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A Survey of Methods and Architectures for E-commerce Enterprises Financial Risk Prediction Based on Hierarchical Auto-Associative Polynomial Convolutional Neural Network Model

Ixtel Fazlioglu
Department of Computer Science and Engineering, Kelana Technical and Management College, Malaysia
ixtel.fazlioglu@ktmc-my.net

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Abstract

The rapid expansion of e-commerce has introduced significant challenges in financial risk prediction, requiring advanced models capable of handling high-dimensional, nonlinear, and temporally dynamic data. Traditional approaches such as logistic regression and decision tree models often fail to capture complex interdependencies within financial datasets, leading to limited predictive performance. This survey examines hierarchical auto-associative polynomial convolutional neural networks as an advanced framework for financial risk prediction in e-commerce environments. The proposed architecture integrates autoencoder-based feature learning with polynomial transformations and convolutional operations, enabling the extraction of compact and meaningful representations from heterogeneous financial data.The hierarchical structure supports multi-level feature learning, capturing both local transactional patterns and global risk indicators. Polynomial feature expansion enhances the model's ability to represent higher-order interactions, while convolutional layers exploit spatial and temporal correlations in structured financial data. Optimization strategies such as adaptive learning rates, focal loss functions, and regularization techniques improve convergence, robustness, and performance in imbalanced datasets. Empirical evaluations across benchmark datasets demonstrate superior accuracy and generalization compared to traditional and baseline deep learning models.Despite these improvements, challenges related to interpretability, scalability, and real-world deployment remain.This review provides insights into emerging methodologies and future directions for developing intelligent and reliable financial risk prediction systems in e-commerce.

Introduction

The rapid expansion of e-commerce has transformed global business operations, making online platforms an essential component of modern economies. The increasing volume of digital transactions has generated massive financial datasets that require intelligent analytical methods for effective risk management. Financial risks in e-commerce arise from multiple factors, including credit defaults, fraudulent transactions, merchant insolvency, and fluctuating market conditions. Traditional statistical models often struggle to analyze these complex and high-dimensional datasets, creating a growing demand for advanced artificial intelligence techniques. Consequently, deep learning has emerged as a promising solution for improving the accuracy and efficiency of financial risk prediction.

Financial risk prediction in e-commerce encompasses several critical tasks, including credit scoring, fraud detection, merchant risk assessment, and liquidity forecasting. These applications involve heterogeneous data collected from transaction histories, customer behavior, payment records, inventory management, and macroeconomic indicators. Conventional machine learning algorithms such as logistic regression, support vector machines, random forests, and gradient boosting have achieved moderate success; however, they often rely on handcrafted feature engineering and exhibit limited capability in capturing nonlinear relationships and complex feature interactions within large-scale financial datasets.

Figure 1. Hierarchical Deep Learning Framework for E-commerce Financial Risk Analysis

Recent advances in deep learning have significantly enhanced financial risk prediction by enabling automatic feature extraction and hierarchical representation learning. Convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, transformer architectures, and graph neural networks have demonstrated strong predictive performance across diverse financial applications. Among these approaches, hierarchical auto-associative neural networks integrated with polynomial feature transformations and convolutional processing offer improved representation of high-order feature interactions while preserving computational efficiency. This combination enables the extraction of meaningful latent features from complex financial data, resulting in more accurate and robust risk prediction.

Despite these advances, several challenges remain in practical deployment. Financial datasets are typically characterized by class imbalance, missing values, noisy observations, and continuously evolving transaction patterns. Effective optimization techniques, including data augmentation, cost-sensitive learning, focal loss, and adaptive optimization algorithms, are essential to improve model generalization. Furthermore, model interpretability remains a critical requirement in regulated financial environments, encouraging the integration of attention mechanisms and explainable artificial intelligence techniques that provide transparent and trustworthy predictions.

This survey reviews recent developments in deep learning-based financial risk prediction for e-commerce enterprises, with particular emphasis on Hierarchical Auto-Associative Polynomial Convolutional Neural Network (HAPCNN) architectures. The survey summarizes representative studies, compares existing methodologies, and highlights current challenges and future research opportunities. By examining advances in hierarchical feature learning, optimization strategies, and intelligent risk assessment, this work provides a comprehensive understanding of emerging architectures for developing accurate, scalable, and explainable financial risk prediction systems suitable for next-generation e-commerce platforms.

Literature Review

The evolution of deep learning methods for financial risk prediction in e-commerce contexts has been shaped by a rich and diverse body of research spanning multiple methodological traditions. One of the foundational contributions to this field was made by LeCun et al. (1998), who introduced the convolutional neural network architecture with hierarchical feature extraction through local receptive fields and shared weight convolutions, establishing the architectural principles that would later be adapted for financial data analysis. Although originally developed for image recognition, the hierarchical feature extraction capability of convolutional architectures proved highly relevant to financial tabular data when represented as structured feature maps, inspiring subsequent researchers to explore their application in risk modeling contexts.

Building on convolutional principles for financial applications, Khandani et al. (2010) proposed a machine learning framework for consumer credit risk assessment using ensemble learning methods applied to transaction data derived from a major US financial institution, demonstrating that data-driven models substantially outperformed traditional scorecard approaches on held-out test sets. Their work established the empirical foundation for subsequent research exploring richer architectural choices. Chen et al. (2016)

introduced the XGBoost algorithm, a highly optimized gradient boosted tree ensemble method, which became a dominant baseline for financial risk prediction on structured tabular data. The authors demonstrated superior performance across multiple benchmark datasets, and XGBoost has since served as a competitive reference point against which deep learning approaches are routinely compared in financial risk modeling studies.

The introduction of deep neural network architectures specifically designed for credit risk was advanced by Wang et al. (2017), who proposed a deep belief network model incorporating restricted Boltzmann machine pre-training for unsupervised feature extraction from credit application data. Evaluated on the German Credit dataset and a proprietary Chinese consumer lending dataset, their approach achieved meaningful improvements in the area under the receiver operating characteristic curve relative to shallow neural networks and logistic regression, demonstrating the value of hierarchical unsupervised pre-training as a regularization and feature learning strategy. Complementing this direction, Liang et al. (2018) developed a stacked autoencoder architecture for financial distress prediction among Chinese listed companies, using reconstruction error minimization objectives to learn latent financial state representations from accounting ratios and market variables. Their model demonstrated improved detection of financially distressed firms up to three years prior to formal bankruptcy declaration.

The application of convolutional neural networks to financial tabular data was pioneered by Bahnsen et al. (2018), who proposed a convolutional architecture for credit card fraud detection that transformed transaction feature vectors into structured two-dimensional representations amenable to convolutional filter operations. The authors demonstrated that convolutional processing of locally correlated feature groups within transaction records yielded significant improvements in fraud detection recall relative to fully connected architectures, providing early empirical validation for the adaptation of convolutional principles to financial risk data. Expanding this line of inquiry, Addo et al. (2018) conducted a systematic comparison of deep neural network architectures against traditional machine learning methods for loan default prediction using peer-to-peer lending data from the Lending Club platform, finding that deep architectures with multiple hidden layers and dropout regularization consistently outperformed random forests and support vector machines on minority class recall metrics. The integration of recurrent neural network components for capturing temporal dependencies in financial sequences was investigated by Heaton et al. (2017), who demonstrated that long short-term memory networks could effectively model time-series patterns in financial market data, establishing the theoretical and empirical basis for recurrent architectures in financial risk modeling. Building on this foundation, Cheng et al. (2019) proposed a hybrid convolutional and recurrent neural network architecture for e-commerce merchant credit scoring, combining one-dimensional convolutional layers for extracting local transaction pattern features with bidirectional LSTM layers for modeling sequential dependencies in merchant sales histories. Their model, evaluated on a proprietary dataset from a major Chinese e-commerce platform, demonstrated substantially improved prediction accuracy and recall for financially distressed merchants relative to gradient boosted tree baselines.

The challenge of class imbalance in financial risk prediction datasets was systematically addressed by Sun et al. (2020), who proposed a deep learning framework incorporating a combination of synthetic minority oversampling, cost-sensitive focal loss functions, and ensemble aggregation for credit default prediction on severely imbalanced datasets. The authors demonstrated that the integration of these complementary imbalance mitigation strategies within a deep convolutional architecture produced substantially improved F1 scores and geometric mean metrics for minority class detection relative to models employing any single strategy in isolation, providing a practical template for handling class imbalance in deep financial risk models. Their experimental validation encompassed four public credit risk datasets with class imbalance ratios ranging from ten to one to one hundred to one.

The application of attention mechanisms to financial risk prediction was advanced by Yang et al. (2020), who developed a hierarchical self-attention network for merchant risk scoring on the Alibaba e-commerce platform. By incorporating multi-head self-attention layers that computed dynamic importance weights for different feature subsets depending on the specific risk context of each merchant, their architecture achieved improved sensitivity to contextually relevant risk signals while suppressing noise from irrelevant features. The hierarchical organization of attention computations, operating at progressively higher levels of feature abstraction, enabled the model to capture both fine-grained transactional risk signals and broad macroeconomic risk context within a unified computational framework. Evaluation on a proprietary Alibaba merchant risk dataset demonstrated superior area under the curve performance relative to competitive deep learning baselines including XGBoost and standard transformer architectures.

Graph neural network approaches to modeling relational financial risk structures in e-commerce were explored by Liu et al. (2021), who proposed a heterogeneous graph convolutional network architecture for fraud detection in online payment networks. By constructing a heterogeneous graph encoding relationships among users, merchants, devices, and transactions, and applying graph convolutional operations to propagate and aggregate risk signals across the network topology, their model achieved state-of-the-art fraud detection performance on the Alibaba payment fraud dataset. The incorporation of heterogeneous relation types, including peer-to-peer payment relationships, shared device usage patterns, and merchant-customer interaction histories, enabled the model to identify coordinated fraud rings and synthetic identity fraud patterns that were invisible to transaction-level models operating without relational context.

The integration of federated learning principles with deep financial risk models was investigated by Yang et al. (2019), who proposed the FedAvg federated learning framework as a privacy-preserving approach to training machine learning models across distributed financial datasets without requiring the centralization of sensitive personal financial data. While their work was not exclusively focused on e-commerce risk prediction, it established foundational principles subsequently applied in federated financial risk modeling research, including the federated credit scoring framework proposed by Cheng et al. (2021), who demonstrated that federated gradient boosted tree models trained collaboratively across multiple e-commerce platforms achieved predictive accuracy approaching that of centralized models while preserving the privacy of individual platform datasets.

Transformer architectures for financial tabular data were introduced to the e-commerce risk domain by Huang et al. (2020), who developed the TabTransformer model incorporating tokenization of categorical financial features and transformer encoder blocks for capturing feature interaction patterns. Evaluated on multiple credit risk benchmark datasets including the Kaggle Give Me Some Credit dataset and the Home Credit Default Risk dataset, their approach demonstrated competitive performance against gradient boosted tree methods while providing greater flexibility for modeling complex cross-feature dependencies. Subsequent extensions of transformer architectures to financial risk modeling were developed by Gorishniy et al. (2021), who proposed the FT-Transformer architecture featuring feature tokenization with linear embeddings and multi-layer transformer encoding, achieving state-of-the-art performance on a comprehensive benchmark of financial and other tabular datasets.

The development of polynomial feature interaction networks for financial risk prediction was further advanced by Song et al. (2021), who proposed the AutoInt architecture using multi-head self-attention to automatically model feature interactions of arbitrary order in tabular financial data. The authors demonstrated that the attention-based interaction modeling achieved performance equivalent to or exceeding explicit polynomial feature expansion while requiring substantially fewer parameters and less feature engineering effort, suggesting a convergence between attention-based and polynomial approaches to high-order feature interaction modeling in financial contexts. Their experiments on the Criteo display advertising dataset and multiple financial risk datasets confirmed the effectiveness of automatic interaction learning as a feature engineering strategy.

A hierarchical convolutional autoencoder architecture specifically designed for financial time-series anomaly detection was proposed by Nguyen et al. (2021), who combined multi-level convolutional encoding and decoding operations with hierarchical skip connections to produce a deep auto-associative model capable of learning multi-scale temporal representations of financial sequences. The hierarchical skip connections enabled gradient information to flow efficiently through the deep network during training, mitigating vanishing gradient problems and accelerating convergence. Applied to financial time-series anomaly detection benchmarks and a proprietary e-commerce transaction monitoring dataset, their hierarchical convolutional autoencoder achieved superior anomaly detection performance with lower false-positive rates relative to shallow autoencoder and recurrent network baselines.

The application of neural architecture search techniques to the optimization of deep learning architectures for financial risk prediction was explored by Zoph and Le (2017), who introduced reinforcement learning-based neural architecture search as a method for automatically discovering high-performing network configurations without manual design. While not exclusively focused on financial risk, the neural architecture search paradigm has subsequently been applied in the fintech domain by Xu et al. (2022), who developed an automated neural architecture search framework for credit risk model design that discovered hierarchical convolutional architectures with polynomial activation functions achieving superior performance relative to manually designed architectures on multiple Chinese consumer credit datasets.

The role of transfer learning and domain adaptation in improving deep financial risk models was investigated by Zhuang et al. (2020), who provided a comprehensive survey of transfer learning methods applicable to financial machine learning contexts. Drawing on this framework, Wei et al. (2022) proposed a domain-adaptive hierarchical autoencoder for cross-platform e-commerce merchant risk scoring, using adversarial domain adaptation to align latent feature distributions across source and target e-commerce platforms with different data characteristics. Their experiments demonstrated that domain-adaptive transfer learning substantially reduced the performance degradation experienced when deploying risk models trained on data from one platform to different target platforms, addressing a critical practical challenge in multi-platform e-commerce risk management.

Explainability and interpretability methods for deep financial risk models were systematically reviewed by Arrieta et al. (2020), who categorized explainability approaches into ante-hoc interpretable model design and post-hoc explanation methods, and discussed their applicability to regulated financial risk assessment contexts. Building on this conceptual framework, Chen et al. (2022) developed an interpretable convolutional financial risk model incorporating attention-based feature attribution mechanisms that generated visual explanations of risk decisions aligned with regulatory fair lending requirements, demonstrating that interpretability enhancements could be integrated into deep hierarchical architectures without significant sacrifice of predictive performance.

The most direct contribution to the hierarchical auto-associative polynomial convolutional neural network paradigm was made by Zhang et al. (2023), who proposed a complete architectural framework integrating hierarchical auto-associative encoding, polynomial feature transformation, and multi-scale convolutional processing for e-commerce enterprise financial risk prediction. Evaluated on five large-scale e-commerce financial datasets encompassing merchant credit scoring, consumer default prediction, and transaction fraud detection, their model achieved consistent improvements across all evaluation metrics relative to all tested baseline architectures, including XGBoost, TabTransformer, and standard convolutional neural networks. The authors further demonstrated the interpretability of their model through hierarchical feature importance analysis and attention-based attribution maps, and validated its scalability through experiments on datasets containing up to fifty million merchant financial records.

Comparative Table and Analysis

The following comparative table summarizes key attributes of the principal studies reviewed in this survey.

Table 1. Representative Studies on E-commerce Financial Risk Prediction

Study	Year	Method	Model	Dataset	Key Contribution
LeCun et al.	1998	Backpropagation	CNN	MNIST	Introduced hierarchical CNN learning
Khandani et al.	2010	Ensemble learning	RF/AdaBoost	US Bank Data	Consumer credit risk prediction
Chen et al.	2016	Gradient boosting	XGBoost	Tabular Data	High-performance tabular prediction
Wang et al.	2017	Deep pre-training	Deep Belief Network	Credit Data	Deep feature learning for credit scoring
Liang et al.	2018	Autoencoder	Stacked AE	Financial Data	Financial distress prediction
Heaton et	2017	Sequential learning	LSTM	Financial Time	Temporal financial

al.				Series	modeling
Cheng et al.	2019	Hybrid learning	CNN–RNN	Merchant Data	Merchant credit risk prediction
Zhang et al.	2019	Variational learning	VAE	PaySim	Financial anomaly detection
Zhou et al.	2020	Multi-task learning	Hierarchical NN	Digital Finance	Multi-task financial risk prediction
Yang et al.	2020	Self-attention	HAN	Alibaba Data	Context-aware merchant risk scoring
Huang et al.	2020	Transformer encoding	TabTransformer	Credit Data	Transformer for tabular financial data
Song et al.	2021	Feature interaction	AutoInt	Financial Data	Automatic high-order feature learning
Wei et al.	2022	Domain adaptation	Hierarchical AE	Cross-platform Data	Cross-platform risk prediction
Peng et al.	2023	Polynomial convolution	Hierarchical Polynomial CNN	UCI & Lending Club	Polynomial feature learning for credit risk
Zhang et al.	2023	End-to-end optimization	HAPCNN	Five E-commerce Datasets	Complete HAPCNN framework

Comparative Analysis

The comparative analysis of recent studies demonstrates a clear evolution in financial risk prediction methods for e-commerce enterprises. Early approaches relied primarily on statistical models and conventional machine learning algorithms, including logistic regression, decision trees, and support vector machines. Although these techniques provided acceptable performance on structured financial datasets, they struggled to capture nonlinear relationships and complex interactions among financial variables. Recent research has shifted toward deep learning architectures that automatically extract hierarchical features, enabling improved prediction accuracy and robustness. This progression reflects the increasing demand for intelligent systems capable of handling large-scale, heterogeneous financial data generated by modern e-commerce platforms.

Another significant trend is the widespread adoption of unsupervised feature learning and hybrid neural network architectures. Autoencoders and hierarchical auto-associative networks are increasingly employed to learn compact latent representations from unlabeled financial data, reducing dependence on manual feature engineering. These learned representations are frequently combined with convolutional neural networks, polynomial feature transformations, and attention mechanisms to capture high-order feature interactions and enhance predictive performance. Such hybrid architectures demonstrate greater flexibility in modeling complex financial behavior while maintaining computational efficiency.

The reviewed studies also highlight advances in computational platforms and dataset utilization. GPU-accelerated training and modern deep learning frameworks have enabled the development of large-scale financial risk prediction models using extensive transaction and credit datasets. However, challenges such as class imbalance, limited public benchmark datasets, and model interpretability continue to restrict practical deployment. Future research should focus on developing standardized datasets, explainable deep learning techniques, and scalable architectures that provide reliable, transparent, and accurate financial risk assessment for real-world e-commerce applications.

Discussion

The reviewed studies demonstrate that hierarchical auto-associative polynomial convolutional neural network (HAPCNN) architectures have significantly advanced financial risk prediction for e-commerce enterprises. Unlike conventional statistical and machine learning approaches, these architectures effectively learn hierarchical feature representations from large-scale financial datasets, enabling accurate identification of credit risk, fraud, and merchant financial distress. Their ability to integrate convolutional feature extraction, auto-associative learning, and polynomial feature transformations provides improved representation of complex financial relationships. The consistent superiority of hierarchical deep learning models across diverse datasets suggests that financial risk is best characterized through multi-level feature learning rather than simple linear modeling.

Another important finding is the effectiveness of auto-associative learning in extracting meaningful latent representations from unlabeled financial data. By utilizing unsupervised pre-training, these models reduce dependence on manually engineered features while improving generalization on limited labeled datasets. Polynomial feature transformation further enhances prediction by modeling higher-order interactions among financial variables that traditional approaches frequently overlook. Together, these techniques improve the ability of deep learning models to identify subtle financial patterns associated with default risk, fraudulent transactions, and operational instability. Consequently, HAPCNN architectures provide a flexible and scalable framework capable of adapting to the increasingly complex data environments of modern e-commerce platforms.

Despite these advantages, several challenges remain before widespread industrial adoption can be achieved. Model interpretability continues to be a critical concern in regulated financial systems, where transparent explanations are required for automated decisions. Additionally, class imbalance, evolving transaction behavior, distributional shifts, and high computational requirements affect long-term model reliability. Future research should focus on explainable artificial intelligence, lightweight model optimization, continual learning, and robust domain adaptation techniques. Addressing these challenges will improve the practical deployment of HAPCNN-based financial risk prediction systems across diverse e-commerce and fintech applications.

Conclusion

This survey presents a comprehensive review of hierarchical auto-associative polynomial convolutional neural network (HAPCNN) architectures for e-commerce financial risk prediction. The reviewed studies demonstrate a clear evolution from traditional statistical techniques to advanced deep learning frameworks capable of learning hierarchical representations from large-scale financial data. By integrating convolutional feature extraction, auto-associative learning, and polynomial feature transformations, these architectures achieve superior predictive performance for tasks such as credit risk assessment, fraud detection, and merchant financial analysis. The findings confirm that hierarchical deep learning provides an effective framework for modeling the complex and nonlinear relationships present in modern e-commerce ecosystems.

The survey further highlights the importance of unsupervised feature learning, higher-order interaction modeling, and hybrid neural architectures in improving prediction accuracy and robustness. Despite these advances, challenges related to model interpretability, computational complexity, data imbalance, and changing financial environments continue to limit practical deployment. Future research should focus on explainable artificial intelligence, federated learning, graph neural networks, and multimodal financial data integration to enhance model transparency and adaptability.

Overall, HAPCNN-based financial risk prediction represents a promising direction for next-generation fintech applications. Continued innovation in efficient, scalable, and interpretable deep learning models will support more reliable financial decision-making and strengthen the security and sustainability of global e-commerce ecosystems.

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