-world conditions [27]. These simulation-based studies highlight both the potential and constraints of virtual experimentation in AV safety evaluation.

2.5 Human factors and biomechanics

In addition to external traffic risks, occupant responses during sudden maneuvers or collisions remain a critical research focus. Naturalistic experiments have recorded the kinematics of unrestrained passengers in autonomous shuttles during emergency braking, showing that postural variation significantly influences segmental motion and overall injury risk [28]. Cognitive and behavioral aspects are equally important. Studies have shown that executive functions strongly affect safe driving behaviors [29], while risk perception differs across user groups and influences exposure to danger [30]. Pedestrian behavior classification, intent recognition, and situational awareness further connect human factors with predictive safety models [23, 24, 30]. These findings underline that biomechanical and behavioral research must be integrated into AV safety systems to ensure that system-level improvements translate into actual reductions in occupant injury.

3. Methodology

This review follows an integrative methodology designed to connect big-data analysis, machine learning models, and simulation-based biomechanics into a unified framework for assessing collision safety in autonomous vehicles. The approach combines three main steps: (i) acquisition and processing of large-scale driving and crash-related datasets, (ii) modeling and simulation of traffic dynamics and occupant biomechanics, and (iii) integration of results into a cross-disciplinary framework.

3.1 Data acquisition and processing

Multi-source datasets from naturalistic driving studies, crash databases, and vehicle sensors provide the basis for collision risk assessment. Data preprocessing includes cleaning, filtering, and spatio-temporal alignment. Extracted features, such as vehicle speed, acceleration, and relative position, support both descriptive statistics and predictive models. Figure 1 shows the data flow from collection to analysis, highlighting the multi-layered nature of safety-related data.

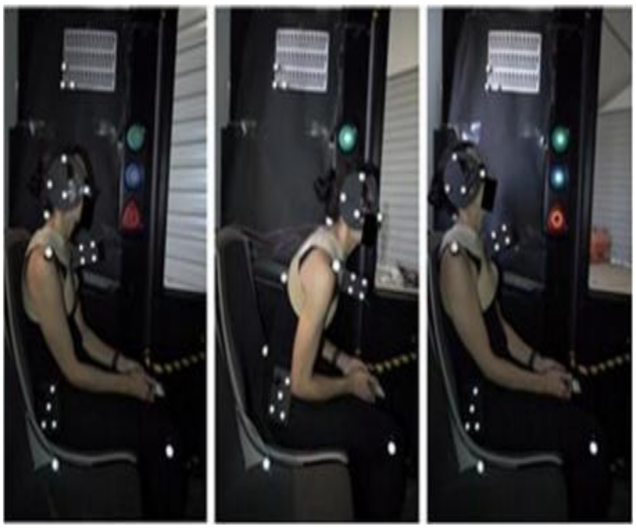

Figure 1 Movement of a subject during the emergency braking test [21]

3.2 Machine learning models

Machine learning enables proactive identification of high-risk scenarios and adaptive safety interventions. Supervised models are used to classify crash severity or predict accident likelihood, while spatio-temporal learning frameworks capture dynamic risk in traffic flows. For vulnerable road users, pedestrian intent recognition and multispectral detection improve early-warning performance. At the decision-making level, probabilistic frameworks support motion planning under uncertainty. Figure 2 illustrates a generic prediction – control loop where perception feeds into risk models that inform planning.

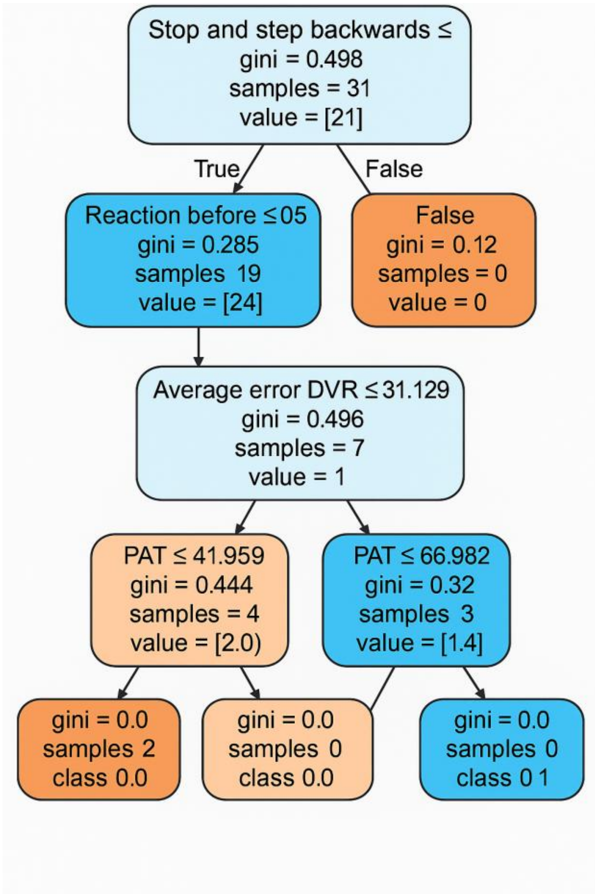

Figure 2. Individual tree of the Random Forest ensemble [15]

3.3 Simulation of traffic and occupant safety

Simulation extends safety evaluation beyond what is feasible with physical experiments. Traffic-level simulations test cooperative braking or connected vehicle strategies, while Monte Carlo models estimate crash frequencies under varied conditions. Driving simulators are employed to investigate human factors such as driver workload and attention. At the occupant level, finite element and multi-body models describe how bodies respond to impact, while naturalistic experiments provide validation data. Figure 3 depicts the layered structure of these simulation approaches.

3.4 Biomechanics and Human Factors

Occupant biomechanics translates external crash forces into internal physiological responses. Kinematic measurements from shuttle experiments have shown that posture affects motion trajectories during sudden maneuvers. Human cognitive factors and risk perception also influence safety outcomes. Figure 4 presents representative biomechanical motion data, emphasizing the variability of occupant responses.

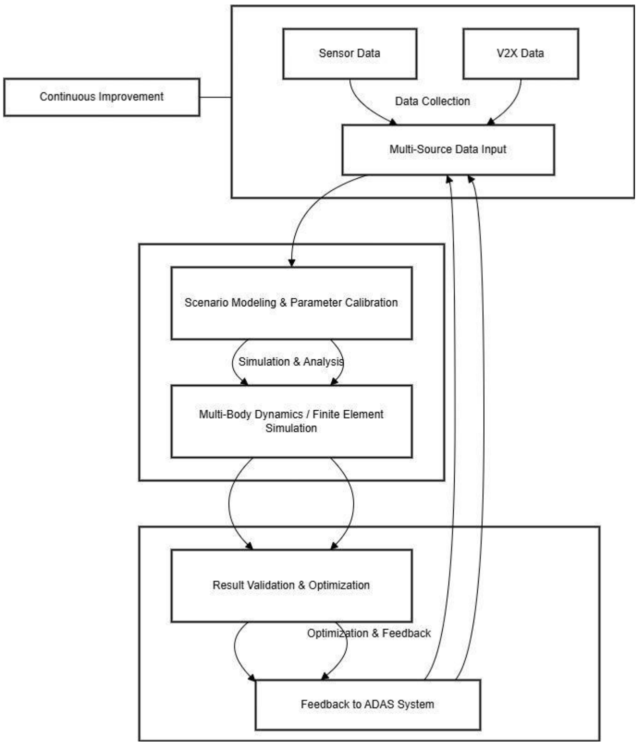

Figure 3. Integration process of simulation technology in collision prediction

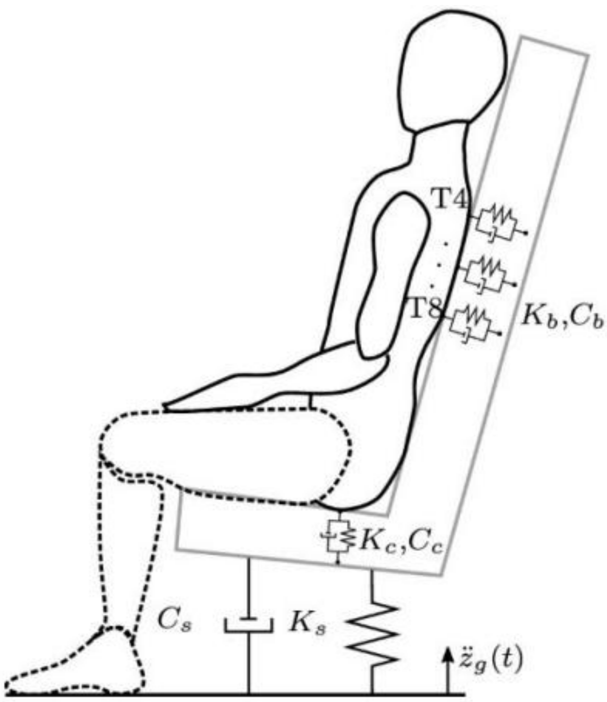

Figure 4. A schematic representation of the seat model

3.5 Integrated framework

By linking risk identification, machine learning, simulation, and biomechanics, the methodology ensures that safety is assessed across multiple scales−from traffic-level conflict metrics to tissue-level injury mechanisms. Figure 5 illustrates this integrative framework.

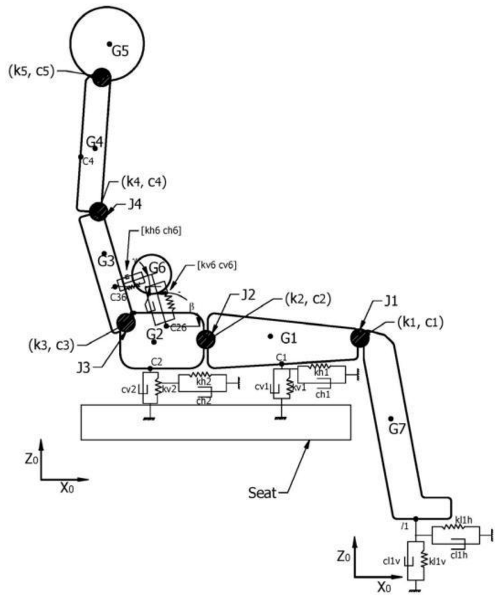

Figure 5. A two-dimensional multi-body biomechanical model of the human body with seated posture

4. Results and discussion

4.1 Data-driven risk identification

Large datasets have revealed consistent spatial and temporal patterns of crashes. Hotspots emerge in dense urban environments, and statistical models improve the estimation of crash severity. Machine learning further enhances predictive performance, confirming that data-driven approaches can provide early insights for safety planning.

4.2 Machine learning applications

Machine learning improves traffic safety in several ways. Deep models capture complex temporal dependencies in traffic flow data, enhancing real-time risk prediction. Pedestrian detection systems achieve higher accuracy when enriched with multimodal sensing, and intent recognition helps anticipate conflicts. Decision-making models reduce unnecessary interventions, striking a balance between safety and efficiency. Figure 6 demonstrates an example of improved classification performance in pedestrian risk prediction.

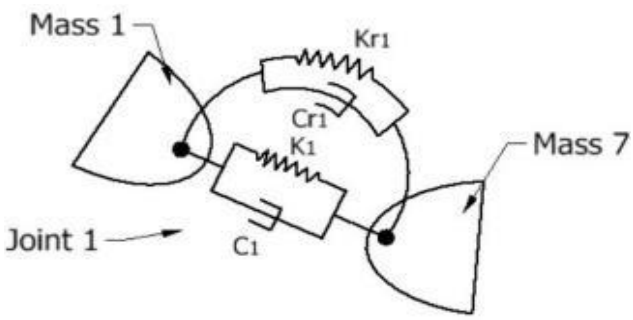

Figure 6. Joint representation

4.3 Simulation outcomes

Simulation studies confirm the benefits of connected and automated driving. Cooperative braking reduces response delays, microscopic traffic simulations show smoother flows with fewer critical events, and Monte Carlo models provide more reliable frequency estimates when combined with near-miss data. However, limitations remain in simulator fidelity, as experimental setups do not always capture real-world biomechanical responses.

4.4 Biomechanical insights

Occupant experiments reveal that unrestrained passengers experience large variability in kinematic responses. Posture, body segment coordination, and cognitive factors such as attention influence injury risk. These results underscore the importance of integrating biomechanical evidence into system-level evaluations. Figure 7 and Figure 8 present examples of occupant kinematic trajectories under emergency braking. To synthesize the results across different methodological approaches, Table 1 provides a comparative summary of the main advantages, limitations, and applications of big data analytics, machine learning, simulation technologies, and biomechanics in the context of autonomous vehicle safety.

Table 1. Comparative summary of different approaches for collision safety

Approach	Advantages	Limitations	Applications in AV Safety
Big Data Analytics	Captures large-scale crash patterns; identifies hotspots and trends	Limited by data quality, missing exposure measures	Crash severity prediction; hotspot identification
Machine Learning	Improves detection, classification, and prediction; adaptable to real-time	Often lacks uncertainty quantification; dataset bias	Pedestrian intent prediction; decision-making
Simulation (FEA/MBD, traffic models)	Enables virtual testing; cost-effective; multi-scale analysis	Limited fidelity; results may not transfer to real-world conditions	Cooperative braking evaluation; traffic oscillation
Biomechanics	Links system-level risk to human injury outcomes; posture-specific insights	Requires complex experiments; high variability among occupants	Injury mechanism analysis; occupant protection

The reviewed studies collectively show that integrating big data, machine learning, and simulation-based biomechanics provides a more complete picture of collision safety. Big-data methods identify when and where risks are likely to occur. Machine learning extends this by predicting future scenarios and supporting decision-making. Simulation bridges the gap between abstract risk indicators and measurable occupant outcomes, while biomechanics ensures that safety is defined not only in terms of crash avoidance but also in terms of human injury mitigation.

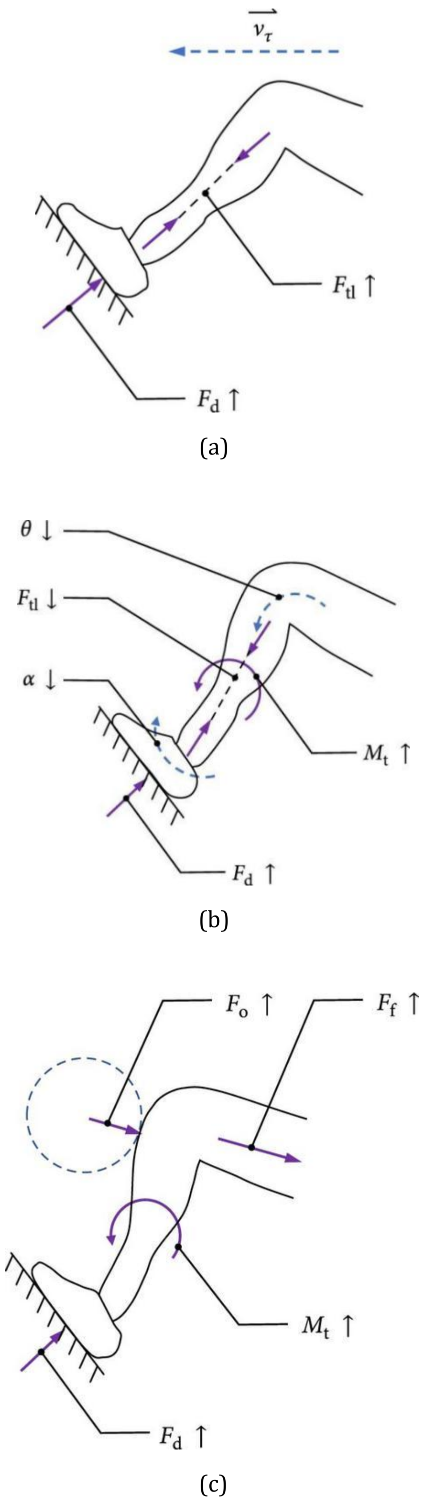

Figure 7. Collision process and movement form of lower limbs (a) phase 1; (b) phase 2; (c) phase 3

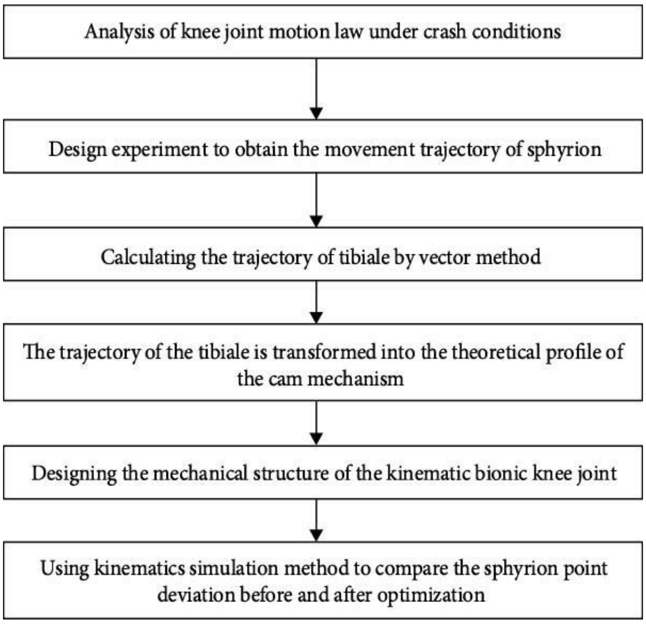

Figure 8. Design scheme of bionic knee joint

Nevertheless, several challenges remain. First, data limitations restrict generalizability, with issues such as inconsistent event definitions and demographic bias. Second, machine learning models often lack uncertainty quantification, making it difficult to judge reliability. Third, simulation fidelity and transferability remain concerns, as results may not fully reflect real-world conditions. Finally, there is limited cross-layer integration – advances in perception and communication are seldom connected directly to occupant injury outcomes. Future research should aim to create standardized, open datasets with harmonized definitions, incorporate robust uncertainty estimation into prediction models, and strengthen validation of simulations against biomechanical experiments. A closer alignment with international safety standards will also ensure that findings are transferable to practice.

5. Conclusion

This review has synthesized recent advances in big-data analytics, machine learning, simulation technologies, and biomechanics to evaluate and optimize collision safety in autonomous vehicles. The analysis demonstrates that data-driven methods are effective for identifying crash hotspots and predicting severity, while machine learning significantly enhances detection, intent recognition, and decision-making in complex urban environments. Simulation studies validate the benefits of cooperative driving strategies but continue to face challenges in model fidelity and transferability. Biomechanical investigations further reveal the variability of occupant responses, emphasizing the influence of posture, cognition, and human factors on injury outcomes. The novelty of this work lies in offering an integrative perspective that explicitly links large-scale risk analysis, predictive machine learning, simulation environments, and biomechanical validation. By bridging these domains, the review moves beyond traditional crash testing and demonstrates the potential for adaptive, personalized, and biomechanically informed safety systems. Looking forward, several research directions are critical. First, the development of multi-scale human body models and digital twin systems will enable real-time coupling between external crash dynamics and internal injury mechanisms. Second, cloud-based simulation and edge-AI frameworks should be explored to achieve scalable, low-latency, and computationally efficient safety evaluation. Third, greater attention must be given to uncertainty quantification, dataset bias, and privacy protection, ensuring that predictive models remain reliable and ethically robust. Finally, closer alignment with international safety assessment protocols−such as Euro NCAP and NHTSA guidelines−will accelerate the translation of biomechanically informed findings into practical vehicle safety standards. By addressing these challenges, future research can support the development of autonomous vehicles that are not only capable of navigating safely but also capable of providing transparent, human-centered, and regulation-compliant crash protection.

Ethical issue

The author is aware of and complies with best practices in publication ethics, specifically with regard to authorship (avoidance of guest authorship), dual submission, manipulation of figures, competing interests, and compliance with policies on research ethics. The author adheres to publication requirements that the submitted work is original and has not been published elsewhere.

Data availability statement

The manuscript contains all the data. However, more data will be available upon request from the author.

Conflict of interest

The author declares no potential conflict of interest.

References

[1] Pomerleau, D. A. (1988). ALVINN: An autonomous land vehicle in a neural network. Advances in Neural Information Processing Systems, 1. DOI: not found

[2] Yang, T., Murguia, C., Nesi, D., & Yuen, C. (2024). Towards crash-free autonomous driving: Anomaly detection and control for resilience to stealthy sensor attacks. IEEE Internet of Things Journal, 12(1). DOI: 10.1109/JIOT.2024.3459590

[3] Lee, S., Lee, S., Seong, H., Hyun, J., & Kim, E. (2023). Fallen person detection for autonomous driving. Expert Systems with Applications, 213, 119242. DOI: 10.1016/j.eswa.2022.119242.

[4] Wang, Y., Jiang, Y., Wu, Y., & Yao, Z. (2023). Mitigating traffic oscillation through control of connected automated vehicles: A cellular automata simulation. Expert Systems with Applications, 235, 121275. DOI: 10.1016/j.eswa.2023.121275.

[5] Chekired, D. A., Togou, M. A., Khoukhi, L., & Ksentini, A. (2019). 5G-slicing-enabled scalable SDN core network: Toward an ultra-low latency of autonomous driving service. IEEE Journal on Selected Areas in Communications, 37(8), 1769‑1782. DOI: 10.1109/JSAC.2019.2927065

[6] Massa, F., Bonamini, L., Settimi, A., Pallottino, L., & Caporale, D. (2020). LiDAR-based GNSS-denied localization for autonomous racing cars. Sensors, 20(14), 3992. DOI: 10.3390/s20143992

[7] Deilamsalehy, H., & Havens, T. C. (2016). Sensor fused three-dimensional localization using IMU, camera and LiDAR. IEEE SENSORS (Orlando). DOI: 10.1109/ICSENS.2016.7808523

[8] Hess, W., Kohler, D., Rapp, H., & Andor, D. (2016). Real-time loop closure in 2D LiDAR SLAM. ICRA 2016, 1271‑1278. DOI: 10.1109/ICRA.2016.7487258.

[9] P. Agrawal, A. Iqbal, B. Russell, M. K. Hazrati, V. Kashyap and F. Akhbari, "PCE-SLAM: A real-time simultaneous localization and mapping using LiDAR data," 2017 IEEE Intelligent Vehicles Symposium (IV), Los Angeles, CA, USA, 2017, pp. 1752-1757, doi: 10.1109/IVS.2017.7995960.

[10] Shi, A., Tao, Z., Xinming, Z., & Jian, W. (2014). Unrecorded accidents detection on highways based on temporal data mining. Mathematical Problems in Engineering, 2014, 852495. DOI: 10.1155/2014/852495.

[11] Xie, K., Ozbay, K., Kurkcu, A., & Yang, H. (2017). Analysis of traffic crashes involving pedestrians using big data: Investigation of contributing factors and identification of hotspots. Risk Analysis, 37(8), 1459-1476. DOI: 10.1111/risa.12751.

[12] Zhuang, Y., Dong, C., Li, P., & Xu, B. (2024). Identifying spatio-temporal pattern of electric vehicles involved traffic accidents. Journal of Transportation Safety & Security, 16(12), 1448-1468. DOI: 10.1080/19439962.2024.2342478

[13] Abeyratne, D., & Halgamuge, M. N. (2023). Applying big data analytics on motor vehicle collision predictions in New York City. (Book chapter). DOI: 10.1002/9781119544487.ch11

[14] Zhou, Z. (2024). Applied mathematics and nonlinear sciences. Sciences, 9(1), 1-18. DOI: 10.2478/amns.2023.2.00338

[15] Losada, Á., Páez, F. J., Luque, F., & Piovano, L. (2022). Application of machine learning techniques for predicting potential vehicle-to-pedestrian collisions in virtual reality scenarios. Applied Sciences, 12(22), 11364. DOI: 10.3390/app122211364.

[16] Iftikhar, S., Zhang, Z., Asim, M., Muthanna, A., Koucheryavy, A., & Abd El-Latif, A. A. (2022). Deep learning-based pedestrian detection in autonomous vehicles: Substantial issues and challenges. Electronics, 11(21), 3551. DOI: 10.3390/electronics11213551.

[17] Zhang, Y., Zhang, D., & Jiang, H. (2023). A review of artificial intelligence-based optimization applications in traditional active maritime collision avoidance. Sustainability, 15(18), 13384. DOI: 10.3390/su151813384

[18] Papathanasopoulou, V., Spyropoulou, I., Perakis, H., Gikas, V., & Andrikopoulou, E. (2021). Classification of pedestrian behavior using real trajectory data. MT-ITS 2021, 1-6. DOI: 10.1109/MT-ITS49943.2021.9529266.

[19] Chen, M., Zhan, X., Tu, J., & Liu, M. (2019). Vehicle-localization-based and DSRC-based autonomous vehicle rear-end collision avoidance concerning measurement uncertainties. IEEJ Transactions on Electrical and Electronic Engineering, 14(9), 1348-1358. DOI: 10.1002/tee.22936.

[20] Chen, Z., Ngai, D. C. K., & Yung, N. H. C. (2008). Pedestrian behavior prediction based on motion patterns for vehicle-to-pedestrian collision avoidance. ITSC 2008, 316-321. DOI: 10.1109/ITSC.2008.4732782.

[21] Santos-Cuadros, S., Page del Pozo, Á., Álvarez-Caldas, C., & San Román García, J. L. (2024). Kinematic analysis of an unrestrained passenger in an autonomous vehicle during emergency braking. Frontiers in Bioengineering and Biotechnology, 12, 1270181. DOI: 10.3389/fbioe.2024.1270181.

[22] Xu, C., Gao, J., Zuo, F., & Ozbay, K. (2024). Estimating urban traffic safety and analyzing spatial patterns through the integration of city-wide near-miss data: A New York City case study. Applied Sciences, 14(14), 6378. DOI: 10.3390/app14146378.

[23] Zhang, C., He, J., Wang, H., Ye, Y., Yan, X., Wang, C., & Zhang, X. (2024). A systematic review of the application and prospect of road accident blackspots identification approaches. Transportation Letters. DOI: 10.1080/19427867.2024.2416304

[24] Ugurel, E., Wu, X., Wang, R., Lee, B. H. Y., & Chen, C. (2024). Metropolitan Planning Organizations' uses of and needs for big data. Findings. DOI: 10.32866/001c.127143.

[25] Gálvez-Pérez, D., Guirao, B., & Ortuño, A. (2024). Analysis of the elderly pedestrian traffic accidents in urban scenarios: The case of the Spanish municipalities. International Journal of Injury Control and Safety Promotion, 31(3), 376-395. DOI: 10.1080/17457300.2024.2335482.

[26] Völz, B., Mielenz, H., Agamennoni, G., & Siegwart, R. (2015). Feature relevance estimation for learning pedestrian behavior at crosswalks. ITSC 2015, 854-860. DOI: 10.1109/ITSC.2015.7323382.

[27] Schratter, M., Bouton, M., Kochenderfer, M. J., & Watzenig, D. (2019). Pedestrian collision avoidance system for scenarios with occlusions. IEEE Intelligent Vehicles Symposium (IV), 1054-1060. DOI: 10.1109/IVS.2019.8813822.

[28] Badhon, F. A., Chowdhury, S. S., Haque, T., Rahman, S., Raihan, M. A., Hossain, M., & Al Mamun, M. A. (2023). Risk perception of vehicle-to-vehicle vendors and general pedestrians: A comparative study. Transportation Research Record. DOI: 10.1177/03611981231182927

[29] De Winter, J., van Leeuwen, P. M., & Happee, R. (2012). Advantages and disadvantages of driving simulators: A discussion. Measuring Behavior 2012 (conference). DOI: not found

[30] León-Domínguez, U., Solís-Marcos, I., Barrio-Álvarez, E., Barroso, Y., Martín, J. M., & León-Carrión, J. (2017). Safe driving and executive functions in healthy middle-aged drivers. Applied Neuropsychology: Adult, 24(5), 395-403. DOI: 10.1080/23279095.2015.1137296.