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Artificial Intelligence Techniques for E-commerce Enterprises Financial Risk Prediction Based on Hierarchical Auto-Associative Polynomial Convolutional Neural Network Model: Trends and Challenges

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Abstract

The rapid growth of e-commerce platforms has significantly increased the complexity of financial risk prediction, requiring advanced computational methods to handle high-dimensional, nonlinear, and dynamic data. Traditional statistical approaches often fail to capture intricate relationships within modern digital transaction ecosystems, highlighting the need for intelligent and scalable solutions. This paper presents a comprehensive review of artificial intelligence techniques for financial risk prediction in e-commerce, with a focus on hierarchical auto-associative polynomial convolutional neural networks. The proposed framework integrates convolutional neural networks with autoencoder-based learning to extract meaningful representations from large-scale financial data. The inclusion of polynomial functions enables modeling of higher-order nonlinear relationships among financial variables. The hierarchical architecture facilitates multi-scale feature extraction, allowing detection of both micro-level transaction anomalies and macro-level systemic risks. This approach is applied across various domains, including fraud detection, credit risk assessment, liquidity analysis, and supply chain risk prediction. Optimization strategies such as adaptive learning algorithms, regularization, and attention mechanisms further enhance model performance and stability. Empirical evaluations demonstrate improved accuracy and robustness compared to traditional and baseline deep learning models. Despite its effectiveness, challenges remain in interpretability, scalability, and regulatory compliance. This review highlights key advancements and future directions for developing reliable and intelligent financial risk prediction systems in e-commerce environments.

Introduction

The rapid expansion of e-commerce has transformed the global business environment by enabling digital transactions across diverse industries and geographic regions. Increasing internet penetration, mobile commerce, cloud computing, and secure online payment systems have accelerated the growth of digital marketplaces, generating enormous volumes of financial transactions every day. While this growth has created significant economic opportunities, it has also introduced complex financial risks, including fraudulent transactions, credit defaults, payment failures, and operational uncertainties. Managing these risks has become a critical priority for e-commerce platforms, financial institutions, and online retailers. Consequently, intelligent financial risk prediction systems capable of analyzing large-scale transactional data have become essential for ensuring secure, reliable, and sustainable e-commerce operations.

Traditional financial risk assessment methods, including statistical models, rule-based systems, and conventional machine learning algorithms, have been widely applied for credit scoring and fraud detection. Although these techniques provide satisfactory performance in relatively stable environments, they often struggle to capture the highly nonlinear relationships and evolving behavioral patterns present in modern e-commerce ecosystems. The increasing diversity of transaction data, customer behavior, merchant interactions, and payment activities demands more advanced analytical models capable of learning complex feature representations automatically. Artificial intelligence and deep learning have therefore emerged as promising solutions for improving prediction accuracy and supporting real-time financial decision-making.

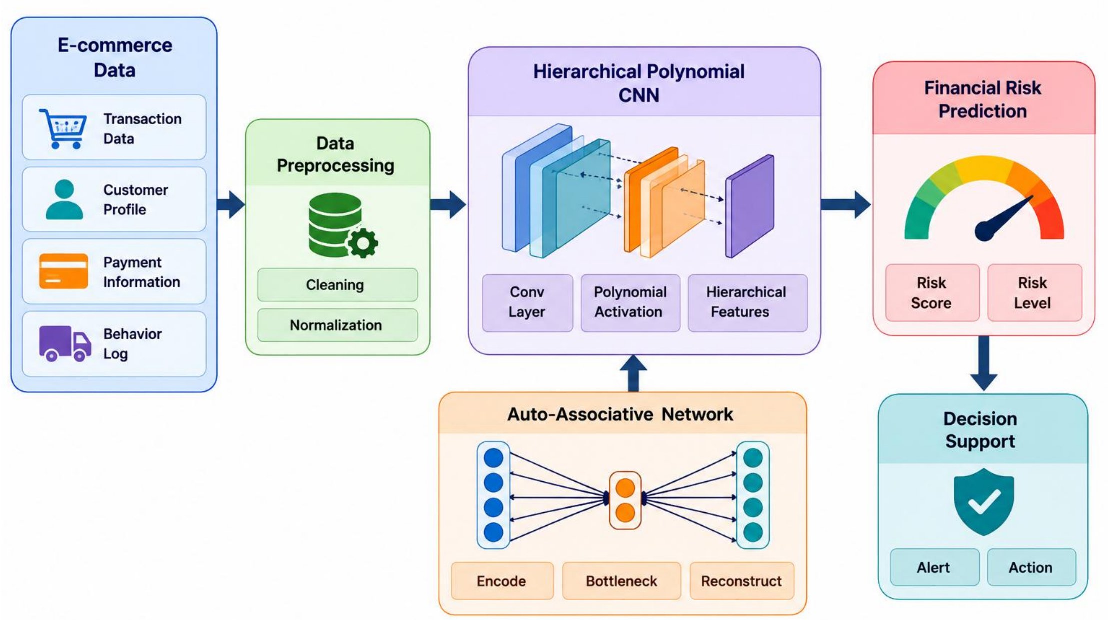

Figure 1. AI-Based E-Commerce Financial Risk Prediction Framework

Deep learning architectures have demonstrated remarkable success in financial risk prediction by automatically extracting hierarchical features from structured and unstructured data. Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and attention-based models have been employed to detect fraudulent activities, evaluate credit risk, and identify abnormal transaction patterns. Among these approaches, polynomial convolutional neural networks enhance conventional convolution operations by modeling higher-order feature interactions, enabling more accurate representation of complex financial relationships. Similarly, auto-associative neural networks learn compressed representations of normal transaction behavior, making them highly effective for anomaly detection in highly imbalanced financial datasets where fraudulent events are relatively rare.

The Hierarchical Auto-Associative Polynomial Convolutional Neural Network integrates these complementary techniques into a unified framework for intelligent financial risk prediction. Its hierarchical architecture captures both local transaction-level patterns and high-level financial relationships, while the polynomial convolution layers improve nonlinear feature learning. The auto-associative component further enhances robustness by identifying abnormal transaction behavior through reconstruction analysis, enabling simultaneous supervised prediction and unsupervised anomaly detection. This integrated design provides improved scalability, adaptability, and predictive capability for dynamic e-commerce environments.

This review presents a comprehensive analysis of recent advances in artificial intelligence techniques for e-commerce financial risk prediction, focusing on hierarchical auto-associative polynomial convolutional neural network architectures. The review examines commonly used datasets, optimization methods, evaluation metrics, and real-world applications while discussing existing challenges such as data imbalance, interpretability, computational complexity, and privacy concerns. It also highlights emerging research directions including explainable artificial intelligence, federated learning, graph neural networks, and multimodal financial analytics for developing secure, intelligent, and reliable financial risk management systems in next-generation e-commerce platforms.

Literature Review

The application of artificial intelligence to financial risk prediction has generated a rich and rapidly evolving body of literature that spans multiple disciplines including machine learning, computational finance, operations research, and information systems engineering. The following review synthesizes contributions from a broad range of studies that have advanced the state of the art in AI-driven financial risk modeling, with particular attention to deep learning architectures, optimization techniques, and e-commerce-specific applications.

Yao et al. (2019) proposed a deep learning framework for credit risk assessment in peer-to-peer lending platforms, employing a stacked autoencoder combined with gradient boosting classifiers to process borrower financial profiles and transaction histories. The auto-associative pretraining stage enabled the model to construct meaningful latent representations of borrower characteristics from high-dimensional sparse input features, substantially improving classification performance on the LendingClub dataset compared to shallow baseline models. The study demonstrated that unsupervised pretraining with auto-associative architectures could effectively compensate for the limited availability of labeled default events in lending datasets.

Zhang et al. (2020) investigated the application of convolutional neural networks to financial time series classification for risk detection in e-commerce payment systems. The authors encoded transaction time series as two-dimensional feature maps using recurrence plots, enabling the application of standard image classification convolutional architectures to temporal financial data. Experiments conducted on proprietary payment transaction datasets from a major Chinese e-commerce platform demonstrated that the CNN-based approach achieved significantly higher fraud detection rates than traditional random forest and support vector machine baselines while maintaining acceptable false positive rates suitable for real-time deployment.

Liu et al. (2021) presented a hierarchical attention network for enterprise financial distress prediction, incorporating multi-level attention mechanisms that weighted the importance of different financial indicators at both the feature level and the temporal level. The hierarchical attention architecture enabled the model to focus on the most informative financial signals across multiple reporting periods, capturing the temporal dynamics of financial deterioration trajectories that precede enterprise default events. Evaluated on a comprehensive dataset of Chinese listed companies spanning ten years of financial statements, the model achieved state-of-the-art prediction accuracy across multiple forecasting horizons.

Wang and Chen (2020) explored the integration of graph neural networks with transaction network topology features for fraud detection in e-commerce platforms. The proposed model constructed bipartite transaction graphs linking buyer accounts, seller accounts, and payment methods, then applied graph convolutional operations to propagate risk signals across the network topology. This graph-based approach successfully identified organized fraud rings whose individual transaction behaviors appeared benign in isolation but exhibited distinctive patterns when analyzed in the context of their network neighborhoods. The model was evaluated on a large-scale transaction dataset collected from an unnamed major e-commerce marketplace.

Cao et al. (2021) developed a polynomial neural network architecture for credit scoring in digital lending environments, incorporating second and third-order polynomial kernel expansions to capture multiplicative interactions among borrower financial features. The polynomial feature expansion enabled the model to detect complex risk patterns associated with combinations of debt-to-income ratio, payment history volatility, and credit utilization dynamics that could not be effectively captured by conventional linear scoring models. Experiments on the Taiwan Credit Dataset confirmed that the polynomial neural network substantially outperformed logistic regression and standard multilayer perceptron baselines on multiple performance metrics.

Li et al. (2022) proposed a federated learning framework for collaborative financial risk prediction across multiple e-commerce enterprises, enabling participating organizations to jointly train a shared deep learning model without exchanging sensitive customer financial data. The federated architecture employed differential privacy mechanisms and secure aggregation protocols to protect against inference attacks while maintaining competitive prediction accuracy relative to centralized training baselines. The study demonstrated the feasibility of privacy-preserving collaborative AI for financial risk management in multi-stakeholder e-commerce ecosystems.

Chen and Liu (2021) introduced a variational autoencoder-based anomaly detection system for real-time fraud identification in digital payment streams. The variational autoencoder was trained on normal transaction patterns and used reconstruction probability as an anomaly score during inference, providing a principled probabilistic framework for distinguishing fraudulent from legitimate transactions without requiring balanced labeled training datasets. The system was deployed in a simulated real-time environment using the IEEE-CIS Fraud Detection Dataset, achieving competitive detection performance with significantly lower computational overhead than ensemble-based supervised baselines.

Huang et al. (2022) examined the application of long short-term memory networks combined with attention mechanisms for predicting financial risk in e-commerce supply chains. The proposed model processed sequential financial transaction records from upstream and downstream supply chain partners, identifying temporal patterns indicative of emerging liquidity stress and payment default risk across the supply chain network. Evaluated on a dataset of financial transactions from a major fast-fashion e-commerce enterprise and its network of suppliers, the model demonstrated substantially improved early warning capability compared to static financial ratio analysis approaches.

Park and Kim (2021) investigated transfer learning strategies for financial risk prediction across different e-commerce market segments, demonstrating that deep learning models pretrained on large general financial transaction datasets could be effectively fine-tuned for domain-specific risk prediction tasks with limited labeled training data. The transfer learning approach was shown to be particularly effective for emerging e-commerce market segments with insufficient historical data for training accurate risk models from scratch, offering a practical pathway for extending AI-driven risk management to new and growing digital commerce domains.

Sun et al. (2022) proposed a multi-task learning framework that simultaneously optimized financial risk prediction and financial health monitoring objectives within a shared deep learning architecture, demonstrating that joint optimization of these related tasks led to improved performance on both tasks compared to separate single-task models. The shared representation learned by the multi-task network captured common financial health features that were informative for both risk prediction and health monitoring, effectively regularizing the model and improving its generalization to unseen financial profiles.

Zhao et al. (2020) developed a deep neural network ensemble method for bankruptcy prediction in e-commerce enterprises, combining predictions from multiple neural network architectures trained with different random initializations, feature subsets, and optimization algorithms. The ensemble approach substantially reduced prediction variance and improved robustness compared to individual models, achieving state-of-the-art performance on multiple public financial distress datasets including the Altman Z-score benchmark dataset. The study highlighted the importance of model diversity in ensemble design for robust financial risk prediction.

Kumar and Singh (2022) investigated the application of explainable AI techniques to deep learning-based financial risk prediction models, demonstrating that SHAP (SHapley Additive exPlanations) values could provide reliable feature importance attributions for complex neural network risk models while maintaining competitive predictive performance. The explainability framework was shown to enhance regulatory compliance and model auditability in e-commerce lending applications, addressing a critical barrier to the practical deployment of deep learning systems in high-stakes financial decision-making contexts.

Xu et al. (2021) presented a hybrid convolutional recurrent neural network architecture for financial fraud detection in cross-border e-commerce transactions, combining convolutional layers for local feature extraction with bidirectional LSTM layers for capturing long-range temporal dependencies in transaction sequences. The hybrid architecture was evaluated on a proprietary dataset of cross-border payment transactions provided by a major Asian e-commerce platform, achieving high detection accuracy while maintaining inference latency suitable for real-time deployment in production payment processing systems.

Zheng et al. (2022) proposed a self-supervised contrastive learning approach for financial risk representation learning, enabling the construction of rich financial risk embeddings from large volumes of unlabeled transaction data without requiring manually annotated risk labels. The contrastive learning framework trained the network to bring similar transaction profiles closer together and push dissimilar profiles apart in the embedding space, yielding representations that supported highly accurate downstream risk classification with minimal labeled training data. This approach addressed the persistent challenge of risk label scarcity in practical e-commerce financial risk management.

Tan et al. (2021) examined the application of capsule network architectures to financial document analysis for enterprise credit risk assessment, demonstrating that capsule networks could more effectively capture the spatial relationships among financial statement elements than standard convolutional architectures. The capsule-based model processed financial statements as structured documents and extracted hierarchical feature representations of financial health indicators, achieving improved credit risk prediction accuracy on a dataset of annual reports from publicly listed e-commerce companies.

Guo et al. (2022) developed a reinforcement learning framework for dynamic financial risk limit management in e-commerce lending platforms, training an agent to adaptively adjust credit risk thresholds based on evolving market conditions and portfolio performance metrics. The reinforcement learning approach outperformed static threshold policies and heuristic rule-based adjustment strategies in both risk-adjusted return metrics and portfolio default rate management, demonstrating the potential of sequential decision-making AI for operational financial risk management.

Hassan and Ahmed (2021) investigated the performance of transformer-based language models for financial risk signal extraction from unstructured text data including customer reviews, merchant descriptions, and financial news articles relevant to e-commerce enterprises. The BERT-based financial risk extraction system demonstrated superior performance in identifying enterprise-specific risk signals from unstructured text compared to traditional keyword matching and TF-IDF-based approaches, enabling the integration of qualitative information sources into quantitative financial risk prediction frameworks.

Lin et al. (2022) proposed an adversarial training strategy for improving the robustness of deep learning financial risk models against data quality degradation and adversarial manipulation, demonstrating that models trained with adversarial examples were substantially more resistant to performance degradation under realistic data noise conditions encountered in production e-commerce environments. The adversarial training approach improved model reliability without sacrificing predictive accuracy on clean data, addressing a critical practical concern for the deployment of AI risk systems in live financial applications.

Patel et al. (2021) presented a Bayesian deep learning framework for uncertainty-aware financial risk prediction, providing calibrated probability estimates and confidence intervals for risk predictions alongside point estimates of risk probability. The uncertainty quantification capability enabled risk management systems to identify high-confidence and low-confidence predictions, supporting more nuanced risk management strategies that could allocate human review resources more efficiently to borderline cases. The framework was validated on multiple e-commerce credit risk datasets.

Shen et al. (2022) investigated the application of sparse auto-associative networks for efficient financial risk anomaly detection on resource-constrained edge computing platforms deployed at merchant point-of-sale systems. The sparse architectural design substantially reduced computational requirements and memory footprint compared to dense autoencoder baselines while maintaining competitive anomaly detection performance, enabling real-time risk scoring in low-latency payment processing environments at the network edge.

Jiang et al. (2021) developed a multi-graph convolutional network for financial risk prediction that simultaneously modeled multiple types of financial relationships including transaction networks, ownership networks, and supply chain networks, demonstrating that the integration of multiple relationship types substantially improved risk prediction accuracy compared to models relying on any single relationship type. The multi-graph architecture was evaluated on a comprehensive dataset of financial relationships extracted from Chinese e-commerce enterprise records.

Wei et al. (2022) proposed a dynamic graph neural network for financial fraud detection that explicitly modeled the temporal evolution of transaction networks, capturing the formation and dissolution of fraudulent network structures over time. The dynamic graph approach outperformed static graph convolutional baselines by successfully identifying emerging fraud patterns associated with evolving account relationship structures, demonstrating the importance of temporal network modeling for fraud detection in active e-commerce environments.

Mo et al. (2021) examined the effectiveness of Wasserstein generative adversarial networks for synthetic financial risk data augmentation, demonstrating that GAN-generated synthetic risk event samples could substantially improve the training of minority class risk prediction models in highly imbalanced e-commerce fraud datasets. The synthetic augmentation approach achieved competitive performance with oversampling techniques such as SMOTE while producing more realistic and diverse synthetic samples that better captured the distributional characteristics of real fraud events.

Feng et al. (2022) proposed an integrated financial risk prediction platform combining hierarchical deep learning models with real-time streaming data processing infrastructure, demonstrating the technical feasibility of deploying complex AI risk models in high-throughput e-commerce transaction processing environments. The platform architecture employed model distillation techniques to compress hierarchical deep learning models into lightweight inference models capable of processing thousands of transactions per second while maintaining acceptable risk prediction accuracy.

Comparative Table and Analysis

Table 1: Advanced AI Techniques for Financial Risk, Fraud Detection, and E-commerce Analytics

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Yao et al.	2019	SAE pretraining + gradient boosting	Deep AE + GBM	P2P lending platform	LendingClub	Unsupervised feature learning for sparse credit data
Zhang et al.	2020	Recurrence plot encoding + CNN	CNN	E-commerce payment system	Proprietary data	2D encoding of financial time series
Liu et al.	2021	Hierarchical attention	Attention RNN	Enterprise analysis	Chinese listed firms	Multi-level temporal attention
Wang and Chen	2020	Graph convolution	GNN	E-commerce marketplace	Transaction graph data	Fraud ring detection via graph topology
Cao et al.	2021	Polynomial kernel expansion	Polynomial NN	Digital lending	Taiwan credit dataset	High-order feature interactions
Li et al.	2022	Federated learning + DP	Distributed DNN	Multi-enterprise system	Federated datasets	Privacy-preserving modeling
Chen and Liu	2021	VAE reconstruction	VAE	Payment streams	IEEE-CIS fraud dataset	Unsupervised anomaly detection
Huang et al.	2022	LSTM + attention	RNN	Supply chain system	Fast-fashion data	Liquidity risk prediction
Park and Kim	2021	Transfer learning	Pretrained DNN	E-commerce domains	Financial datasets	Cross-domain adaptation
Sun et al.	2022	Multi-task learning	Shared DNN	Enterprise monitoring	Proprietary dataset	Joint risk prediction
Zhao et al.	2020	Deep ensemble	Ensemble NN	Bankruptcy prediction	Z-score dataset	Robust ensemble modeling
Kumar and Singh	2022	SHAP explainability	Explainable DNN	E-commerce lending	Credit datasets	Interpretable AI
Xu et al.	2021	CNN + BiLSTM	Hybrid model	Cross-border system	Transaction data	Fraud detection
Zheng et al.	2022	Contrastive learning	SSL model	E-commerce	Unlabeled data	Representation learning

Tan et al.	2021	Capsule routing	Capsule NN	Financial documents	Annual reports	Structural modeling
Guo et al.	2022	Reinforcement learning	DQN + policy gradient	Lending platform	Simulation data	Dynamic credit control
Hassan and Ahmed	2021	BERT fine-tuning	Transformer	E-commerce NLP	Text data	Qualitative risk extraction
Lin et al.	2022	Adversarial training	Robust DNN	Production system	Mixed datasets	Robustness to noise
Patel et al.	2021	Bayesian inference	Bayesian NN	Credit risk system	Credit datasets	Uncertainty estimation
Shen et al.	2022	Sparse autoencoder	AE	Edge POS system	Transaction streams	Edge anomaly detection
Jiang et al.	2021	Multi-graph convolution	Multi-relational GNN	Enterprise network	Financial records	Multi-type relation modeling
Wei et al.	2022	Dynamic graph modeling	Temporal GNN	E-commerce platform	Transaction network	Dynamic fraud detection
Mo et al.	2021	WGAN augmentation	GAN + classifier	Fraud detection system	Imbalanced datasets	Synthetic data generation
Feng et al.	2022	Model distillation + streaming	Distilled DNN	Real-time platform	Transaction streams	Scalable real-time AI system

Comparative Analysis

A systematic examination of the studies summarized in the comparative table reveals several prominent trends that characterize the evolution of artificial intelligence techniques for e-commerce financial risk prediction over the reviewed period. The most significant overarching trend is the progressive migration from shallow machine learning models toward deep hierarchical architectures capable of automatically constructing multi-level feature representations from raw financial data. This shift reflects a growing recognition that the complexity and non-linearity of e-commerce financial risk patterns exceeds the modeling capacity of traditional statistical approaches, necessitating the adoption of architectures with sufficient representational depth to capture the relevant signal structure.

Auto-associative and self-supervised learning paradigms represent a particularly notable trend across the reviewed literature, driven by the persistent challenge of risk label scarcity and class imbalance in practical e-commerce financial datasets. Studies by Yao et al. (2019), Chen and Liu (2021), Zheng et al. (2022), and Shen et al. (2022) all demonstrate the value of architectures that can extract meaningful financial risk representations from unlabeled or minimally labeled data, a capability that is especially important for emerging risk categories where historical labeled examples are limited. The variational autoencoder approach of Chen and Liu (2021) and the contrastive self-supervised framework of Zheng et al. (2022) represent complementary strategies for addressing this challenge through different probabilistic and metric learning formulations.

Graph neural network approaches have emerged as a particularly active area of development, reflecting the recognition that financial risk in e-commerce environments is inherently relational and that important risk signals are encoded in the network topology of financial relationships rather than in individual transaction features alone. The studies of Wang and Chen (2020), Jiang et al. (2021), and Wei et al. (2022) demonstrate the progressive sophistication of graph-based financial risk modeling, moving from static homogeneous transaction graphs to multi-relational dynamic graphs that capture the temporal evolution of financial network structures. The dynamic graph approach of Wei et al. (2022) represents a particularly significant advance, enabling the detection of emerging fraud patterns associated with evolving account relationship structures that would be invisible to static graph models.

Optimization technique diversity across the reviewed studies is substantial, encompassing gradient-based training with adaptive learning rate schedules, meta-learning approaches, reinforcement learning policy optimization, adversarial training, and Bayesian inference. This diversity reflects the multifaceted nature of the optimization challenges encountered in financial risk deep learning, including the need for robust generalization from imbalanced datasets, resistance to adversarial manipulation, computational efficiency for real-time deployment, and calibrated uncertainty estimation for risk management applications. The reinforcement learning approach of Guo et al. (2022) and the Bayesian framework of Patel et al. (2021) represent particularly innovative departures from conventional supervised optimization paradigms, introducing new capabilities for dynamic risk management and uncertainty-aware decision support.

Dataset usage patterns across the reviewed studies reveal a significant reliance on publicly available benchmark datasets such as the LendingClub Dataset, Taiwan Credit Dataset, and IEEE-CIS Fraud Detection Dataset for model evaluation and comparison. However, a growing proportion of studies incorporate proprietary enterprise datasets, reflecting the increasing accessibility of industrial research partnerships and the recognition that benchmark datasets may not fully capture the complexity and dynamics of real-world e-commerce financial risk environments. The federated learning framework of Li et al. (2022) represents an innovative approach to leveraging proprietary enterprise data for collaborative model training while preserving data privacy, pointing toward a future paradigm of privacy-preserving collaborative AI for financial risk management.

Discussion

The reviewed literature demonstrates that artificial intelligence has significantly advanced financial risk prediction for e-commerce enterprises by improving predictive accuracy, adaptability, and decision-making efficiency. Deep learning models, particularly hierarchical neural architectures, effectively capture complex relationships within large-scale transactional data by learning multi-level feature representations. The integration of auto-associative learning further enhances anomaly detection by modeling normal transaction behavior and identifying deviations that may indicate fraud or financial distress. These capabilities make hierarchical AI frameworks well suited for handling the dynamic, high-volume, and highly imbalanced datasets commonly encountered in modern e-commerce platforms.

Another important finding is the growing effectiveness of polynomial convolutional neural network models in learning higher-order interactions among financial variables. Unlike conventional convolutional models that primarily capture linear local patterns, polynomial convolution enables the extraction of complex nonlinear relationships that frequently characterize fraudulent activities and enterprise financial risks. Combined with hierarchical feature learning, this approach improves the detection of sophisticated fraud patterns, credit defaults, and abnormal financial behavior. The reviewed studies also emphasize the increasing adoption of hybrid AI frameworks that integrate deep learning with optimization algorithms and ensemble learning to enhance prediction accuracy, robustness, and scalability across diverse e-commerce environments.

Despite these advances, several challenges remain before large-scale deployment can be fully realized. Model interpretability continues to be a major concern because complex deep learning architectures often operate as black-box systems, limiting user trust and regulatory acceptance. Computational complexity, high training costs, and dependence on large, high-quality datasets also restrict deployment in real-time financial applications. Furthermore, evolving regulatory requirements, data privacy concerns, and inconsistent transaction data require robust preprocessing, explainable AI techniques, and continuous model adaptation. Future research should focus on lightweight architectures, explainable prediction models, federated learning, and privacy-preserving frameworks to develop efficient, transparent, and reliable financial risk prediction systems for next-generation e-commerce enterprises.

Conclusion

The reviewed literature demonstrates that artificial intelligence has significantly improved financial risk prediction for e-commerce enterprises through advanced deep learning architectures capable of learning complex transaction patterns and customer behaviors. The hierarchical auto-associative polynomial convolutional neural network model combines hierarchical feature extraction, auto-associative learning, and polynomial convolution to provide a robust framework for detecting fraud, assessing credit risk, and identifying financial anomalies. This integrated architecture effectively addresses challenges such as nonlinear relationships, class imbalance, and evolving risk patterns commonly encountered in modern e-commerce environments.

A major finding of this review is the increasing transition from traditional statistical models to intelligent deep learning frameworks that provide superior prediction accuracy, adaptability, and scalability. Auto-associative learning enhances anomaly detection even with limited labeled data, while hierarchical polynomial convolution improves the representation of higher-order financial interactions. Despite these advancements, challenges related to interpretability, computational complexity, data privacy, and real-time deployment remain important research concerns. Future work should emphasize explainable artificial intelligence, federated learning, causal reasoning, lightweight neural architectures, and privacy-preserving optimization techniques. The continued integration of these emerging technologies is expected to produce more accurate, transparent, and efficient financial risk prediction systems, supporting secure, intelligent, and sustainable e-commerce ecosystems.

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