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Denoised Vibration Modeling for Early Fault Identification in Metro Track Monitoring

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ABSTRACT

Metro track monitoring systems continuously collect vibration time series from rail fasteners, track beds, wheel-rail contact points, tunnel structures, and onboard inspection devices. These signals are strongly affected by train speed, passenger load, tunnel echo, wheel condition, and environmental vibration, making early fault detection difficult under noisy operating conditions. This study proposes a denoised vibration sequence modeling method for early fault detection in metro track monitoring systems. The method uses a diffusion-based denoising module to recover stable vibration patterns from noisy temporal signals. A disentangled representation layer separates train-operation noise, structural vibration variation, and fault-related residual components. Anomaly scores are then calculated from denoised residual energy and component-specific deviation boundaries. Experiments are conducted on a metro vibration dataset covering 11 subway lines, 286 track sections, 740 vibration sensors, and 5-second records collected over 14 months. The dataset contains 218 million vibration records and 1,540 maintenance-confirmed abnormal events, including rail corrugation, fastener loosening, track-bed settlement, wheel-rail impact, and tunnel segment vibration abnormality. The proposed method reduces median early-warning delay from 6.8 days to 2.1 days compared with a wavelet-denoising autoencoder baseline. False maintenance alerts are controlled at 1.9 cases per track section per quarter. Diffusion denoising improves the average vibration signal-to-noise ratio by 6.2 dB, and event-boundary deviation decreases by 11.6 hours. The model completes daily line-level assessment in 8.4 minutes. The results show that diffusion-driven denoising and component disentanglement can improve robust anomaly detection in noisy metro vibration time series.

1. Introduction

Metro track monitoring systems continuously collect vibration signals from rail fasteners, track beds, wheel–rail contact regions, tunnel structures, axle-box sensors, and onboard inspection devices. These signals contain important information on the dynamic interaction among vehicles, tracks, and underground structures and are therefore widely used to detect rail corrugation, fastener loosening, track-bed settlement, wheel defects, abnormal wheel–rail impacts, and excessive tunnel vibration (Castillo Mingorance, 2025; Gui et al., 2025). Continuous vibration monitoring can reveal structural deterioration before visible damage or severe operational disturbance occurs, providing

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a technical basis for preventive maintenance and condition-based inspection (Zhang et al., 2026; Narayanan & Harsha, 2025). However, metro vibration measurements are highly nonstationary and are strongly influenced by train speed, passenger load, wheel condition, vehicle suspension, track geometry, tunnel reverberation, adjacent construction activities, and environmental vibration. The superposition of these factors can obscure weak fault-related components, alter signal distributions across operating periods, and generate transient fluctuations that resemble actual structural defects. The difficulty of early fault detection is further increased by the coupled nature of metro vibration signals. A localized defect in a fastener, rail surface, wheel, or track bed may produce abnormal vibration responses at several neighboring sensors, while normal changes in operating conditions may simultaneously affect multiple measurement channels. Consequently, identifying whether an observed deviation represents an initiating fault, a propagated structural response, or ordinary operational variation requires more than independent analysis of individual signals. Fine-grained multivariate time-series anomaly detection research has demonstrated that causal relationships among variables can help distinguish primary abnormal variables from downstream responses and thereby improve anomaly localization (Chen et al., 2025). This insight is relevant to metro track monitoring because vibration disturbances often propagate through rails, sleepers, fastening systems, tunnel walls, and vehicle components. Nevertheless, causal inference alone cannot eliminate the substantial background noise and nonstationary interference present in raw metro vibration sequences. Reliable early detection therefore requires both effective noise suppression and preservation of weak fault-related temporal structures (Omer et al., 2025; Qi & Qiao, 2026).

Existing metro and railway fault detection methods include wavelet analysis, empirical mode decomposition, variational mode decomposition, entropy-based feature extraction, support vector machines, convolutional neural networks, autoencoders, recurrent networks, and graph-based models (Su & Dong, 2026; Aguayo-Tapia et al., 2024). Signal-processing approaches decompose vibration measurements into different frequency bands or intrinsic components and then construct indicators such as energy distribution, spectral entropy, kurtosis, and envelope characteristics (Ma, 2026; Gao et al., 2026). These indicators are effective when fault frequencies are sufficiently clear and operating conditions remain relatively stable. Machine-learning methods further improve classification performance by learning nonlinear relationships between extracted features and predefined fault categories (Shakiba et al., 2023; Chen et al., 2025). Deep-learning models can reduce dependence on manually designed indicators by automatically extracting temporal, spectral, or spatial representations from raw signals (Liang et al., 2025; Garcia et al., 2022). Despite these advances, most existing approaches face limitations in practical metro environments. Feature-based methods usually rely on fixed frequency ranges, decomposition parameters, or statistical thresholds that may not remain valid across different train speeds, vehicle types, track structures, and tunnel sections. Supervised models require large numbers of accurately labeled fault samples, whereas early-stage defects are rare, difficult to confirm, and frequently mixed with maintenance interventions or operational disturbances. Models trained on a limited set of fault conditions may therefore perform poorly when deployed on another line or track section. In addition, conventional classifiers often treat each analysis window as an independent sample and provide limited information about the temporal development of weak faults, making it difficult to distinguish persistent degradation from isolated vibration impulses. Wavelet denoising, filtering, and autoencoder-based reconstruction methods have been applied to reduce the influence of measurement noise and environmental interference (Wu & Chen, 2025; Yin et al., 2026). However, aggressive filtering may suppress low-amplitude fault components together with unwanted noise, particularly when the fault frequency overlaps with wheel–rail excitation or tunnel resonance.

Reconstruction-based models may also learn dominant operational patterns while ignoring weak residual structures that contain early degradation information (Rafieizadeh et al., 2025; Yang, 2026). When train speed, passenger load, or track geometry changes, the resulting reconstruction error may increase even in the absence of faults, leading to false maintenance alerts. Conversely, if an autoencoder reconstructs recurring abnormal patterns too accurately, its sensitivity to progressive faults may gradually decline. Diffusion-based generative models provide a potential solution by learning the probability distribution of complex signals through progressive noise addition and reverse denoising (Zhang, 2026; Hadiyya et al., 2025). Unlike fixed filters that remove predefined frequency components, diffusion-based denoising can recover signal structures according to the learned distribution of normal vibration sequences. This property makes diffusion models suitable for vibration data containing nonlinear, non-Gaussian, and time-varying disturbances. However, directly applying diffusion denoising to metro monitoring remains challenging. Operational vibration, environmental noise, structural responses, and fault-related residuals may be entangled within the same latent representation. A model that only optimizes overall reconstruction quality may preserve irrelevant operating fluctuations or eliminate subtle fault signatures (Li & Liu, 2026; Devi Gayadri et al., 2026). Moreover, the computational cost of generative inference must be controlled before the method can be deployed for daily assessment across hundreds of sensors and long-term monitoring records. A practical early-warning framework must therefore distinguish among train-operation interference, normal structural vibration variation, and residual components associated with physical deterioration. Train-operation noise is primarily related to speed, axle load, wheel condition, and vehicle dynamics, whereas structural variation reflects differences in track form, tunnel geometry, support stiffness, and sensor location. Fault-related residuals are usually weaker and more localized but may exhibit persistent temporal evolution or repeated responses under comparable operating conditions (Xu et al., 2026). Separating these components can prevent the denoising model from confusing normal operating variation with defects and can preserve small deviations that appear before conventional maintenance thresholds are exceeded.

To address these limitations, this study proposes a denoised vibration sequence modeling method for early fault detection in metro track monitoring systems. The proposed framework applies diffusion-based denoising to reconstruct stable vibration sequences from measurements contaminated by operational and environmental interference. A disentangled representation layer is then introduced to separate train-operation noise, structural vibration variation, and fault-related residual information. Rather than relying only on signal amplitude or reconstruction error, the method models the temporal continuity and local evolution of residual vibration patterns to identify weak anomalies before they develop into clearly observable defects. The evaluation uses 14 months of monitoring data collected from 11 subway lines, 286 track sections, and 740 vibration sensors. Detection performance is assessed using early-warning delay, false maintenance alerts, signal-to-noise ratio, event-boundary deviation, and daily line-level assessment time. The purpose of this study is to develop a scalable and noise-robust early fault detection approach that remains reliable under heterogeneous metro operating conditions. By combining diffusion-based signal recovery with disentangled sequence representation, the proposed method seeks to suppress irrelevant vibration interference without removing weak physical signatures associated with rail, fastener, track-bed, wheel–rail, and tunnel abnormalities. The study is expected to improve the timeliness of fault warnings, reduce unnecessary inspections caused by operational fluctuations, and provide more accurate event boundaries for maintenance planning. Its practical significance lies in supporting condition-based maintenance across large metro networks, where inspection resources must be allocated according to fault probability and deterioration urgency rather than fixed schedules alone. The resulting framework also provides a basis for integrating vibration monitoring with track geometry data, maintenance records, and causal anomaly localization, thereby enhancing the safety, efficiency, and long-term reliability of urban rail transit infrastructure.

2. Materials and Methods

2.1. Samples and Study Area Description

This study used a metro track vibration dataset collected from 11 subway lines and 286 track sections. The monitored objects included rail fasteners, track beds, wheel–rail contact areas, tunnel segments, and onboard inspection units. A total of 740 vibration sensors recorded signals every 5 s over 14 months. After screening, 218 million vibration records were retained. The dataset contained 1,540 maintenance-confirmed abnormal events, including rail corrugation, fastener loosening, track-bed settlement, wheel–rail impact, and tunnel segment vibration abnormality. The samples covered normal operation, peak and off-peak traffic, different train speeds, passenger-load changes, tunnel echo, and environmental vibration.

2.2. Experimental Design and Control Settings

The denoised vibration sequence modeling method was used as the proposed approach. A wavelet-denoising autoencoder and a temporal reconstruction model were used as baseline methods. All methods used the same vibration records, track-section labels, sampling interval, and maintenance-confirmed fault events. The wavelet-denoising autoencoder was selected because wavelet filtering is commonly used for vibration signal cleaning. The temporal reconstruction model was used to represent standard time-series anomaly detection. An ablation model without the disentangled representation layer was also tested to assess whether separating train-operation noise, structural variation, and fault-related residuals improved early fault detection. Experiments were repeated across different subway lines, track sections, and operating periods to evaluate model stability.

2.3. Measurement Methods and Quality Control

Vibration signals were collected from fixed trackside sensors and onboard inspection devices. The measured variables included vibration amplitude, frequency-band energy, acceleration response, wheel–rail impact intensity, tunnel structural vibration, and sensor operating status. Train speed, service interval, and track-section identifiers were aligned with vibration records using unified timestamps. Quality control included duplicate removal, timestamp correction, incomplete-window exclusion, and sensor-dropout detection. Maintenance-confirmed faults were checked using inspection logs, repair records, vibration trend curves, and engineering review. Random checks were performed on normal and abnormal segments to reduce labeling errors. Continuous vibration variables were standardized, and operating states were encoded as binary indicators.

2.4. Data Processing and Model Formulation

Cleaned vibration records were divided into fixed-length track-section windows and converted into multivariate vibration vectors. Each window was defined as , where denotes vibration amplitude, frequency response, band energy, wheel–rail impact intensity, train-speed state, and environmental noise level. The denoised residual energy was calculated as:

$$\mathrm{Score}(x_t)=\sum_{i=1}^{n} w_i \cdot |x_{t,i}-\hat{x}_{t,i}|$$

where is the observed vibration value, is the denoised reconstruction, and is the number of variables. The improvement in signal-to-noise ratio was calculated as: where is the stable vibration power and is the noise power. These indicators were used to measure fault-related residual strength and denoising quality.

$$C_j = \max_i \left| \frac{\partial \mathrm{Score}(x_t)}{\partial x_{t,i}} \right|$$

2.5. Statistical Analysis and Evaluation Metrics

Model performance was evaluated using early-warning delay, false maintenance alert rate, signal-to-noise ratio improvement, event-boundary deviation, and daily line-level assessment time. Early-warning delay was defined as the interval between the first detected abnormal vibration pattern and the maintenance-confirmed fault event. False maintenance alerts were reported as cases per track section per quarter. Event-boundary deviation was calculated as the absolute difference between the model-detected abnormal boundary and the engineering-confirmed boundary. Daily line-level assessment time was measured under the same computing environment. Results were averaged across subway lines, fault types, and track sections to evaluate robustness under different operating and structural conditions.

3. Results and Discussion

3.1. Early-Warning Performance under Noisy Vibration Conditions

The proposed denoised vibration sequence modeling method showed better early fault detection than the wavelet-denoising autoencoder baseline. The median early-warning delay decreased from 6.8 days to 2.1 days, indicating that weak fault-related vibration patterns were identified earlier. This improvement was mainly due to the diffusion-based denoising module, which restored stable vibration patterns before residual scoring (Rezaei & Mirtalebi, 2026; Xu et al., 2026). By contrast, wavelet filtering may remove part of the weak fault signal when train speed, passenger load, and tunnel echo change at the same time. The railway vibration time-series structure is shown in Fig. 1 and provides a reference for the present sequence-modeling task.

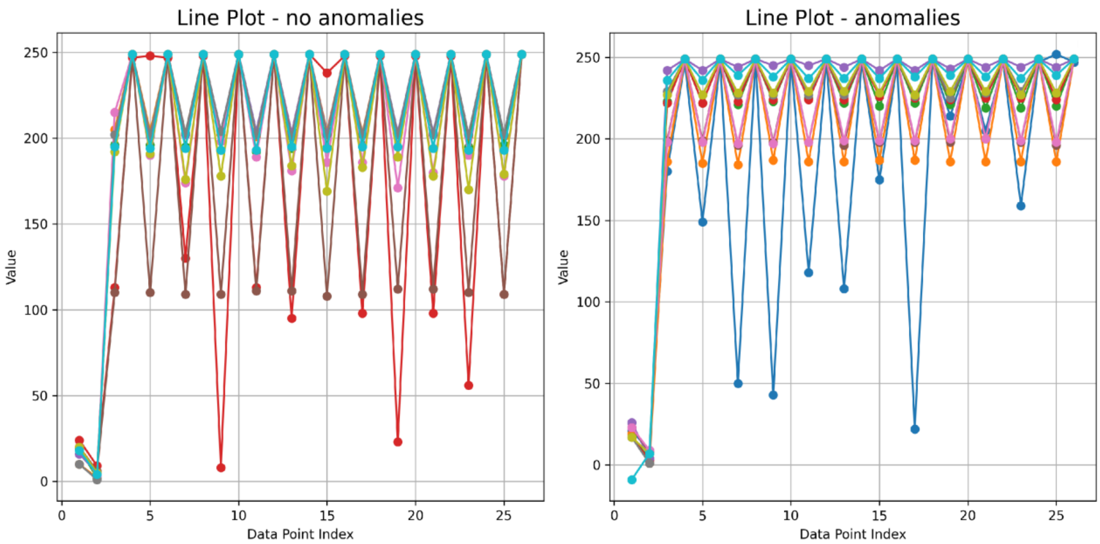

Fig. 1. Railway vibration time-series pattern used for anomaly detection.

3.2. False Maintenance Alerts and Operational Stability

False maintenance alerts were controlled at 1.9 cases per track section per quarter. This result shows that the proposed method reduced unnecessary inspection work while keeping sensitivity to real faults. In metro operation, frequent false alerts increase maintenance cost and may disturb routine inspection plans. The disentangled representation layer separated train-operation noise, structural vibration variation, and fault-related residuals. This separation reduced the risk of treating normal speed changes, wheel-condition differences, or tunnel vibration as early track faults (Matviienko et al., 2022; Xu & Zhou, 2025). Compared with standard reconstruction methods, the proposed method produced more stable anomaly scores during both peak and off-peak periods.

3.3. Denoising Quality and Event-Boundary Accuracy

Diffusion denoising increased the average vibration signal-to-noise ratio by 6.2 dB, showing that fault-related residual patterns became clearer after noise reduction. Event-boundary deviation decreased by 11.6 h, indicating closer agreement between detected abnormal intervals and maintenance-confirmed events. This improvement is important because accurate event boundaries help engineers determine the track section and inspection time more precisely (Gheorghe et al., 2024; Pei et al., 2026). A related railway anomaly study showed that model performance differs greatly across methods, especially under noisy sensor conditions. This finding supports the need for noise-aware modeling in metro vibration monitoring, as shown in Fig. 2.

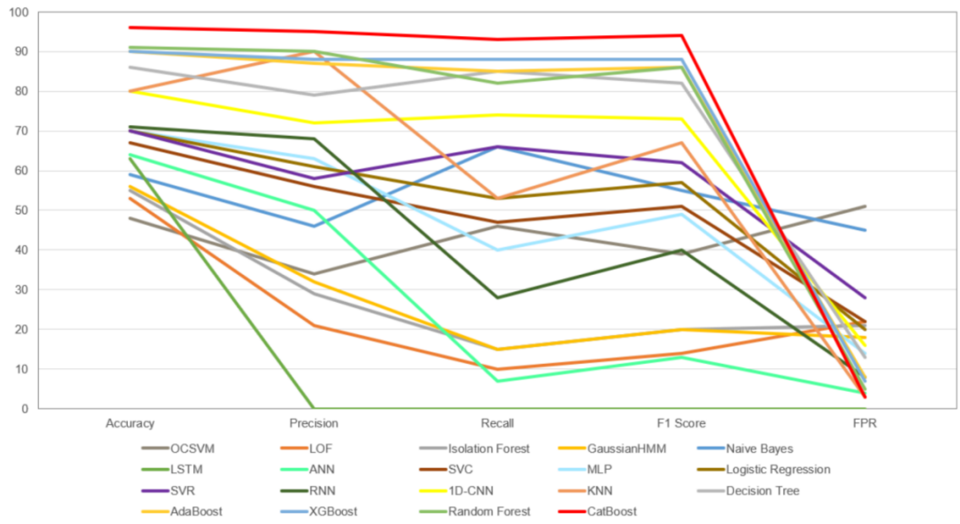

Fig. 2. Performance metrics of railway sensor anomaly detection models.

3.4. Comparison with Existing Studies

Overall, the proposed method improved early-warning delay, false alert control, signal-to-noise ratio, and event-boundary accuracy. Existing railway anomaly detection methods often use wavelet features, time-frequency images, autoencoders, or classical machine learning models. These methods can detect clear vibration abnormalities, but their performance may decline when train-operation noise and structural vibration variation are mixed with weak fault signals. The proposed method addressed this limitation by combining diffusion denoising with component disentanglement. Daily line-level assessment was completed in 8.4 min, indicating that the method can be used for large-scale metro track monitoring. These results show that denoised sequence modeling is suitable for early fault detection in noisy metro vibration time series.

4. Conclusion

This study developed a denoised vibration sequence modeling method for early fault detection in metro track monitoring systems. The method used diffusion-based denoising to recover stable vibration patterns from noisy signals. It also used a disentangled representation layer to separate train-operation noise, structural vibration changes, and fault-related residuals. Experiments on 11 subway lines, 286 track sections, and 740 vibration sensors showed that the method reduced the median early-warning delay from 6.8 days to 2.1 days compared with the wavelet-denoising autoencoder baseline. False maintenance alerts were limited to 1.9 cases per track section per quarter, and the average vibration signal-to-noise ratio increased by 6.2 dB. Event-boundary deviation was reduced by 11.6 h, and daily line-level assessment was completed in 8.4 min. These results show that denoising and component separation can improve early fault detection under noisy metro operating conditions. The main contribution of this work is the joint modeling of noise reduction and fault-related residual extraction for vibration-based track monitoring. The method can support preventive maintenance, early warning of track defects, and more efficient inspection planning in urban rail systems. However, this study used one large metro vibration dataset, and further tests are needed across different cities, track structures, train models, and environmental conditions. Future work should combine vibration data with inspection images and maintenance records to improve fault interpretation and field use.

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References

1. Aguayo-Tapia, S., Avalos-Almazan, G., & Rangel-Magdaleno, J. D. J. (2024). Entropy-based methods for motor fault detection: a review. Entropy, 26(4), 299.

2. Castillo Mingorance, J. M. (2025). Desarrollo de elementos elásticos sostenibles e inteligentes para la monitorización de vías de ferrocarril (Doctoral dissertation, Universidad de Granada).

3. Chen, F., Liang, H., Li, S., Yue, L., & Xu, P. (2025). Design of Domestic Chip Scheduling Architecture for Smart Grid Based on Edge Collaboration.

4. Chen, X., Xiao, H., Zeng, Z., Zhang, S., & Xiao, R. (2025). Fine-Grained Multivariate Time Series Anomaly Detection via Causal Inference. Knowledge-Based Systems, 114765.

5. Devi Gayadri, S. V., Kanagaraj, G., Giri, J., & Kanan, M. (2026). An optimized ensemble framework for machinery fault detection in IoT environments. Scientific Reports, 16(1), 10357.

6. Gao, G., Gao, R., Lu, C., Gao, R., & Kuang, Y. (2026, March). Security Governance Methods and Quantitative Evaluation for Enterprise SMS and Verification Code Systems. In 2026 International Conference on Generative Artificial Intelligence and Information Security (GAIIS) (pp. 455-458). IEEE.

7. Garcia, G. R., Michau, G., Ducoffe, M., Gupta, J. S., & Fink, O. (2022). Temporal signals to images: Monitoring the condition of industrial assets with deep learning image processing algorithms. Proceedings of the institution of mechanical engineers, part O: journal of risk and reliability, 236(4), 617-627.

8. Gheorghe, C., Duguleana, M., Boboc, R., & Postelnicu, C. (2024). Analyzing real-time object detection with YOLO algorithm in automotive applications: A review. Computer Modeling in Engineering & Sciences, 141(3), 1939.

9. Gui, H., Wang, B., Lu, Y., & Fu, Y. (2025). Computational Modeling-Based Estimation of Residual Stress and Fatigue Life of Medical Welded Structures.

10. Hadiyya, K., Dina, R., & Mokhtar, B. (2025). Diffusion Models in Generative AI: Principles, Applications, and Future Directions.

11. Li, Y., & Liu, S. (2026, May). A Study on Dynamic Optimization of Alerting Policies and Multi-Agent Decision-Making Mechanisms in Cloud Environments. In 2026 7th International Seminar on Artificial Intelligence, Networking and Information Technology (AINIT) (pp. 703-706). IEEE.

12. Liang, R., Ye, Z., Liang, Y., & Li, S. (2025). Deep Learning-Based Player Behavior Modeling and Game Interaction System Optimization Research.

13. Ma, Y. (2026). Industrial Financial Risk Prediction Model Based on Graph Neural Network and Knowledge Graph Inference. Journal of Circuits, Systems and Computers, 35(16), 2650103.

14. Matviienko, A., Müller, F., Zickler, M., Gasche, L. A., Abels, J., Steinert, T., & Mühlhäuser, M. (2022, April). Reducing virtual reality sickness for cyclists in VR bicycle simulators. In Proceedings of the 2022 CHI conference on human factors in computing systems (pp. 1-14).

15. Narayanan, N., & Harsha, S. P. (2025). Advancements in vibration-based damage detection for railway tracks: a review on techniques and emerging trends in predictive maintenance. International Journal of Structural Stability and Dynamics, 2630006.

16. Omer, A. M., Abdul, Z. K., & Asaad, S. M. (2025). Bearing Fault Detection Using an Enhanced Multi-Reservoir Echo State Network. Journal of Vibration Engineering & Technologies, 13(8), 549.

17. Pei, Z., Huang, Q., & Wang, S. (2026). When LLMs Develop Languages: Symbolic Communication for Efficient Multi-Agent Reasoning. arXiv preprint arXiv:2606.29354.

18. Qi, C., & Qiao, X. (2026). Using AI to Monitor AI: Automated Operations Through Log-Driven Intelligence. Available at SSRN 6795840.

19. Rafieizadeh, H., Zare, H., Ghassemi Parsa, M., & Cherifi, H. (2025). Dual contrastive learning-based reconstruction for anomaly detection in attributed networks. PLoS One, 20(11), e0335135.

20. Rezaei, N., & Mirtalebi, Z. (2026). Quantifying the Impact of Data Cleaning on Deep Learning-Based Bearing Fault Diagnosis: A Multidataset, Multiarchitecture Study. Concurrency and Computation: Practice and Experience, 38(10), e70654.

21. Shakiba, F. M., Azizi, S. M., Zhou, M., & Abusorrah, A. (2023). Application of machine learning methods in fault detection and classification of power transmission lines: a survey. Artificial Intelligence Review, 56(7), 5799-5836.

22. Su, D., & Dong, Y. (2026). Classroom-Based Assessment with Bayesian Learning Analytics for Instructional Decision-Making in ASD Inclusive Education.

23. Wu, C., & Chen, H. (2025). Research on system service convergence architecture for AR/VR system.

24. Xu, S., & Zhou, Y. (2025). Machine Learning Applications in Financial Statement Fraud Detection: A Comparative Analysis. Annals of Applied Sciences, 6(1).

25. Xu, T., Zhang, J., & Zhu, W. (2026). Reproducible Modeling Pipelines and Cross-Window Stability in Subprime Auto Loan Credit Risk Assessment. Available at SSRN 6893861.

26. Xu, T., Zhu, W., & Zhang, J. (2026). Stability and Consistency of Explainable Deep Learning Methods in Credit Risk Assessment. Available at SSRN 6893938.

27. Yang, J. (2026). Stage-Coupled Computational Framework for Stratified Accessibility and Equity Analysis in Community-Based Elderly Care Services.

28. Yin, J., Huang, Y., & Rao, H. (2026). A Study on User Behavior Signal-Driven Predictive Models for Digital Platform Consumption Trends. Available at SSRN 6607298.

29. Zhang, Z. (2026). A Study on Return Optimization in E-commerce for Complex Consumer Goods Driven by Installation Information Quality. Available at SSRN 6734720.

30. Zhang, Z., Tong, Y., & Gao, Y. (2026). Retrieval-Augmented Generation with Low-Latency Deployment for Vertical Domains Question Answering: A Case Study on Economic Resource Platforms.