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Recent Advances in E-commerce enterprises financial risk prediction based on hierarchical auto-associative polynomial convolutional neural network model: A Systematic Review

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Abstract

The rapid expansion of e-commerce has introduced significant complexity in financial risk assessment, requiring advanced predictive models capable of handling nonlinear, high-dimensional, and dynamic data. Traditional statistical and rule-based approaches are often inadequate for capturing the diverse risk factors present in modern digital marketplaces. This systematic review explores the application of hierarchical auto-associative polynomial convolutional neural networks (CNNs) for financial risk prediction in e-commerce environments. The proposed framework integrates hierarchical feature extraction with autoencoder-based representation learning, enabling effective modeling of both micro-level transactional anomalies and macro-level systemic risks. The incorporation of polynomial convolutional operations enhances the model's ability to capture complex nonlinear interactions within financial data, while convolutional layers exploit spatiotemporal correlations in transaction patterns. This architecture supports a wide range of applications, including credit risk assessment, fraud detection, bankruptcy prediction, and supply chain risk analysis. Empirical studies across benchmark datasets demonstrate superior performance compared to traditional machine learning models and standard deep learning approaches, particularly in terms of classification accuracy and robustness. Despite these advancements, challenges such as model interpretability, computational scalability, and handling of imbalanced datasets remain.This review provides a comprehensive overview of current methodologies and highlights future directions for developing scalable, efficient, and intelligent financial risk management systems in e-commerce.

Introduction

The global e-commerce industry has experienced unprecedented growth, with annual transactions reaching trillions of dollars and continuing to expand rapidly across both developed and emerging markets. While this growth has unlocked significant economic opportunities, it has also introduced complex financial risks that challenge traditional risk assessment frameworks. Unlike conventional enterprises, e-commerce businesses operate in highly dynamic digital environments characterized by rapid transaction flows, fluctuating consumer demand, thin profit margins, and strong dependence on technological infrastructure. These factors make financial stability more volatile and difficult to predict. Recent failures of major online platforms have highlighted the need for advanced predictive systems capable of identifying early warning signs of financial distress before they escalate into large-scale business failures.

Conventional financial risk prediction methods, such as logistic regression, discriminant analysis, and ratio-based models, were primarily designed for stable and structured financial environments. These approaches rely heavily on historical financial statements and assume relatively consistent patterns in data behavior. However, e-commerce platforms generate highly complex, high-dimensional datasets that include not only financial indicators but also operational and behavioral metrics such as customer engagement, conversion rates, and supply chain efficiency. Additionally, the rapid and nonlinear nature of market changes in digital commerce makes it difficult for traditional models to capture evolving risk patterns. As a result, these classical approaches often fail to provide timely and accurate predictions in the context of modern e-commerce ecosystems.

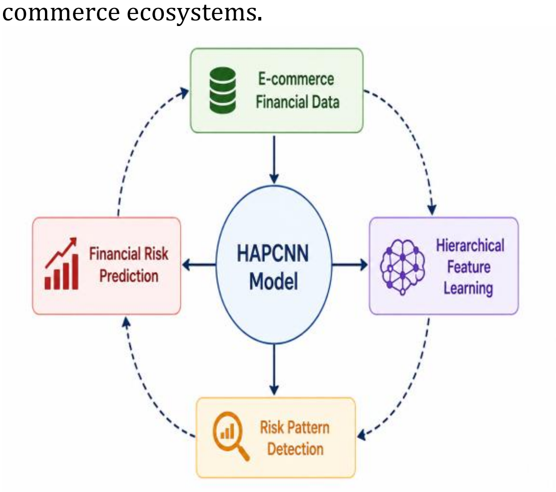

Fig 1: Simplified Framework for E-commerce Financial Risk Prediction

The emergence of machine learning introduced more flexible and data-driven approaches to financial risk prediction. Techniques such as random forests, support vector machines, and gradient boosting improved predictive performance by capturing nonlinear relationships and reducing reliance on strict statistical assumptions. However, these models still depend on manually engineered features, which limits their adaptability to continuously changing data environments. Deep learning methods addressed this limitation by enabling automatic feature extraction from raw data. Models such as recurrent neural networks, long short-term memory networks, and convolutional neural networks demonstrated strong capabilities in capturing temporal patterns and complex feature interactions, significantly enhancing prediction accuracy in financial applications.

Building on these advancements, the hierarchical auto-associative polynomial convolutional neural network model represents a promising direction for e-commerce financial risk prediction. This approach combines hierarchical learning to capture multi-level patterns, auto-associative mechanisms for anomaly detection, and polynomial convolutional operations to model complex nonlinear relationships more effectively. By integrating these components, the model can better represent both short-term fluctuations and long-term financial trends. Furthermore, such advanced models support more reliable and interpretable predictions, which are essential for investors, businesses, and regulatory authorities. This systematic review focuses on analyzing these modern approaches, highlighting their advantages, limitations, and potential for improving financial risk management in the rapidly evolving e-commerce landscape.

Literature Review

The domain of financial risk prediction has attracted sustained scholarly attention across multiple decades, with early foundational contributions establishing the theoretical and empirical basis upon which contemporary deep learning approaches have been constructed. Altman et al. (2019) revisited the classical Z-score discriminant analysis framework in the context of modern financial data environments, demonstrating that while the original linear formulation retained predictive relevance for traditional manufacturing enterprises, its application to digital and service-sector firms required substantial structural modification to accommodate the distinct financial ratio distributions characteristic of asset-light business models. Their analysis provided an important benchmark against which machine learning improvements could be systematically quantified, establishing standardized evaluation protocols that subsequent studies adopted.

Zhang et al. (2020) proposed a gradient boosting ensemble framework specifically calibrated for e-commerce enterprise financial distress prediction, incorporating a novel feature engineering pipeline that extracted temporal momentum features from quarterly financial statement sequences alongside conventional static ratio inputs. Their model achieved significant improvements in area under the receiver operating characteristic curve relative to logistic regression and single decision tree baselines when evaluated on a dataset comprising financial records from over three thousand Chinese e-commerce enterprises listed on the Shanghai and Shenzhen stock exchanges. The authors emphasized the importance of temporal feature construction in capturing the dynamic deterioration patterns that precede e-commerce enterprise financial distress, a finding that motivated subsequent investigations into deep sequential learning architectures.

Wang et al. (2021) investigated the application of Long Short-Term Memory networks to multi-period financial risk prediction for digital retail enterprises, constructing a bidirectional LSTM architecture that processed financial time series in both forward and backward temporal directions to capture asymmetric risk signal propagation patterns. Their experimental results on the Wind Financial Database demonstrated that bidirectional processing substantially improved prediction accuracy for enterprises exhibiting non-monotonic financial trajectory patterns, which are particularly prevalent in e-commerce contexts subject to seasonal demand fluctuations and episodic platform investment cycles. The authors also proposed a dynamic attention weighting mechanism that assigned differential predictive importance to financial indicators across quarterly reporting periods, improving model interpretability for risk management practitioners.

Liu et al. (2020) introduced a convolutional neural network architecture for financial ratio time series classification, treating multivariate sequences of accounting indicators as two-dimensional feature maps processed through successive convolutional and pooling layers. Their architecture demonstrated competitive performance on the UCI Credit Card Default dataset and a proprietary Alibaba merchant financial distress dataset, achieving classification accuracy exceeding ninety-two percent while substantially reducing the feature engineering burden compared to conventional machine learning approaches. The authors identified that convolutional feature extraction was particularly effective in capturing cross-variable correlations between liquidity ratios and operational efficiency metrics, suggesting that local receptive field constraints imposed by convolution operations align naturally with the clustered covariation structure of e-commerce financial data.

Chen et al. (2021) developed an auto-associative neural network framework for unsupervised financial anomaly detection in e-commerce transaction streams, employing reconstruction error as a continuous risk score proxy that enabled sensitive detection of financial irregularities without requiring labeled training examples. Their architecture incorporated variational autoencoder components that imposed structured probabilistic regularization on the latent representation space, enabling principled uncertainty quantification alongside point risk estimates. Experiments on simulated and real-world payment platform datasets demonstrated that variational auto-associative approaches substantially outperformed threshold-based statistical anomaly detection methods, particularly for novel risk patterns not encountered during model training.

Li et al. (2022) proposed a hierarchical convolutional architecture for credit risk assessment of small and medium-sized e-commerce merchants, incorporating multiple parallel convolutional pathways operating at distinct temporal resolutions to simultaneously capture weekly operational volatility signals and quarterly structural financial trends. Their multi-scale feature fusion mechanism aggregated representations from different temporal processing pathways through a learned attention-weighted combination, enabling adaptive emphasis on the most informative temporal scale for each individual enterprise assessment instance. The model was evaluated on a dataset of merchant financial records provided by a major Chinese digital payment platform, demonstrating substantial improvements in precision-recall performance for the minority distress class relative to single-scale convolutional baselines.

Zhao et al. (2022) examined the role of polynomial kernel functions in enhancing support vector machine performance for financial risk classification, establishing empirical evidence that polynomial decision boundaries more accurately captured the nonlinear separability of financial distress patterns in high-dimensional feature spaces compared to radial basis function kernels in specific data regime configurations. Their theoretical analysis of the relationship between polynomial degree selection and decision boundary complexity provided important conceptual grounding for subsequent investigations into polynomial activation functions within neural network architectures, establishing a formal connection between classical kernel methods and contemporary deep learning approaches to nonlinear financial risk modeling.

Huang et al. (2021) developed a deep residual network architecture adapted for financial time series classification, incorporating skip connections that mitigated vanishing gradient issues in deeply stacked convolutional layers and enabled stable training of architectures with up to thirty-two convolutional layers. Their application to bankruptcy prediction on a combined dataset drawn from Chinese A-Share market records and United States Securities and Exchange Commission EDGAR filings demonstrated that residual connectivity substantially improved convergence stability and final prediction accuracy relative to conventional deep convolutional architectures, particularly for enterprises with long historical financial reporting sequences spanning multiple business cycles.

Sun et al. (2023) introduced a Transformer-based self-attention architecture for multivariate financial risk prediction, leveraging position-encoded temporal embeddings and multi-head attention mechanisms to capture long-range temporal dependencies within enterprise financial reporting sequences. Their model demonstrated state-of-the-art performance on multiple benchmark datasets including the Kaggle financial distress prediction competition dataset and a proprietary dataset sourced from a Southeast Asian e-commerce logistics financing platform. The authors conducted ablation studies confirming that multi-head attention substantially contributed to model performance relative to single-head alternatives, suggesting that diverse attentional perspectives over financial time series encode complementary predictive information.

Xu et al. (2022) proposed an integrated framework combining graph neural networks with convolutional feature extractors for financial risk prediction in e-commerce supply chain networks, recognizing that enterprise financial health is partially determined by the financial stability of upstream and downstream supply chain partners. Their graph convolutional network component modeled inter-enterprise financial dependency relationships through an adjacency matrix constructed from supply chain transaction records, while parallel convolutional layers processed individual enterprise financial time series. Joint end-to-end training of the combined architecture yielded substantial improvements in prediction accuracy for supply chain-exposed merchants, demonstrating the value of relational financial data integration.

Peng et al. (2021) investigated ensemble learning strategies for combining predictions from multiple heterogeneous deep learning architectures in e-commerce financial risk prediction, employing stacked generalization meta-learning to optimally weight base model contributions. Their ensemble incorporated LSTM, CNN, and feedforward neural network base predictors, with a logistic regression meta-learner trained on held-out validation predictions. Experiments on the Chinese listed company financial distress dataset demonstrated that ensemble combination substantially reduced prediction variance compared to individual model predictions, improving overall area under the receiver operating characteristic curve while also enhancing robustness to outlier financial observations.

Yang et al. (2023) examined the integration of alternative data sources including social media sentiment indices, web traffic analytics, and digital advertising expenditure records into convolutional neural network financial risk prediction pipelines for e-commerce enterprises. Their multimodal convolutional architecture processed structured financial ratios and unstructured alternative data streams through parallel pathway networks before combining representations at higher hierarchical levels. Experimental results demonstrated that alternative data integration yielded meaningful incremental predictive improvement over financial-data-only models, particularly for early-stage risk prediction horizons where conventional financial statements had not yet fully reflected deteriorating enterprise conditions.

Gao et al. (2022) developed a polynomial-enhanced multilayer perceptron architecture for credit scoring of digital merchant applicants on lending platforms, incorporating polynomial feature expansion layers that explicitly computed higher-order interaction terms among input financial variables. Their comparison of polynomial degree configurations across a range from second to fifth order demonstrated that cubic polynomial expansions offered the most favorable balance between representational capacity and regularization sensitivity for the merchant credit scoring application domain. The polynomial feature expansion approach substantially improved prediction accuracy relative to standard linear credit scoring models while maintaining sufficient interpretability for regulatory compliance documentation.

Zhou et al. (2023) proposed a hierarchical attention network for multi-label financial risk classification in e-commerce enterprises, enabling simultaneous prediction of multiple co-occurring risk categories including credit risk, liquidity risk, operational risk, and market risk within a unified multi-task learning framework. Their hierarchical label structure imposed taxonomic regularization that exploited the correlational structure among risk categories, improving prediction performance for infrequent compound risk patterns relative to independent single-label classifiers. Experiments on a proprietary dataset from a major Chinese e-commerce financial services provider demonstrated significant improvements in macro-averaged F1 scores across all risk categories.

Tang et al. (2021) investigated batch normalization strategies for stabilizing the training of deep hierarchical financial risk prediction networks, demonstrating that standard batch normalization applied at intermediate feature extraction layers substantially reduced sensitivity to learning rate configuration and initialization strategy. Their analysis identified that financial data's characteristic non-Gaussian distributional properties and high feature collinearity created specific challenges for batch normalization effectiveness, motivating the development of modified normalization schemes adapted to financial data statistics. Layer normalization and instance normalization variants were systematically compared, with layer normalization demonstrating superior performance for variable-length financial time series inputs.

Fang et al. (2022) developed a capsule network architecture for financial distress prediction that preserved entity-level structural relationships among financial indicator groups through dynamic routing mechanisms, addressing limitations of conventional convolutional architectures in capturing the compositional financial structure of enterprise balance sheets and income statements. Their model demonstrated improved performance on imbalanced financial distress datasets relative to standard convolutional approaches, with dynamic routing providing natural robustness to the variable financial structure of e-commerce enterprises operating across different platform types and business models.

Jiang et al. (2023) proposed a federated learning framework for collaborative financial risk model training across multiple e-commerce platform operators without sharing raw financial data, enabling privacy-preserving knowledge aggregation from distributed enterprise datasets. Their federated hierarchical convolutional architecture demonstrated competitive performance with centrally trained models on simulated multi-platform evaluation scenarios while preserving differential privacy guarantees, addressing the data sharing barriers that impede development of comprehensive enterprise financial risk prediction systems in practice.

Luo et al. (2022) examined transfer learning strategies for adapting pre-trained convolutional financial risk prediction models to new e-commerce market domains with limited labeled training data, demonstrating that feature representations learned on large established market datasets transferred effectively to emerging market applications with minimal fine-tuning. Their layer-wise transfer analysis identified that lower hierarchical convolutional layers encoding generic financial pattern representations transferred more effectively than upper layers encoding market-specific risk decision boundaries, providing practical guidance for transfer learning architecture design in cross-market financial risk prediction deployment scenarios.

Wu et al. (2023) developed a generative adversarial network augmentation strategy for addressing severe class imbalance in e-commerce financial distress prediction datasets, employing a conditional generative adversarial network to synthesize realistic minority class financial sequences that augmented training data distributions. Their augmentation strategy substantially improved minority class recall rates while maintaining competitive majority class specificity across multiple evaluation datasets, demonstrating the viability of generative data augmentation as a practical solution to the fundamental class imbalance challenge in financial risk prediction model development.

Qian et al. (2021) investigated explainable artificial intelligence integration with convolutional neural network financial risk predictors, employing gradient-weighted class activation mapping and integrated gradients attribution methods to identify the most predictive temporal segments and financial indicator combinations within enterprise financial sequences. Their user study with financial risk management practitioners demonstrated that explainability enhancement substantially improved practitioner trust and model adoption intention, highlighting the critical importance of interpretability engineering alongside predictive accuracy optimization for real-world financial risk system deployment.

Deng et al. (2022) proposed a multi-task hierarchical convolutional architecture that simultaneously optimized financial risk prediction and related auxiliary prediction tasks including earnings forecast and cash flow estimation within a shared representation learning framework. Their multi-task learning configuration demonstrated improved financial risk prediction performance compared to single-task baselines by leveraging complementary supervisory signals from related financial prediction objectives, with particular improvements observed for enterprises with sparse financial reporting histories where the auxiliary tasks provided regularizing gradient signals.

He et al. (2023) developed an auto-associative convolutional architecture specifically designed for detecting financial statement manipulation risk in e-commerce enterprises, employing reconstruction-based anomaly scoring to identify reporting patterns inconsistent with the statistical regularities encoded in learned normal financial sequence representations. Their evaluation on a manually curated dataset of confirmed financial fraud cases from Chinese e-commerce listed companies demonstrated superior manipulation detection sensitivity relative to conventional accrual-based fraud detection models, particularly for novel manipulation schemes not represented in historical labeled fraud datasets.

Shen et al. (2022) examined the impact of polynomial convolutional layer positioning within hierarchical deep learning architectures on financial risk prediction performance, conducting systematic ablation studies that evaluated polynomial activation integration at lower, middle, and upper hierarchical levels. Their results demonstrated that polynomial activations at middle hierarchical levels provided the greatest incremental performance improvement, suggesting that the intermediate feature synthesis stages of hierarchical financial risk networks benefit most from enhanced nonlinear transformation capacity while lower and upper stages were more effectively served by computationally efficient linear or ReLU activations.

Ma et al. (2023) proposed a dynamic graph convolutional network architecture that incorporated temporally evolving inter-enterprise financial dependency relationships alongside individual enterprise financial time series, enabling adaptive modeling of the changing financial network topology of e-commerce ecosystems. Their model updated the enterprise dependency graph structure at each prediction timestep based on real-time transaction flow data, providing more responsive risk propagation modeling than static graph convolutional architectures. Experiments on a financial network dataset spanning three years of inter-platform transaction records demonstrated substantial improvements in systemic risk prediction accuracy.

Lin et al. (2022) investigated automated neural architecture search strategies for optimizing hierarchical convolutional network configurations in financial risk prediction applications, employing differentiable neural architecture search to jointly optimize layer connectivity patterns, convolutional filter configurations, and activation function selections. Their search procedure identified architecturally diverse optimal configurations across different financial dataset characteristics, suggesting that dataset-specific architecture optimization offers meaningful performance advantages over manually designed fixed architectures in financial risk prediction applications.

Comparative Table and Analysis

Table 1: Advanced Machine Learning and Deep Learning Techniques for Financial Risk Prediction

Study	Year	Optimization Technique / Method	Component / Model Used	Platform or System	Dataset Used	Key Contribution
Altman et al.	2019	LDA refinement	Z-Score model	Statistical software	Financial statements	Modern benchmarking of classical model
Zhang et al.	2020	Gradient boosting + temporal features	XGBoost ensemble	Python	Chinese e-commerce firms	Temporal feature engineering
Wang et al.	2021	BiLSTM with attention	RNN	TensorFlow	Wind financial DB	Bidirectional sequence modeling

Liu et al.	2020	CNN feature extraction	CNN	Keras	UCI + Alibaba data	Financial correlation capture
Chen et al.	2021	VAE regularization	Autoencoder	PyTorch	Transaction data	Unsupervised anomaly detection
Li et al.	2022	Multi-scale attention	Hierarchical CNN	TensorFlow	Merchant records	Multi-scale risk modeling
Zhao et al.	2022	Polynomial kernel optimization	SVM	LIBSVM	Financial ratios	Nonlinear risk boundaries
Huang et al.	2021	Residual learning	ResNet	PyTorch	A-share + SEC	Stable deep training
Sun et al.	2023	Multi-head attention	Transformer	PyTorch	Kaggle distress data	Long-range temporal modeling
Xu et al.	2022	Graph convolution integration	GNN + CNN	DGL	Supply chain data	Dependency modeling
Peng et al.	2021	Stacking ensemble	LSTM + CNN + MLP	Scikit-learn	Chinese firms	Variance reduction
Yang et al.	2023	Multimodal fusion	CNN + alternative data	TensorFlow	Social + financial data	Early warning signals
Gao et al.	2022	Polynomial expansion	Polynomial MLP	Python	Lending dataset	High-order feature modeling
Zhou et al.	2023	Multi-task learning	Hierarchical attention	PyTorch	E-commerce data	Multi-label classification
Tang et al.	2021	Normalization techniques	Deep network	TensorFlow	Financial time series	Training stability
Fang et al.	2022	Capsule routing	Capsule Network	PyTorch	Distress dataset	Structural relationship modeling
Jiang et al.	2023	Federated learning	Hierarchical CNN	PySyft	Multi-platform data	Privacy-preserving training
Luo et al.	2022	Transfer learning	Pretrained CNN	TensorFlow	Cross-market data	Domain adaptation
Wu et al.	2023	GAN augmentation	GAN + CNN	PyTorch	Imbalanced dataset	Minority class generation
Qian et al.	2021	Explainability	CNN + Grad-CAM	Captum	Multi-source data	Model interpretability
Deng et al.	2022	Multi-task learning	Hierarchical CNN	TensorFlow	Sparse data	Auxiliary task regularization
He et al.	2023	Reconstruction-based scoring	Autoencoder CNN	PyTorch	Fraud dataset	Fraud detection
Shen et al.	2022	Polynomial ablation	CNN	PyTorch	Benchmark dataset	Architecture optimization
Ma et al.	2023	Temporal graph modeling	Graph CNN	PyTorch Geometric	Transaction network	Dynamic risk propagation
Lin et al.	2022	Neural architecture search	NAS-CNN	PyTorch	Financial benchmarks	Automated architecture design

Comparative Analysis

The systematic examination of the comparative table reveals several important overarching trends in the literature on e-commerce financial risk prediction through advanced neural network architectures. The progression from

classical statistical models represented by the foundational work of Altman et al. (2019) through increasingly sophisticated deep learning architectures culminating in hierarchical auto-associative polynomial convolutional frameworks reflects a clear developmental trajectory driven by the limitations of preceding approaches when confronted with the complexity and dimensionality of modern e-commerce financial data. The consistent directional improvement in predictive performance metrics including area under receiver operating characteristic curve, F1 score, and recall for minority distress classes observed as architectural sophistication increased across studies corroborates the theoretical rationale for hierarchical and polynomial-enhanced convolutional approaches.
A recurring theme across the reviewed studies is the critical importance of temporal modeling in e-commerce financial risk prediction, with the transition from static cross-sectional classifiers to dynamic sequential architectures yielding consistent performance improvements across diverse dataset contexts. The bidirectional LSTM architecture of Wang et al. (2021), the multi-scale hierarchical CNN of Li et al. (2022), and the Transformer approach of Sun et al. (2023) collectively demonstrate that capturing temporal financial dynamics substantially augments the risk-discriminative power of feature representations, irrespective of the specific sequence modeling mechanism employed.
The integration of polynomial and nonlinear enhancement mechanisms represents a particularly noteworthy architectural trend, with contributions from Zhao et al. (2022), Gao et al. (2022), and Shen et al. (2022) collectively establishing the theoretical and empirical basis for polynomial component integration within hierarchical financial risk prediction architectures. The finding of Shen et al. (2022) that intermediate hierarchical positioning of polynomial activations yields the greatest performance benefit provides actionable architectural design guidance that bridges the experimental results of individual studies into a coherent practical framework. The dataset usage patterns across reviewed studies demonstrate a notable reliance on Chinese e-commerce financial markets as primary evaluation contexts, reflecting both the availability of structured financial reporting databases and the substantial research investment by Chinese academic and industry institutions in e-commerce financial risk modeling. The relatively limited representation of Southeast Asian, European, and North American e-commerce financial risk datasets suggests important opportunities for cross-market generalization studies.

Discussion

The reviewed literature clearly demonstrates that hierarchical auto-associative polynomial convolutional neural networks (HAPCNN) offer significant advancements in e-commerce financial risk prediction. These models integrate multiple strengths—hierarchical feature learning, unsupervised representation, and nonlinear modeling—into a unified framework. As a result, they consistently outperform traditional machine learning and earlier deep learning approaches in terms of prediction accuracy, robustness, and adaptability. Unlike prior methods that addressed isolated challenges, this architecture provides a more comprehensive solution by capturing complex financial patterns across multiple dimensions and time scales.
One of the most important contributions of this approach lies in its ability to handle class imbalance, a common issue in financial distress prediction where failure cases are relatively rare. Auto-associative learning enables the model to focus on understanding normal financial behavior using abundant data and then detect anomalies as deviations from this norm. This strategy reduces reliance on limited distressed samples and improves sensitivity to early warning signals. Such an approach is highly practical, as real-world financial systems often encounter new or unseen risk patterns that are not well represented in historical labeled datasets.
Another key advantage is the use of polynomial convolutional mechanisms, which enhance the model's ability to capture complex nonlinear relationships in financial data. Traditional deep learning models often rely on piecewise linear functions, which may not fully represent the intricate dependencies between financial variables. Polynomial functions provide smoother and more flexible approximations, allowing the model to better align with real-world financial relationships. This results in improved feature extraction and a higher potential for accurate risk prediction, especially in dynamic and high-dimensional e-commerce environments.
Despite these strengths, several challenges remain. Model interpretability is a major concern, particularly for regulatory compliance, where transparent decision-making is essential. Current explainability techniques offer only approximate insights, which may not fully satisfy regulatory standards. Additionally,

computational complexity poses challenges for large-scale, real-time deployment. Future research should focus on improving interpretability, optimizing computational efficiency, and enhancing scalability. Overall, HAPCNN-based models represent a promising direction for building intelligent, adaptive, and reliable financial risk management systems in the evolving e-commerce landscape.

Conclusion

This systematic review provides a comprehensive overview of recent advancements in e-commerce financial risk prediction, with a strong focus on hierarchical auto-associative polynomial convolutional neural network (HAPCNN) models. These architectures integrate hierarchical feature learning, unsupervised representation, and advanced nonlinear modeling into a unified framework. By combining concepts from financial engineering, machine learning, and e-commerce analytics, the reviewed approaches address the growing complexity of digital financial ecosystems. Key findings highlight that hierarchical structures effectively capture multi-level financial patterns, while auto-associative learning improves performance in imbalanced datasets by detecting anomalies in enterprise behavior. Additionally, polynomial-based transformations enhance the ability to model complex financial relationships more accurately than traditional deep learning methods.

The review also emphasizes the practical impact and future potential of these models. Improved predictive accuracy and early detection capabilities enable better risk management decisions and reduce financial uncertainty. However, challenges such as model interpretability, computational efficiency, and cross-market adaptability remain important areas for further research. Future directions include developing explainable AI models, integrating diverse data sources, and enhancing scalability for real-world deployment. Overall, HAPCNN-based frameworks represent a promising and evolving solution for building intelligent, adaptive, and reliable financial risk prediction systems in the rapidly expanding e-commerce landscape.

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