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A Novel Full-Chain Loop Tracking Auditing Framework for Obtaining Audit Evidence With Reasonable Assurance

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ABSTRACT

As an attestation engagement, auditing is required to provide reasonable assurance for its conclusions. Traditional auditing has limited capacity to handle unstructured data and is usually based on audit sampling techniques, which can lead to the neglect of important audit evidence during the auditing process and result in a higher audit risk, making the assurance level uncontrollably guaranteed. Meanwhile, the nature of attestation risk, which is characterised by multi-factor triggering chain transmission and time evolution, brings difficulties to the acquisition of critical audit evidence. Therefore, this paper realizes the Full-chain Loop Tracking Audit through the business cycle audit process of 'Obtaining Evidence of Internal Sequential Timing Audit—Obtaining Evidence of Horizontal Expansion of Audit Matters—Penetrating the Multi-Dimensional Evidence Association Rules—Achieving the Anchor Point at The Reasonable Assurance Level'. This is called the Full-chain Loop Tracking Auditing framework (FcLTA framework). Firstly, 'Obtaining Evidence of Internal Sequential Timing Audit' is a process of identifying and obtaining abnormal trends in accounting book facts. This process obtains 'Time Series Audit Evidence' by embedding the time characteristics of audit evidence in the risk feature vector within the table. Secondly, 'Obtaining Evidence of Horizontal Expansion of Audit Matters' is a 'Triangular Verification', system constructed by integrating financial, business and public opinion data. This process provides 'Horizontal Expansion Audit Evidence' by identifying isolated risk signals in financial information to address issues such as discrepancies between accounts and reality and performance whitewashing. Thirdly, 'Penetrating the Multi-Dimensional Evidence Association Rules' is a process of integrating audit evidence and resolving conflicts. This process generates 'Multi-Dimensional Penetration Audit Evidence Chain' by constructing a high-order association across modalities and dimensions for verifying risks. Finally, 'Achieving the Anchor Point at The Reasonable Assurance Level' is a testing process for detecting risks with the goal of obtaining high-level assurance of audit evidence. It mainly includes two processes: predicting the level of audit assurance and determining whether to continue the audit. This paper has implemented the full-chain circular tracking audit through the FcLTA framework, and the generated audit evidence can meet the high-level assurance requirements of the attestation engagements, reducing the risk of audit failure.

1 | Introduction

Auditing standards (such as ISA 200 [1] and PCAOB AS 1105 [2]) clearly define the auditing objective as providing reasonable assurance, rather than absolute assurance. They require that the audit risk (i.e., the risk of issuing an incorrect opinion) be controlled within 5%. This threshold is the foundation of auditing value. The loss of control over the level of auditing assurance will directly lead to an audit failure. For example, in

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2020, Ernst & Young's audit failure of Luckin Coffee, the risk value was far beyond 5% [3]. The uncontrolled deterioration of the assurance level is the ultimate manifestation of technical flaws (such as the breakdown of the evidence chain), and it is also the starting point of the collapse of market trust.

The current auditing model is a waterfall-style auditing approach. During the waterfall-style auditing process, all requirements are clearly described and strictly followed according to the predetermined plan. The quality of the plan largely determines the outcome. The process is relatively fixed, and the auditing results are submitted only at the final stage [4]. Furthermore, in the actual auditing process, the collection of audit evidence follows a template and a single-process cyclical thinking approach, without fully implementing risk-oriented thinking. Auditors are confined to the cycle they are responsible for and rigidly apply the template to implement audit procedures and collect and organise audit evidence, focusing only on self-consistency within the single-process cycle rather than overall and internal–external consistency [5]. They ignore the interrelationships of evidence between single-process cycles (such as the sales and collection cycle and the inventory management cycle) and the interaction with external environmental evidence (such as the recognition of revenue not only requires confirming the authenticity of the customer, but also needs to pay attention to the real demand of the industry and the market capacity). This auditing method does not truly follow the repeated process of collecting evidence risk assessment–re-collecting evidence–re-risking assessment. There is a break between evidence and risk assessment, and a complete evidence chain and closed-loop thinking cannot be formed. This article, from the perspective of auditing practice, traces the logical chain of audit documentation and, based on the 'data acquisition–logical construction–goal achievement' risk closed-loop control logic, designs the full-chain iterative tracking process of evidence identification–multidimensional penetration–anchor point achievement for audit evidence. However, during the implementation process, the following difficulties exist:

Q1: It is 'difficult to obtain' full-chain audit evidence. Audit evidence is the core foundation of the five elements of auditing. Audit evidence includes structured data (such as financial statements), unstructured data (such as contract texts and public announcements) and other different modalities of data. The data structures of different modalities vary greatly, and there is a lack of a unified processing framework. Moreover, external data (such as industry reports and public opinions on social media) are disconnected from the enterprise's internal data and are difficult to integrate.

Q2: Multidimensional evidence association is 'difficult to penetrate'. The traditional rules for mining the association of audit evidence rely on the professional judgement of auditors. Fragmented evidence makes it difficult to restore the complete risk transmission chain, and the complex network between evidence nodes is also difficult to be modelled automatically. The existing auditing tools have weak capabilities for cross-modal association analysis. The implicit association across data dimensions (such as finance–business–public opinion) is difficult to penetrate and extract, and the association between different modal data is difficult to be directly captured.

Q3: The audit guarantee is 'difficult to collapse'. The essence of 'reasonable assurance' in auditing standards is risk anchoring (such as ISA 200 requires 'to reduce risks to an acceptable low level'), but the multi-factor triggering, chain transmission and time evolution characteristics of verification risks lead to the degradation of the quantification and achievement of the guarantee level due to real-world constraints, resulting in the inability to control and ensure the level of audit guarantee.

The above three difficulties are also the key issues that need to be overcome in implementing the loop tracking audit in this article. Firstly, this article selects to use the time series data of all A-share listed enterprises in China from 2017 to 2024 (such as financial indicators, management discussion and analysis, etc.) and the horizontal expansion data of audit matters including three dimensions of finance, business and public opinion (such as shareholding distribution, industry benchmark data, rating information, etc.) to construct the full-chain loop tracking audit evidence pool. Regarding the process of obtaining evidence of internal sequential timing audit, in addition to the internal multimodal audit evidence, the incremental information such as the types of fraud and time points contained in various risk warnings of listed companies (such as those marked as ST, etc.) may also become important breakthrough points for the audit. This breakthrough point does not occur regularly but is a local characteristic. This article refers to it as time characteristic information. The accurate embedding of time characteristic information can directly enhance the efficiency of obtaining audit evidence. The temporal modelling of TCN can capture long-term and short-term dependencies through multi-scale receptive fields, and at the same time, alleviate the problem of gradient disappearance in deep networks, making it suitable for long sequence modelling [6]. Additionally, the residual connections in TCN can combine the time characteristic information with the high-level features of the internal indicators to embed local features. This undoubtedly provides a reliable solution for the model selection in this paper. However, although TCN supports parallel computing, the deep network still requires multiple rounds of convolution to transmit information, while a single-stage attention can capture the relationships of the entire sequence [7]. Therefore, this paper selects the combination of TCN and attention as an attempt to globally capture the audit evidence and embed the local time characteristic information. Regarding the process of obtaining evidence of horizontal expansion of audit matters, the biggest difference from the process of obtaining time series audit evidence is that there is no need to overly focus on temporal characteristics, but rather efforts should be made to construct a 'triangular verification' logical framework based on the mutual verification of finance, business and public opinion [8]. The relationship reasoning among multiple sources of audit evidence and the fusion of heterogeneous data are complex associations that traditional methods are difficult to handle. The advantage of GNN is that it models graph-structured data and can explicitly construct a heterogeneous graph among 'finance, business, and public opinion [9]'. Traditional methods may only be able to verify pairwise relationships, while GNN can simultaneously model the data flow of the three parties and identify key paths through node embedding and attention mechanisms [10]. Therefore, this paper chooses to use GNN attention to construct a three-dimensional verification graph as an attempt

to obtain expanded audit evidence. The acquisition of time series audit evidence within the table and the acquisition of evidence for horizontal expansion of audit matters are independent and carried out simultaneously [11], forming a dual-channel multi-scale GTCN-Attention audit evidence acquisition process. This step solves Q1 by first separating and processing data of different modalities and dimensions while focusing on the causal relationship between risks and evidence.

Secondly, the process of penetrating the multidimensional evidence association rule involves treating the risk feature vectors identified by the dual-channel multi-scale GTCN-Attention as nodes (including financial indicator nodes, text data nodes, off-balance sheet data nodes and time slice nodes), defining various horizontal relationships (trends of the same indicator across different years), vertical relationships (the association of indicators and off-balance sheet data within the same year), and conflicting relationships (connections between contradictory pieces of evidence) as edges [12]; binding all relevant evidence of the same risk event into a super-edge [13]; and applying the multi-supergraph attention mechanism combined with the causal graph model to form a higher order association. In this process, with the aim of obtaining three types of information outputs–'consistent audit evidence within the balance sheet and off-balance sheet', 'contradictory audit evidence within the balance sheet and off-balance sheet' and 'new critical audit evidence off-balance sheet'–targeted target identification is carried out to solve Q2.

Finally, the process of ensuring the achievement of the assurance level anchor point is a process of ensuring whether the obtained audit evidence can reach the low level of detection risk. This process not only includes the quantitative prediction process of the assurance level, but also includes the judgement process of whether to continue the cycle, that is, to achieve the high level of assurance of the audit evidence through two steps of quantification and achievement, in order to solve Q3. The specific approach is as follows: Firstly, the prediction of the assurance level is to use 'consistent audit evidence within the balance sheet and off-balance sheet' as the main information input into the MLP model for prediction to obtain the numerical value of the assurance level for this round. Secondly, the judgement of whether to continue the audit process is to determine whether to continue the audit based on the assurance level, to improve the audit evidence chain. The specific judgement rule is as follows: If the assurance level is below the anchor point, then re-perform the audit procedures of 'obtaining evidence of internal sequential timing audit–obtaining evidence of horizontal expansion of audit matters-penetrating the multi-dimensional evidence association rules–achieving the anchor point at the reasonable assurance level' by carrying out the multi-target association rule mining process, and repeat the cycle until the obtained audit evidence chain reaches the high assurance level. The final result shows that the designed iterative tracking audit process in this paper can not only solve the asynchronous problem of risk emergence and identification, but also effectively solve the technical complexity problem of the audit network, and can achieve the improvement of audit quality and the effect of iterative tracking audit. The main contributions of this paper are summarised as follows:

1. Based on the acquisition of dual-channel multi-scale GTCN-Attention audit evidence, data coverage has been achieved, solving the problem of 'difficulty in obtaining audit evidence'. The extraction of audit evidence utilises the dual-channel multi-scale GTCN-Attention to break through the limitations of traditional sampling auditing. Through relationship reasoning and the fusion of heterogeneous data, risk transmission analysis and graph anomaly detection are realized, thereby obtaining full-volume and multidimensional audit evidence.
2. Based on the association rule penetration technology of multiple hypergraphs, full logical association was achieved, solving the problem of 'difficulty in penetrating' in multi-dimensional evidence association. The association rules mining of audit evidence employed multi-hypergraph technology to construct a complex network model among audit evidence nodes and to mine implicit associations across data dimensions (such as finance–business–public opinion). By constructing verification graphs in time and relationship dimensions to restore the complete risk transmission chain, false transactions were discovered and the funds were traced in a closed loop.
3. Based on the anchor point achievement technology of MLP adversarial pruning, full risk quantification was achieved, solving the problem of 'difficulty in collapsing' in audit assurance. The steps for achieving the quantification of audit assurance level utilised the gradient importance pruning technology to eliminate redundant connection weights in MLP, retaining the key risk perception paths, and at the same time, setting the assurance level threshold switch to dynamically adjust the depth and breadth of the auditing procedures, avoiding excessive and insufficient auditing, and achieving controllable assurance level of auditing verification. The remaining part of this article is organised as follows: The second section introduces the current research status in accordance with the logical sequence of evidence acquisition in the risk-based approach; the third section presents the design of the FcLTA framework, along with the key functions and implementation processes of each component; the fourth section demonstrates the effectiveness of the experimental verification process and methods; the fifth section presents the experimental results; the sixth section is the conclusion and the future outlook of this research direction, and it also offers suggestions for future research.

2 | Related Works

2.1 | The Limitations of Traditional Audit Models and the Rise of Digital Audit

Auditing, as a core component of organizational governance and risk management, has long relied on traditional sampling methods to obtain audit evidence. However, with the increasing complexity of business operations and the explosive growth of data volume, the traditional auditing model is facing severe challenges. The inherent limitations of sampling audits, such as insufficient sample representativeness and difficulty in controlling non-sampling risks, often prevent the effective identification of concealed fraud and systemic risks. According to statistics, the current sampling audit has a fraud detection rate

of less than 30% [14]. Additionally, based on the statistics of the China Institute of Certified Public Accountants' (CICPA) quality inspection of accounting firms from 2011 to 2023, the average number of accounting firms punished by the CICPA each year is approximately 104, accounting for about 7.38% of the total inspected firms; the average number of certified public accountants punished each year is approximately 243; and the number of those punished each year is relatively stable and shows no decreasing trend. At the same time, the core pain points of 'difficult to obtain, difficult to penetrate, and difficult to implement' in auditing practice are becoming increasingly prominent: The acquisition of audit evidence is restricted by data silos and collection methods, the logical connections among multidimensional evidence are hard to penetrate, and there is a lack of effective means to quantify the degree of audit assurance.

Against this backdrop, the rise of AudTech offers new possibilities for the transformation of the auditing model. The introduction of emerging digital technologies such as big data, artificial intelligence and blockchain is reshaping the auditing process and organizational ecosystem. Research indicates that digital auditing is not merely a replacement of technical tools but also a methodological leap from 'experience-driven' to 'data-driven'. The supreme audit institutions worldwide have generally incorporated digital transformation into their strategic planning, promoting systematic improvements in auditing efficiency and quality by building data collection systems and analysis platforms. However, existing studies mostly focus on descriptive analyses at the technical application level, lacking systematic exploration of deeper issues such as 'how to intelligently infer auditing conclusions from data' and 'how to convert model outputs into levels of auditing assurance'.

2.2 | Key Technologies in Intelligent Audit: Evolution From Feature Perception to Relationship Inference and Risk Quantification

2.2.1 | Intelligent Perception Technology for Obtaining All Types of Evidence

In the field of obtaining audit evidence, the combination of temporal modelling and attention mechanisms has become a research hotspot. Early studies mainly used recurrent neural networks such as LSTM and GRU to detect anomalies in financial time series data but were limited by their serial computing structure and insufficient ability to capture long-range dependencies. Temporal convolutional networks (TCN) have demonstrated superior performance to recurrent networks in time series modelling due to their parallel computing capabilities and flexible receptive field design [15]. The introduction of the attention mechanism further enhances the model's ability to focus on key information. Wang et al. applied the multi-head self-attention network to accounting transaction anomaly detection. By capturing global dependencies and aggregating multi-perspective features, they significantly improved the ability to identify abnormal patterns [16]. Bineid et al. proposed the CADM model, which integrates LSTM with interpretability design, achieving an accuracy rate of over 95% in creative accounting detection [17]. However, existing research mostly focuses on a single data modality (such as financial data) and pays insufficient attention to the fusion modelling of 'financial-business-public opinion' and other multisource heterogeneous data. Although dual-channel or multi-scale architectures have been maturely applied in the field of image processing, they are still in the exploration stage in the acquisition of audit evidence.

2.2.2 | Graph and Hypergraph Mining Techniques for Multidimensional Association Penetration

The association rule mining technology has evolved from traditional methods such as those involving Apriori [18] and FP-growth [19] algorithms to graph mining. In typical scenarios of fraud detection and risk control, such as in financial risk management, traditional methods are limited by the item set enumeration approach and are unable to discover implicit correlations across dimensions and long paths [20]. The emergence of graph neural networks (GNNs) provides a new paradigm for modelling complex relationships: By modelling the audit objects as nodes and business transactions as edges, GNN can effectively capture abnormal patterns in the flow of funds and equity relationships. Aly et al. applied GNN to the subgraph anomaly detection of audit logs, by learning the behaviour patterns of node neighborhoods rather than fragile attribute features, significantly improving the robustness and interpret ability of the detection. As an extension of the ordinary graph, the hypergraph connects multiple nodes through hyper-edges to break through the limitations of the traditional knowledge graph triples in terms of expression ability [21]. The hypergraph attention network can respectively learn the features of different semantic subgraphs and capture the high-order neighbourhood information across entities through hypergraph convolution [22]. This characteristic makes it particularly suitable for scenarios involving cross-dimensional association mining—for instance, an abnormal transaction might involve financial data, business contracts and public opinion information. Ordinary binary edges are insufficient to fully represent this multi-dimensional relationship structure. However, the application of hypergraphs in the field of auditing is still in its infancy. Current research mainly focuses on social network analysis and recommendation systems, and there is still room for further development in cross-modal hypergraph modelling in the auditing context.

2.2.3 | Towards the Quantitative Interpretation Ability of Audit Assurance and Pruning Techniques

The deep learning models represented by BERT base have demonstrated strong semantic understanding potential in auditing evidence mining, but their high computational costs severely restrict their large-scale application in auditing practice. To break through the key bottleneck between model performance and deployment efficiency in auditing scenarios, pruning technology, as the core means of model compression, has shown new application value in the field of model interpret ability: The retained key paths can be regarded as the 'decision framework' of the model [23], providing an entry point for understanding the reasoning logic of the model. Neural network pruning technology was initially used for model compression and acceleration, reducing computational complexity by removing redundant connection weights. The introduction of adversarial training further enhances the model's robustness

against noisy data and malicious perturbations, which is of particular significance in auditing scenarios—the audited entity may have deliberately modified the data. The research on the application of explainable artificial intelligence (XAI) in the field of auditing is increasing. Methods such as LIME and SHAP have been attempted to explain abnormal detection results, but their outputs are mostly rankings of feature importance, which are difficult to establish a direct mapping with the concepts like 'degree of assurance' and 'risk of material misstatement' in auditing standards. The algorithmic biases and black box issues brought about by technological application may undermine the objectivity and transparency of auditing. How to calibrate the model outputs to an acceptable confidence level in auditing practice and achieve quantitative control over the degree of assurance remains an urgent problem to be solved.

2.3 | Review of Existing Research and Positioning of This Study

Looking at the above literature, the current research has made significant progress in promoting the digital transformation of auditing. However, there are still some shortcomings: Firstly, the problem of fragmented technology is prominent. In recent years, although the development of auditing intelligent technologies has improved auditing efficiency to a certain extent, it has overlooked the issue that fragmented audit evidence and excessive reliance on previous data may lead to audit blind spots. For example, in the integration of diverse heterogeneous data, auditors automatically collect financial and business data through RPA (Robot Process Automation) and IoT sensors [24] and use OCR (document recognition) and NLP (natural language processing) [25] technologies to process unstructured data; however, the evidence obtained through these intelligent auditing technologies is still fragmented, making it difficult to restore the complete fraud (Fraud) chain and being susceptible to the influence of previous audit evidence. Current research mostly focuses on a single technical aspect: either concentrating on the improvement of anomaly detection algorithms, or devoting to the mining of association rules, or exploring the implementation of model explainability, lacking a systematic framework that integrates 'evidence acquisition—association penetration—risk quantification' into an end-to-end audit evidence chain. Secondly, the depth of cross-dimensional association mining is insufficient. Most existing graph methods are of the 'single graph + homogeneous relationship' modelling type, for which it is difficult to handle the complex associations between multidimensional heterogeneous data such as financial, business and public opinion. The business activities of modern enterprises not only involve structured financial data but also include unstructured business data and external public opinion information. Auditing needs to integrate financial, business and public opinion data, essentially building a 'triangular verification' system [26]: (1) linking financial and business data to discover 'account and reality discrepancy' issues, (2) combining financial and public opinion data to identify off-balance sheet risks and (3) cross-linking business and public opinion data: warning of 'performance washing' issues (such as sudden changes in the auditing firm before the release of the annual report) [27]. The relationships between audit evidence are intricate, and traditional auditing exploration of multi-modal audit evidence has been unable to meet the requirements of high assurance (Assurance). The introduction of hypergraph technology provides a theoretical possibility to solve this problem, but the application research in auditing scenarios is still a blank.

In response to the above research gaps, this paper proposes the FcLTA (Full-coverage logical penetration Technology for Audit) framework, achieving breakthroughs in the following three aspects: Firstly, the dual-channel multi-scale GTCN-Attention model is adopted. The advantage of using dual channels is that each channel can have its own customised attention mechanism, enabling more precise extraction of specific types of features [28], and thus achieving intelligent acquisition of all-dimensional multidimensional audit evidence and heterogeneous data fusion. Secondly, a multi-supergraph association rule penetration technology is constructed. Different from ordinary graph structures, supergraphs can connect multiple entity nodes through a single super edge and are naturally suitable for expressing the 'many-to-many' capital circulation chains, cross-entity interest transfer networks and implicit correlations of multidimensional abnormal patterns in the audit scenario [29], completing the complex network modelling and implicit correlation mining of cross-dimensional evidence nodes. Thirdly, an anchor point achievement technology based on MLP adversarial pruning is designed. This paper introduces adversarial learning mechanisms and structural self-distillation strategies to achieve compact compression of the MLP model and enhancement of its discriminative ability without the need for explicit graph structures, resolving the fundamental contradiction between efficiency and structure dependence of GNN in practical deployment, and providing a feasible path for achieving quantifiable controllability of the guarantee level [30]. The integration of these three technologies forms a complete closed loop of 'evidence acquisition—association penetration—risk quantification', aiming to provide a practical technical path for intelligent auditing to move from 'abnormal detection' to 'conclusion formation'.

3 | Main Work

Overall architecture: The proposed Full-chain Loop Tracking Audit framework (FcLTA framework) in this paper is a complete system that integrates multimodal data perception, audit evidence chain construction and assurance level attainment. Its core architecture consists of three modules that work collaboratively, achieving the loop tracking process from raw data input to the formation of high-quality audit conclusions. The overall framework is shown in Figure 1. The modules of this framework are connected in series through feature vector pipelines, forming a closed loop of 'time series perception → horizontal expansion → hypergraph reasoning → anchor point attainment'. Each iteration generates three types of audit evidence (consistent type/contradictory type/new type) and feeds them back to the audit evidence acquisition module to optimise feature extraction. Each iteration is equivalent to implementing one round of supplementary audit procedures. This framework can increase the detection rate of high-risk enterprises and shorten the average audit cycle, and all conclusions met the traceability and reasonable assurance requirements of PCAOB's 2200 standard. Next, this section will focus on the design principles and implementation processes of each module.

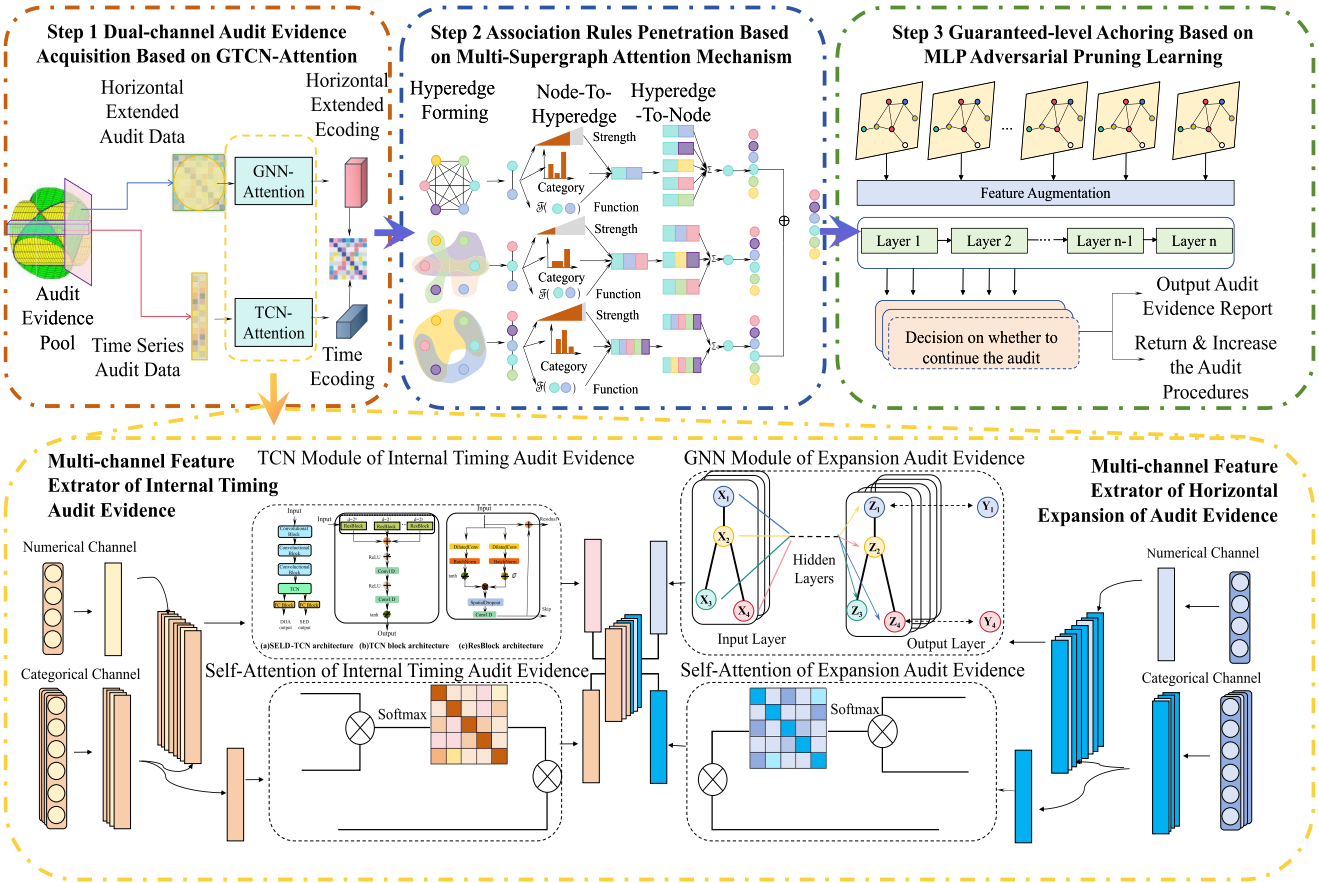


FIGURE 1 | FcLTA framework.

3.1 | Dual-Channel Audit Evidence Acquisition Based on GTCN-Attention

The dual-channel acquisition of audit evidence based on GTCN-Attention involves two independent auditing processes: internal time series audit evidence obtained based on TCN-Attention and horizontal expansion audit evidence obtained based on GNN attention. Among them, the in-table time series audit evidence can reveal abnormal trends, while the horizontal expansion audit evidence can identify isolated risk points based on off-table data. Because the audit evidence identified by the two may be conflicting, and this conflict itself can also serve as audit evidence, this paper must separately identify the time series audit evidence and the horizontal expansion audit evidence. This separated yet collaborative architectural design not only conforms to the 'multi-party verification' principle of audit evidence but also enables the discovery of complex risk patterns that traditional methods may fail to identify through mutual verification of the evidence. In the following section, this paper will specifically introduce the acquisition process of in-table time series audit evidence and the acquisition process of horizontal expansion audit evidence.

3.1.1 | Internal Time Series Audit Evidence Obtained Based on TCN-Attention

TCN-Attention for internal time series audit evidence acquisition: Audit data are essentially time series data, with events preceding and following each other having causal relationships. Traditional audit analysis often treats evidence as independent static data points, ignoring patterns in the temporal dimension. TCN's time series modelling can capture long-term and short-term dependencies through multi-scale receptive fields, while alleviating the problem of gradient disappearance in deep networks, and is suitable for long sequence modelling. The multi-scale design of TCN is achieved through parallel convolutional layers with different expansion coefficients, simultaneously capturing time features at different granularities. However, not all evidence at different time steps contributes equally to the audit conclusion. Therefore, this paper selects Attention to automatically learn the importance scores of time steps, highlighting abnormal periods and locating risk time points through attention weights. The specific implementation mechanism for obtaining time series audit evidence within the table is as follows: At the data input layer, there are mainly three types of data: financial indicators, financial texts and time characteristic information Financial indicators are annual structured data, mainly consisting of numerical indicators, which need to be standardized to form a time series matrix; financial texts are Chinese unstructured texts, which need to be first tokenised; then, use Macbert for word vector embedding to generate text feature vectors [31]; and then, form a time series matrix based on time steps and the number of text features [32]; time characteristic information is only available for some years, so it is nonannual sparse data. The main method for converting such data into vectors is to convert it into binary features, such as for

the ST marker, 1 = present, and 0 = absent, and then, align according to the time steps to form local feature vectors. In the feature extraction layer, a time series feature extraction module and a global feature enhancement module are set up. The time series feature extraction module sets up parallel TCN to process the temporal features of financial indicators and financial texts, respectively. During the specific operation process, the causal convolution module of the TCN structure captures temporal dependencies, and the expansion rate increases with the increase of the number of layers, ensuring the coverage of the entire period from 2017 to 2024; in the skip connections of each residual block, the incremental information needs to be added to the convolution output of the current time step to achieve the injection of coefficient features. The design mechanism of this part is as follows:

$$h_t = \sigma(W * x_{t-k:t} + b). \tag{1}$$

$x_{t-k:t}$ indicates financial data within the time window from $t-k$ to t. $*$ is Dilated Causal Convolution. By adjusting the dilation rate, the dependencies over different time spans can be captured. W is the convolution kernel weight. b is the bias term. h_t is the hidden state at time step t. σ is the RELU activation function, which is used to introduce nonlinearity. Additionally, the incremental information embedding formula is

$$h_l' = h_l + W_m. \tag{2}$$

Among them, h_l' is the hidden state of the l layer of TCN. m is a binary or numeric ST tag. W_m performs a linear transformation on the m vector to make its dimension the same as that of h_l and then adds them directly through residual connections. This step uses sparse labels as local enhancement signals to force the model to pay attention to the influence of time characteristic information. In this paper, financial indicators and the extracted temporal features from financial texts are concatenated, and then, Attention is used for global dependency modelling. This step requires calculating the association weights between each time step and other time steps and finally obtaining the weighted fused global feature vector [33]. The main formula is as follows (Table 1):

$$\alpha_t = \mathrm{softmax}\left(v^\top \tanh(W_a h_t + b_a)\right), \tag{3}$$

TABLE 1 | Notation used in the attention mechanism.

Symbol	Dimension	Meaning
$\mathbf{h}_t$	$\mathbb{R}^{d_h}$	Hidden state output of TCN at time step t
$\mathbf{W}_a$	$\mathbb{R}^{d_a \times d_h}$	Attention mapping weight matrix
$\mathbf{b}_a$	$\mathbb{R}^{d_a}$	Attention mapping bias term
$\tanh(\cdot)$	$\mathbb{R}^{d_a}$	Element-wise activation function and output dimension unchanged
$\mathbf{v}$	$\mathbb{R}^{d_a}$	Learnable context vector (projects features to scalar)
$\mathbf{v}^\top$	$\mathbb{R}^{1 \times d_a}$	Transpose of the context vector
α_t	$\mathbb{R}$	Attention weight (scalar) at time step t

$$s = \sum_{t=1}^{T} \alpha_t h_t. \tag{4}$$

h_t contains all the time step outputs (length T) from TCN. W_a and b_a map h_t to the attention space. v is the attention weight vector. tanh is the activation function that enhances nonlinearity. Softmax ensures that the weights are normalised. s is the weighted global temporal feature, reflecting the contribution of each time step to the risk [34]. The implementation mechanism diagram of this part is as follows (Figure 2).The structural design of this part mainly has three key points: (1) Focus on capturing temporal dependencies: Through the causal convolution and dilated convolution of TCN, identify the temporal trends of financial indicators and text. (2) Local feature injection: Embed incremental information such as ST tags through residual connections into TCN, avoiding the sparse information from being masked by temporal smoothing. (3) Global association modelling: The Attention mechanism focuses on the dependencies at key time points, compensating for the limitations of the local receptive field of TCN. This structure retains the dynamic characteristics of time series, and through the Attention mechanism and residual connections, strengthens the influence of key information on identifying time series audit evidence and is suitable for processing imbalanced time series data [35] (Algorithm 1).

ALGORITHM 1 | Pseudo-code for TCN-Attention in Internal Timing Audit Evidence Acquisition.

```
Class TCN_Attention (nn.Module)
    Constructor __init__(input_dim)
        {TCN-Attention for internal timing audit evidence acquisition}
        {1. Temporal Convolution sNetwork (TCN) layers}
        self.tcn ← nn.Sequential(
            nn.Conv1d(input_dim, hidden_dim, kernel_size, padding = causal_padding),
            nn.ReLU(),
            nn.Conv1d(hidden_dim, hidden_dim, kernel_size, dilation = dilation_rate),
            nn.ReLU())
        {Causal convolution + dilated convolution (TCN core)}
        {2. Multi-head attention mechanism}
        self.query ← nn.Linear(hidden_dim, attn_dim)
        self.key ← nn.Linear(hidden_dim, attn_dim)
        self.value ← nn.Linear(hidden_dim, attn_dim)
        {3. Output layer for audit evidence weighting}
        self.output ← nn.Linear(attn_dim, 1)
    Method forward(x)
        {Input: } x ∈ ℝ^(batch × seq_len × input_dim) (audit time-series features)
        {Step 1: TCN processing (dimension adjustment)}
        tcn_out ← self.tcn(x_{1,2}^T)._{1,2}^T
        {Output: } tcn_out ∈ ℝ^(batch × seq_len × hidden_dim)
        {Step 2: Scaled dot-product attention calculation}
        Q ← self.query(tcn_out) {Query matrix}
```

24: $K \leftarrow$ self.key(tcn_out) {Key matrix}
25: $V \leftarrow$ self.value(tcn_out) {Value matrix}
26: attn_weights $\leftarrow$ softmax$\left(\frac{QK^{\intercal}}{\sqrt{\text{attn_dim}}}\right)$
27: attn_out $\leftarrow$ attn_weights $\cdot V$ {Weighted attention aggregation}
28: {Step 3: Output audit evidence weights}
29: return self.output(attn_out)
30: {Output: } $\in \mathbb{R}^{\text{batch} \times \text{seq_len} \times 1}$ (timing evidence weights)

3.1.2 | *Horizontal Expansion Audit Evidence Obtained Based on GNN Attention*

GNN attention for horizontal expansion audit evidence acquisition: For the cross-sectional expansion data of audit matters, the cross-sectional expansion data pool constructed by financial, business and public opinion data is essentially heterogeneous, multisource and associated [36]. Traditional methods are difficult to discover cross-domain associations of fraud. This paper chooses to model heterogeneous data through GNN to associate the hidden relationships between nodes. Unstructured information in public opinion (such as keywords like 'supply chain disruption') can be propagated to the financial nodes through GNN [37], triggering anomaly detection. Attention can enhance the focusing ability of key associations, allocate the importance of features and help identify the dominant audit evidence.

Firstly, regarding the construction of heterogeneous data graphs, this paper defines the enterprise entity graph as $G = (V, E)$. This entity diagram includes three types of nodes: financial, business and public opinion. (1) Financial nodes v_f: financial indicator vector $x_f \in \mathbb{R}^{d_f}$. (2) Business Node: v_b: financial indicator vector $x_b \in \mathbb{R}^{d_b}$. (3) Public opinion nodes v_s: financial indicator vector $x_s \in \mathbb{R}^{d_s}$.

Secondly, edge e_{ij} represents the relationship between nodes, and the weights can be learned or predefined. Then, the risk signals are transmitted through graph convolution [38]. The formula for GNN to transmit messages is as follows:

$$h_i^{(l+1)} = \sigma\left(\sum_{j \in N(i)} \alpha_{ij} W^{(l)} h_j^{(l)}\right). \tag{5}$$

$h_j^{(l)}$: the embedding of node i at the l-th layer. α_{ij}: the attention weight of edge e_{ij}. $N(i)$: the set of neighbours of node i. Finally, this paper uses Attention to strengthen the characteristics of the dominant risk factors and filter out the noise. The formula for calculating the weights of Attention is as follows:

$$\alpha_{ij} = \text{softmax}\left(\text{LeakyReLU}\left(a^{\intercal}\left[Wh_i \| Wh_j\right]\right)\right). \tag{6}$$

a: a learnable parameter vector. This process maps financial, business and public opinion data into nodes of a heterogeneous

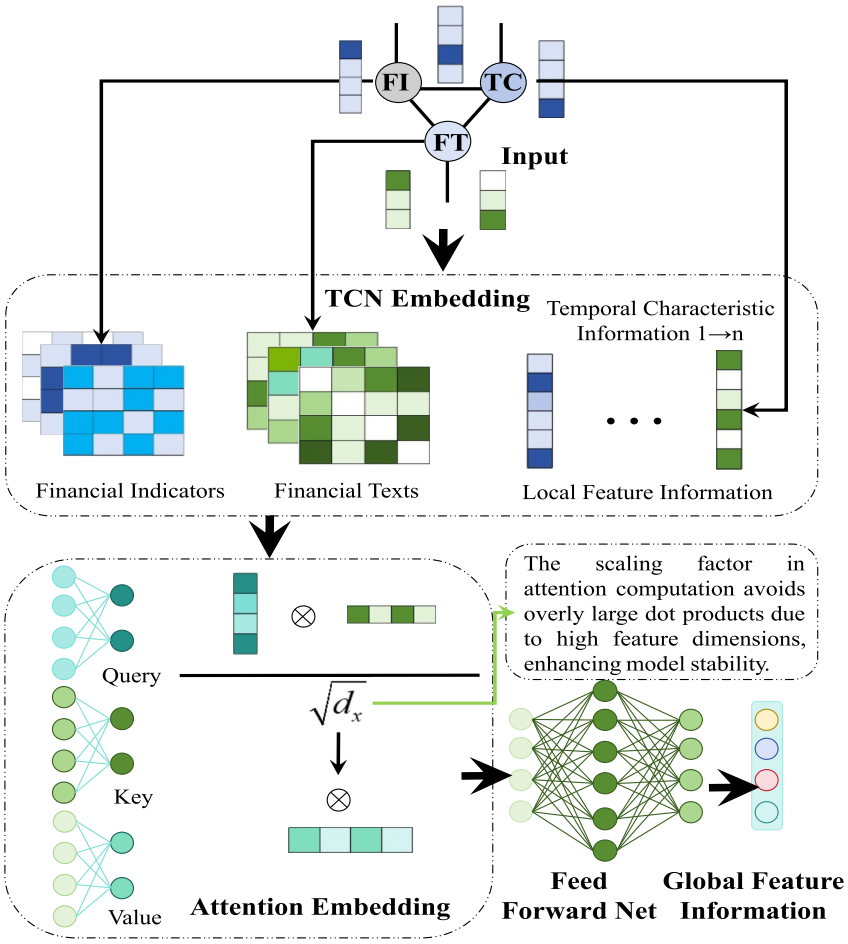


FIGURE 2 | Acquisition of time series audit evidence within the table.

graph, with edges representing potential relationships. The information of neighbouring nodes is dynamically weighted through an attention mechanism (such as GAT). The implementation mechanism diagram of this part is as follows: The structural design of this part mainly has three key points: (1) Heterogeneous association modelling of the triangular verification system: The three-dimensional data of finance, business and public opinion are essentially interrelated carriers of risk signals, but there are naturally 'data islands'. This paper uses GNN to break through data barriers and capture cross-domain hidden relationships. (2) The propagation process of risk signals: This paper uses graph convolution to allow key information to 'flow' to the risk association nodes. (3) Focusing on key evidence: using Attention to strengthen the features of the dominant risk factors and filter out noise [39]. Module output and feature alignment global pooling is performed on all nodes in composition of a picture to obtain the horizontal expansion risk vector $F^h \in \mathbb{R}^{256}$, which is standardized and coordinated in dimension and semantics with $F^t \in \mathbb{R}^{256}$ output by TCN-Attention. This completes the unified alignment of dual-channel evidence features and provides compatible feature inputs for the subsequent hypergraph association rule penetration (Figure 3).

ALGORITHM 2 | Pseudo-code for GNN attention Horizontal Expansion of Audit Evidence Acquisition.

```
Class GNNAttentionAudit
    Constructor __init__(num_nodes, node_feature_dim, time_ steps)
        {GNN attention for audit evidence horizontal expansion}
        self.node_embeddings ← nn.Embedding (num_nodes, node_feature_dim)
        self.temporal_conv ← nn.ModuleList ([TemporalConv1D(node_feature_dim) | 1 ≤ t ≤ time_ steps])
        self.attention ← MultiHeadAttention(node_ feature_dim)
        self.gnn_layers ← nn.ModuleList([GATConv(node_ feature_dim, node_feature_dim) | 1 ≤ l ≤ 2])
    Method forward(audit_logs, temporal_edges)
        {Forward pass for evidence acquisition expansion}
        {Step 1: Temporal feature extraction from audit logs}
        node_features ← self.node_embeddings (audit_logs.node_ids)
        temporal_features ← {conv(node_features) | conv ∈ self.temporal_conv}
        {Step 2: Cross-time attention fusion}
        time_aware_features ← self.attention (temporal_features)
        {Step 3: Graph propagation with GAT layers}
        for layer ∈ self.gnn_layers do
            time_aware_features ← layer (time_aware_features, temporal_edges)
            time_aware_features ← ReLU (time_aware_features)
        end for
        {Step 4: Anomaly scoring for audit evidence}
        anomaly_scores ← self.evidence_scorer (time_aware_features)
        return anomaly_scores
```

Preliminary classification of dual-channel evidence similarity calculation is carried out between the aligned F^t and F^h to initially identify three types of evidence: consistent $(sim(F^t, F^h) \geq 0.7)$, contradictory $(sim(F^t, F^h) < 0.3)$ and incremental $(0.3 \leq sim(F^t, F^h) \leq 0.7)$ (Algorithm 2).

3.2 | Association Rule Penetration Based on Multi-Hypergraph Attention Mechanism

Multi-hypergraph attention for audit evidence fusion and conflict penetration: For the integration of multidimensional audit risk characteristics, risk transmission exhibits temporal and spatial coupling. Fraudsters often use asymmetric information to hide their tracks, and internal anomalies often lag behind external risk events. Therefore, multisource collaboration is necessary, which conforms to the 'multi-party verification' principle of audit evidence and enables the discovery of complex risk patterns that traditional methods cannot identify through mutual verification of evidence [40]. Many cases of discrepancies between accounts and reality in audits rely on long-tail associations of weak signals (such as occasional public opinion of an edge supplier and financial anomalies). Attention can capture sparse associations by calculating feature similarity. Additionally, it can dynamically quantify the importance of different evidence and generate interpretable association logic, which has significant advantages over traditional auditing methods. Audit basis for identifying super-edges can be found in Tables 2–5.

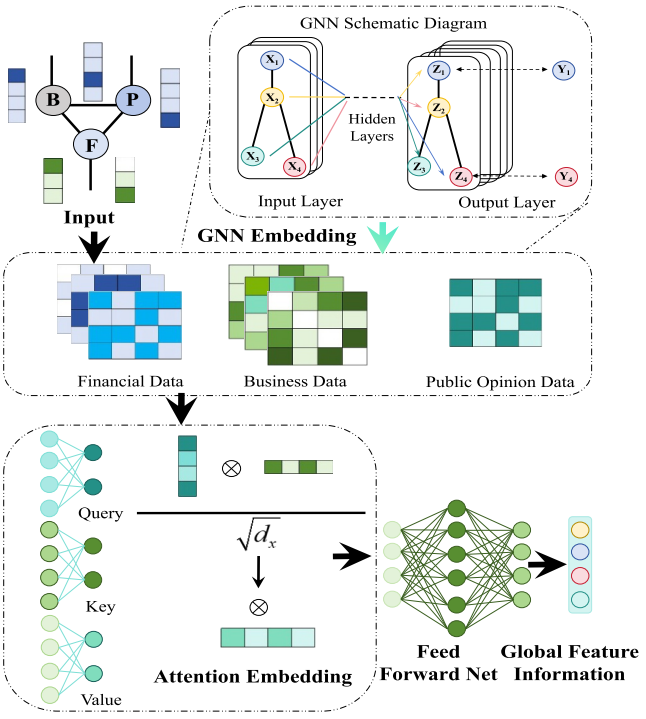


FIGURE 3 | Acquisition of horizontal expansion audit evidence.

TABLE 2 | The logical framework for mining the association rules of audit evidence based on auditing practice.

Main categories	Logical hyper-edge	Explanation and basis
Macro–micro transmission effect	Industry policy tightening + surging investment real estate value	Explanation: The main business is depressed, but the company revalues assets such as office buildings to maintain profits and cover the shrinkage of core business. Basis: hypothesis of financial statement window dressing under main business hollowing out
	Regional epidemic lockdown + declining sales expenses	Explanation: logistics and offline stores were closed during the lockdown, but sales expenses dropped sharply (fixed costs such as rent should still exist with zero revenue), indicating possible prior false expense recognition and write-off during the period. Basis: hypothesis of operating environment cost rigidity
	Rising interest rates + interest income far exceeding expenditure	Explanation: under macrointerest rate hike, a manufacturing enterprise holds huge cash with interest income even exceeding loan interest, implying capital occupied by major shareholders and returned by borrowing at the end of the period. Basis: hypothesis of abnormal high deposits and loans (Kangdexin & Kangmei pharmaceutical model)
Fraud risk triangle	Frequent audit firm changes + accounting error corrections	Explanation: Frequent auditor replacement (refusal to issue unqualified opinions) and multiple financial statement revisions indicate poor financial data quality and obvious intention to cover up the truth. Basis: hypothesis of audit opinion shopping
	Declining industry average gross profit margin + enterprise's countercyclical rising gross profit margin	Explanation: The whole industry faces price wars and rising costs, but the enterprise's gross profit margin surges, usually meaning inflated revenue or hidden costs through related transactions. Basis: hypothesis of countercyclical financial beautification
	High proportion of major shareholder pledge + nonoperating capital outflow	Explanation: Major shareholders are short of funds (stock pledge) and a large amount of listed company capital flows out in the form of 'other receivables', a typical signal of capital occupation or interest transfer. Basis: hypothesis of tunnelling by major shareholders
	Surging overseas business revenue ratio + unsynced overseas freight/tariff growth	Explanation: The company claims a sharp increase in overseas sales, but customs data or logistics costs show no corresponding growth, indicating possible false overseas orders. Basis: hypothesis of cross-border logistics-revenue matching
	Collective reduction of executives' holdings + precise achievement of equity incentive exercise conditions	Explanation: Enterprise performance just meets the exercise conditions, followed by large-scale cash-out by executives, implying that performance is artificially manipulated for cash-out. Basis: hypothesis of precise achievement benefit realization
Book reality consistency conflict	Production capacity bottleneck + sharp growth of accounts receivable	Explanation: Factory equipment operates at full capacity, but financial statements show rapid revenue growth without new equipment, which is inconsistent with production logic. Basis: hypothesis of production capacity output matching

(Continues)

TABLE 2 | (Continued)

Main categories	Logical hyper-edge	Explanation and basis
	Sharp reduction in employee numbers + increase in accrued employee compensation	Explanation: Layoffs in business departments but increased accrued wages and bonuses in financial reports, a logical contradiction implying possible inflated liabilities or capital misappropriation. Basis: hypothesis of employee compensation synchronization
	Declining water and electricity consumption + rising industrial output value	Explanation: manufacturing enterprises have a sharp drop in water and electricity expenses but a surge in disclosed output value/sales volume, violating the law of conservation of mass. Basis: hypothesis of positive correlation between energy consumption and output
	Increasing inventory turnover days + decreasing accounts receivable turnover days	Explanation: inventory backlog but faster capital recovery, which is inconsistent with commercial logic and may mean beautified cash flow through relaxed credit policies or false transactions. Basis: hypothesis of working capital coordination
	Surging R&D capitalization rate + failure of new product launch	Explanation: The enterprise capitalises a large amount of R&D investment as intangible assets to beautify profits, but subsequent R&D project failure leads to zero asset value, implying profit adjustment. Basis: Hypothesis of asset recognition-economic benefit inflow

TABLE 3 | Rationale for ε value settings.

Range	Audit semantics	Interpretation
0.00–0.01	Normal measurement error	Financial statement rounding error ($\leq 1\%$)
0.01–0.05	Tolerable adjustment	Audit materiality level (3%–5%)
0.05–0.10	Significant misstatement risk	Exceeding audit materiality level
0.10–0.20	Fraudulent manipulation	Median of historical fraud cases

Consistent hyperedge: A combination of hypernodes that meet the audit hypothesis (such as 'financial indicator abnormality node + negative public opinion node' meeting the fraud risk hypothesis), bound as consistent audit evidence.

Conflict hyperedge: A combination of hypernodes that violate the audit hypothesis (such as 'sharp increase in business scale node + decline in financial revenue node' violating the book-reality consistency hypothesis), bound as conflicting audit evidence.

The mechanism for the specific implementation of the Association rule penetration is as follows:

Firstly, in this paper, the sequence and the extended features are selected as the nodes of the hypergraph, and the risk feature output by the TCN-Attention is set as $F_{TCN} = \{f_1, f_2, ..., f_m\}$. The features output by GNN attention are $F_{GNN} = \{g_1, g_2, ..., g_n\}$. The

TABLE 4 | Horizontal expansion data of audit matters.

Data type	Source	Key application
Equity/ governance structure	Wind/CSMAR database	Identifying hidden associations parties and co-controllers
Supply chain data	Disclosure of procurement/sales concentration and third-party platforms (such as Lianyi Rong)	Detecting cycles of transactions without substance
Public opinion data	Snowball/BBS Discussion, News Media (Caixin etc.)/ social media (Weibo/ WeChat official account)	Monitor negative public opinion incidents
Industry benchmark	Industry research report/Statistical data by industry category	Calculate the relative deviation of the audit evidence markers

set of supergraph nodes is $V = F_{\mathrm{TCN}} \cup F_{\mathrm{GNN}}$. This article constructs a super-edge based on audit assumptions: super-edge $e_k \subseteq V$ represents the association between features (Association), such as consistent hyperedges: $e_1 = \{f_1, g_2\}$ [41]. Conflict vertex: $e_2 = \{f_3, g_4\}$. Secondly, relevant evidence for each super-edge binding is obtained. Using a multilayer attention mechanism, the weights of node–super-edge–global are calculated: Node-level attention identifies key evidence, and super-edge-level

TABLE 5 | Settings for the ablation experiment.

Experimental group	Erosion module	Business meaning	Technical implementation
FcLTA	—	Full-chain Loop Tracking Audit	FcLTA
No-TCN	Remove multi-scale TCN—attention	Only using static financial indicators	Replace with simple moving average
No-GNN	Remove the space expansion evidence channel	Disable the GNN module	Ignoring the off-balance sheet association risk and relying solely on temporal characteristics
No hypergraph	Replace the multi-supertree with an ordinary tree	Unable to bind multiple-factor combined evidence	Split the super-edge into binary edges
No MLP	Use the original MLP	Assessment of the level of assurance for overfitting	Remove adversarial training and neuron pruning
Baseline	Traditional sampling audit method	Manual sampling and rule engine	Randomly select 30% of the vouchers and fixed rules (such as a warning when ROE is greater than 20%)

attention assesses (Assess) the strength of the risk combination. The specific formula for calculating the super-edge weights is as follows:

$$w_{e_k} = \text{softmax}\left(\alpha \cdot \text{Sim}\left(e_k\right) + (1-\alpha) \cdot \text{Rel}\left(e_k\right)\right). \tag{7}$$

$\text{Sim}\left(e_k\right)$: similarity of hyperedge features. $\text{Rel}\left(e_k\right)$: the correlation between characteristics and assurance levels. $\alpha \in [0, 1]$: balance consistency coefficient and reliability coefficient. Then, by updating the node features, the hyper-edge information is integrated. Each node forms a fused feature by aggregating the information of the hyper-edges it belongs to as follows:

$$h_v^{(t+1)} = \sigma\left(h_v^{(t)} + \sum_{e_k \in \mathcal{E}_v} w_{e_k} \cdot \text{MLP}\left(\sum_{u \in e_k, u \neq v} h_u^{(t)}\right)\right). \tag{8}$$

$h_v^{(t)}$: the feature of the node v at the t-th layer. Finally, for the fused features output by the hypergraph, calculate the global weight, focus on the core evidence, and form an evidence chain. The formula of the global fusion attention mechanism is as follows:

$$\beta_\gamma = \text{softmax}\left(\text{MLP}\left(h_\gamma^{(T)}\right) \cdot \text{Query}\right). \tag{9}$$

Query: query vector. Final evidence chain feature:

$$H = \sum_\gamma \beta_\gamma \cdot h_\gamma^{(T)}. \tag{10}$$

The penetration mechanism of association rules based on multiple hypergraphs is shown in Figure 4. The core logic of this part of the design is as follows: (1) Hypergraphs can model 'many-to-many' high-order relationships, which is suitable for integrating the dual-channel output of GTCN-Attention for risk features. (2) The attention mechanism module dynamically adjusts the weights. (3) The 'super edges' of hypergraphs can represent the logical relationships between risk features, and through feature propagation, scattered risk points can form structured evidence (Algorithm 3).

ALGORITHM 3 | Pseudo-code for Multi-Hypergraph-Attention in Audit Evidence Fusion and Conflict Penetration.

```
Class MultiHyperGAT (nn.Module)
    Constructor __init__(num_hypergraphs, node_dim, num_ heads)
        {Multi-hypergraph attention for audit evidence fusion}
        self.hyper_proj ← nn.ModuleList ([HyperGraphProj(node_dim) | 1 ≤ i ≤ num_hypergraphs])
        {Multi-supergraph parallel processing layer}
        self.cross_hyper_attn ← MultiHeadAttention (node_dim, num_heads)
        {Cross-supergraph attention fusion layer}
        self.conflict_detector ← nn.Sequential(
            nn.Linear(node_ dim, node_dim//2), nn.ReLU(), nn.Linear(node_dim//2, 1))
        {Conflict penetration detection module}
    Method forward(evidence_dict)
        {Forward pass for multi-hypergraph evidence fusion}
        hyper_embeddings ← ∅
        for i, (etype, (nodes, hyperedges)) ∈ enumerate (evidence_dict.items()) do
            {Step 1: Parallel encoding of multi-hypergraph evidence}
            h ← self.hyper_proj[i](nodes, hyperedges)
            hyper_embeddings.append(h)
        end for
        {Step 2: Cross-supergraph attention fusion}
        fused_evidence, attn_weights ← self.cross_hyper_attn(hyper_embeddings)
        {Step 3: Conflict penetration detection}
        conflict_scores ← self.conflict_detector (fused_evidence)
        return fused_evidence, attn_weights, conflict_scores
Class HyperGraphProj (nn.Module)
    Method forward(nodes, hyperedges)
```

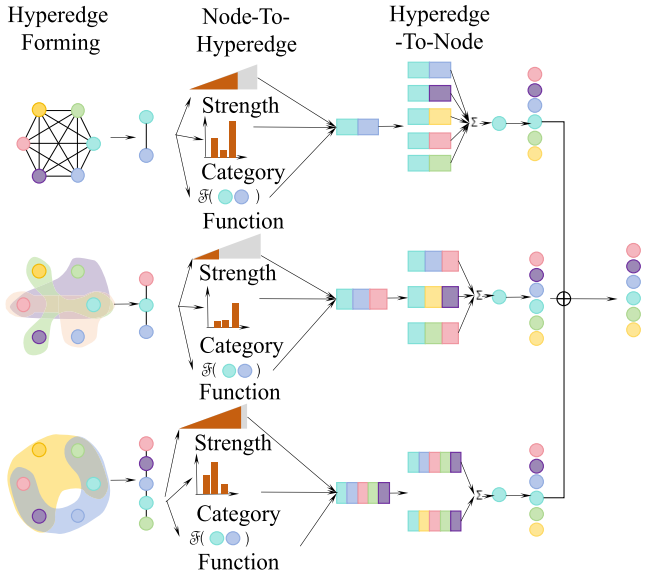


FIGURE 4 | Association rules penetration based on multiple hypergraphs.

{Hypergraph projection (simplified version)}
{Super-edge aggregation: }
$e \leftarrow \text{mean}(\{\text{nodes}[i] \mid i \in \text{hyperedges}\}, \text{dim} = 0)$
{Node update: aggregate hyperedge features for each node}
$v_{\text{new}} \leftarrow \text{mean}(\{e[j] \mid j \in v.\text{belonging_hyperedges}\}, \text{dim} = 0)$
return v_{new}

3.3 | Assurance-Level Anchoring Based on MLP Adversarial Pruning Learning

The process of achieving the assurance level anchor point is a process of ensuring whether the obtained audit evidence can reach the low level of detection risk. This process mainly consists of two parts: predicting the assurance level and determining whether to continue the iterative audit. These two parts are used to achieve the quantitative attainment of the assurance level. In the process of auditing risk detection, adversarial training helps to enhance the model's robustness against noise and unstable sampling in financial data, thereby better capturing stable and reliable risk signals. Structured pruning can effectively reduce the resource requirements for deployment by removing redundant model parameters [42]. Existing studies have demonstrated that on MLP-like architectures, 'masking/pruning' of inputs can alleviate overfitting. When considering robustness in pruning, the importance of model weights is estimated based on neural networks to induce the sparsity required for the pruning task. Adversarial training enhances the model's generalisation ability and anti-overfitting capability, while pruning effectively reduces the complexity of the model and retains the key features related to risks. This combination achieves a balance among robustness, efficiency and risk identification performance, which is particularly beneficial in practical auditing applications.

The auditing standards clearly define the auditing objective as providing reasonable assurance (Assurance). According to Equation (11), if auditors want to increase the level of auditing assurance (Assurance), they must reduce the level of auditing risk (Audit risk). And the level of auditing risk (Audit risk) depends on the risk of material misstatement and the detection risk (Detection risk) (as shown in Equation 12). The risk of material misstatement is fixed, so auditors must reduce the detection risk (Detection risk) by obtaining sufficient and appropriate audit evidence, thereby providing reasonable assurance (Assurance) for the overall audit conclusion of the financial statements.

$$S + R = 100\%. \tag{11}$$

$$P \times B = T. \tag{12}$$

S represents the level of audit assurance; R represents the risk level; P represents the risk of material misstatement; B represents the inspection risk; and T represents the audit risk.

3.3.1 | *MLP Against Pruning Ensures Level Prediction*

The prediction of audit assurance level is a quantitative assessment process of checking risk, which calculates the contribution of the current evidence set to reducing the checking risk in real time. This paper takes 'consistent audit evidence within the balance sheet and off-balance sheet' as the main information input to the MLP adversarial pruning model for prediction to obtain the audit assurance level value of this round. The MLP adversarial pruning model targets the fully connected layer after the output of the hypergraph attention. The hypergraph has completed feature fusion and evidence chain construction and outputs the simplified global risk features. MLP acts as the 'prediction head', pruning its redundant neurons or connections, which can significantly reduce complexity while retaining key risk signals [43]. The most important aspect of the MLP adversarial pruning process is the design of adversarial pruning.

3.3.2 | *The Judgement on Whether to Continue the Cycle of Audits*

Determining whether to continue the audit is part of the decision-making control process. It is based on the difference between the predicted value and the target value to decide whether to add audit procedures. If the assurance level fails to meet the standard, it indicates the existence of unclosed high-risk nodes, and thus, the cycle needs to continue; if the assurance level is met, it means that all key risks have been covered, and the remaining risks are below the tolerable level, and the cycle terminates. The rule for continuing the cycle is that if the assurance level is lower than the audit importance level, then carry out the re-execution of the 'obtaining evidence of internal sequential timing audit– obtaining evidence of horizontal expansion of audit matters-penetrating the multi-dimensional evidence association rules–achieving the anchor point at the reasonable assurance level' audit procedures, and repeat this process until the obtained audit evidence chain reaches the high assurance level.

The specific implementation mechanism of the assurance level anchoring process is as follows:

First, input the hypergraph features, and initialise the MLP. The global risk feature output by the hypergraph attention is $H \in \mathbb{R}^d$ (where d is the feature dimension), and the MLP contains 2 hidden layers with the structure as follows:

The first hidden layer, with a dimension of d_1:

$$z_1 = \sigma(W_1 H + b_1). \tag{13}$$

The second hidden layer, with a dimension of d_2:

$$z_2 = \sigma(W_2 z_1 + b_2). \tag{14}$$

Initial risk prediction:

$$\hat{y}_{\text{start}} = \text{Sigmoid}\,(W_3 z_2 + b_3). \tag{15}$$

Secondly, pruning is achieved by controlling the retention of neurons through masking. Binary mask matrices $M_1 \in \{0,1\}^{d_1}$ and $M_2 \in \{0,1\}^{d_2}$ are introduced. Control the activation of neurons in the hidden layer (1 = retain, 0 = prune): $z_1' = z_1 \odot M_1$, $z_2' = z_2 \odot M_2$. Here, $\odot$ represents the element-wise product. After pruning, only the neurons corresponding to $M = 1$ are retained. Mask learning constrains the sparsity of the mask through L0 regularisation, and retains the key neurons:

$$\zeta_{\text{Pruning}} = \underbrace{\zeta_{\text{pred}}(\hat{y}, y)}_{\text{Predicted loss}} + \lambda \underbrace{\left(\|M_1\|_0 + \|M_2\|_0\right)}_{\text{Sparsity constraint}}. \tag{16}$$

λ represents the regularisation coefficient. $\|M\|_0$ represents the number of nonzero elements in the mask, which is the number of neurons that are retained. Next, adversarial training is conducted to enhance the robustness of the pruned model. Adversarial perturbations are introduced during the pruning process. $\delta \sim \mathcal{N}(0, \varepsilon^2)$ (ε is the amplitude of the disturbance), forcing the model to remain sensitive to the key features.

$$\begin{aligned}\mathcal{L}_{\text{adversary}} = \mathcal{L}_{\text{pred}}(\hat{y}(\delta), y) = -\mathbb{E}[y \log \hat{y}(H+\delta) \\ + (1-y)\log(1-\hat{y}(H+\delta))].\end{aligned} \tag{17}$$

Finally, the final prediction result of the guarantee level is output. This step retains only the outputs of the key neurons that have been filtered by the pruning mask, significantly reducing the complexity of the model (Figure 5) (Algorithm 4).

$$\hat{y}_{\text{Ultimately}} = \text{Sigmoid}\,(W_3 z_2 + b_3). \tag{18}$$

ALGORITHM 4 | Pseudo-code for Audit Assurance Level Anchoring with Pruning-Resistant MLP.

```
Class AuditAssuranceAnchoring
  Constructor __init__(input_dim, hidden_dim, target_ level)
    {Pruning-resistant MLP for audit assurance level prediction}
    self.mlp ← PrunedMLP(input_dim, hidden_dim, 1)
    {input_dim: Feature dimension of consistent audit evidence (on/off balance sheet)}
    self.target_level ← target_level
    {target_level: Desired audit assurance threshold}
  Method predict_assurance(evidence_features)
    {Predict assurance level of current evidence set}
    return σ(self.mlp(evidence_features))
    {σ(·): Sigmoid activation (output ∈ [0, 1])}
  Method audit_cycle(initial_evidence)
    {Main loop for assurance level anchoring}
    current_evidence ← initial_evidence
    while True do
      assurance_level ← self.predict_assurance (current_evidence)
      if assurance_level ≥ self.target_level then
        break
        {Terminate: target assurance level achieved}
      end if
      incremental_evidence ← self.get_incremental_evidence(
          current_evidence, rules = ['temporal', 'spatial', 'multidimensional'])
      {Mine incremental evidence via 3 association rule types}
      current_evidence ← self.update_evidence (current_evidence, incremental_evidence)
    end while
    return current_evidence, assurance_level
Class PrunedMLP (nn.Module)
  Constructor __init__(input_dim, hidden_dim, output_ dim)
    self.fc1 ← nn.Linear(input_dim, hidden_dim)
    self.fc2 ← nn.Linear(hidden_dim, output_dim)
    self.prune_mask ← None
    {Dynamic pruning mask (updated during adversarial learning)}
  Method forward(x)
    if self.prune_mask ≠ None then
      self.fc1.weight.data ← self.fc 1.weight.data ⊙ self.prune_mask
    end if
    return self.fc2(ReLU(self.fc1(x)))
    {⊙: Element-wise multiplication (pruning operation)}
```

4 | Experimental Process

4.1 | Experimental Design

This paper selects the financial data of all A-share listed enterprises in China from 2017 to 2024 as the research sample. Enterprises with more than 20% of data missing are excluded. Finally, 2754 enterprises are selected as the objects for Full-chain Loop Tracking Audit. When implementing audit procedures using the FcLTA framework, the required sequential audit evidence includes: (1) structured financial indicators such as debt ratio, cash flow, ROE and inventory turnover rate obtained from the annual reports of listed companies [44], (2) unstructured texts such as management discussion and analysis

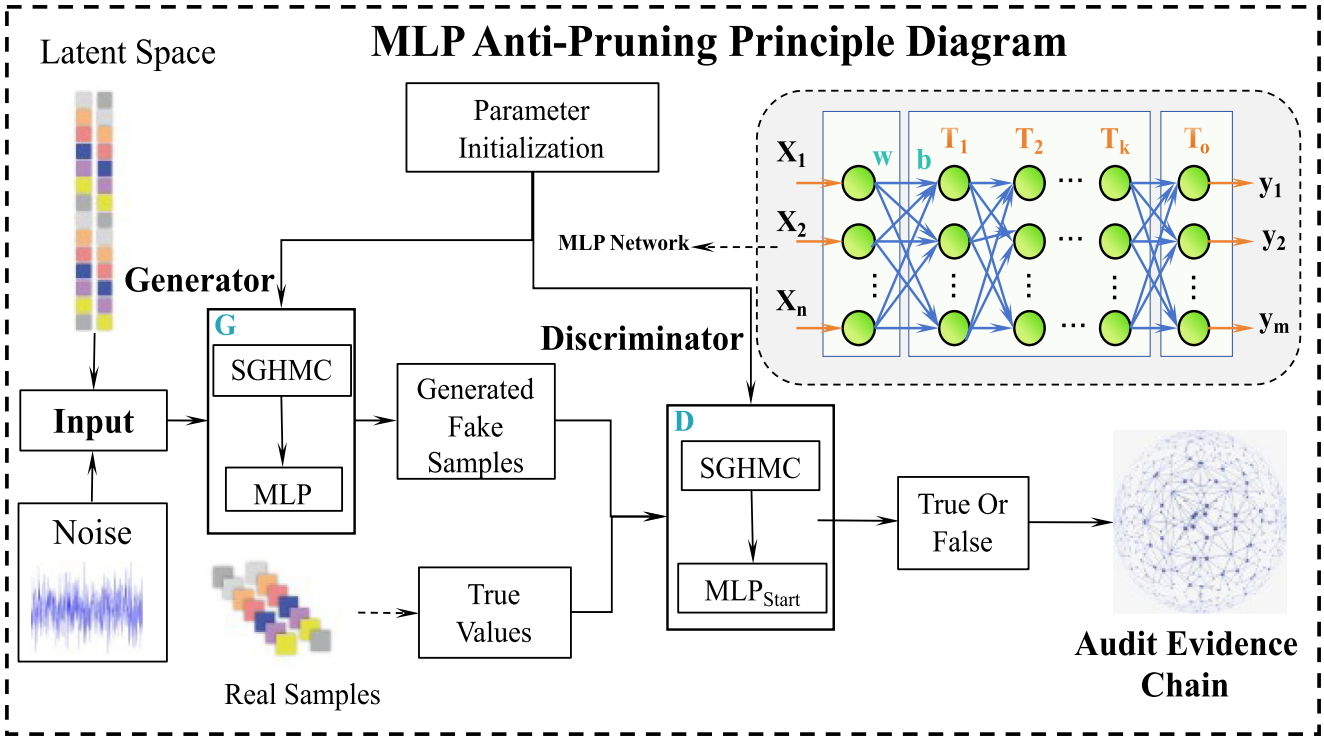


FIGURE 5 | The process of anchoring the assurance level.

(MD&A), audit report notes, etc, (3) incremental information such as fraud types, penalty amounts, and time points contained in the CSRC administrative penalty announcements and the risk warnings (ST/*ST) of listed companies. The spatially expanded audit evidence data not only include the internal data of the current year, but also considers business data, public opinion data and other external environmental data related to the audit matters, mainly including the following contents.

This paper enriches the evidence pool for tracking enterprise risks from various perspectives, different data sources and subjective/objective aspects, providing a solid foundation for the Full-chain Loop Tracking Audit. The experimental process of this paper is implemented based on the 'obtaining evidence of internal sequential timing audit–obtaining evidence of horizontal expansion of audit matters–penetrating the multi-dimensional evidence association rules–achieving the anchor point at the reasonable assurance level' business loop audit process, as shown in Figure 6.

4.2 | Implementation Procedure

In machine learning, the training set and the test set are important components of the dataset. Usually, the dataset can be directly divided into the training set and the test set using the hold-out method. Generally, 2/3 to 4/5 of the samples are used for training, and the remaining samples are used for testing. The division should maintain the consistency of data distribution as much as possible. The k-fold cross-validation method can also be used. The initial data are randomly divided into k mutually exclusive subsets, and k-1 of them are alternately selected for training, while the remaining one is used for testing. This proves that the training and test datasets contain approximately the same proportion of two values of the same class labels, avoiding sample selection bias, that is, the overall representation skew. This paper uses the k-fold cross-validation method and maintains the same data partitioning in all methods when representing. The experimental results and discussion on the test samples are given in the next section. Additionally, to verify the auditing ability of each component module of FcLTA, ablation experiments are set up, and their effects in terms of achieving the Assurance level and other aspects are compared.

4.3 | Evaluation Indicators

To quantitatively analyse the accuracy of all methods in audit risk forecasting of listed companies, we chose the following four assessment metrics, namely root mean square error (RMSE), mean absolute error (MAE), mean squared error (MSE) and Nash–Sutcliffe efficiency (NSE). RMSE is a commonly used measure of error and is calculated as

$$V_{\mathrm{RMSE}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2}. \tag{19}$$

MAE is the average of the absolute value of the error, which is more robust to outliers than RMSE and is calculated as

$$V_{\mathrm{MAE}} = \frac{1}{N}\sum_{i=1}^{N}\left|\hat{y}_i - y_i\right|. \tag{20}$$

In this paper, MSE is used as the loss function for model training. The MSE function curve is conductible everywhere and has a more stable gradient, which is calculated as

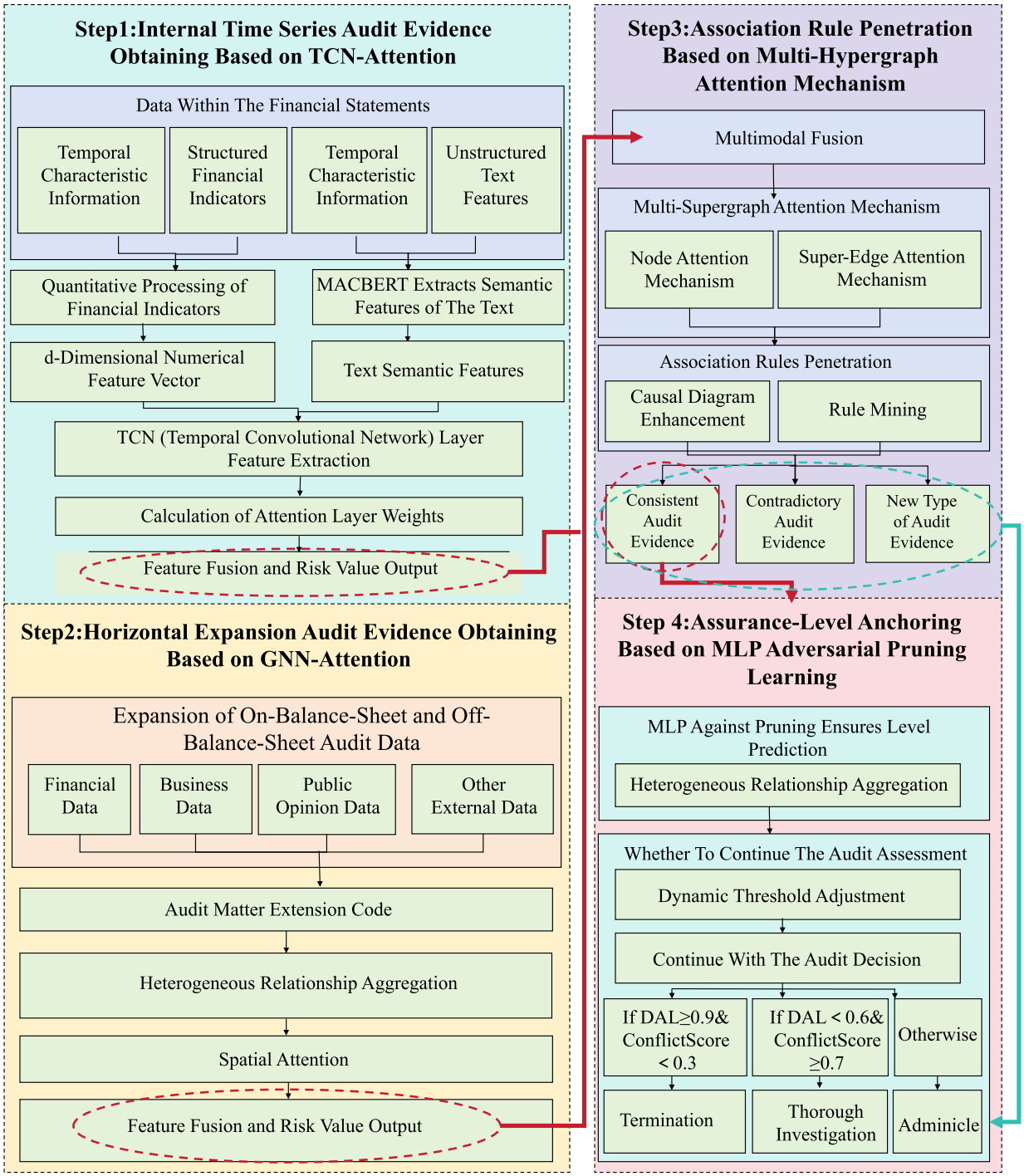


FIGURE 6 | Flow chart of the FcLTA experiment.

$$V_{\mathrm{MSE}} = \frac{1}{N}\sum_{i=1}^{N}\left(\hat{y}_i - y_i\right)^2. \tag{21}$$

In this paper, NSE is used to quantify the forecasting accuracy of the model. The closer the NSE value is to 1, the better the model forecasting ability, and its calculation formula is

$$V_{\mathrm{NSE}} = 1 - \frac{\sum\left(y_i - y_i^{\mathrm{pred}}\right)^2}{\sum\left(y_i - \bar{y}\right)^2}. \tag{22}$$

5 | Results and Discussion

5.1 | Main Experimental Results

This section demonstrates the effectiveness of the FcLTA framework in obtaining audit evidence at a high level of assurance. In this study, we used the training set to train the proposed FcLTA framework and then used the test set to verify the effectiveness of obtaining audit evidence. After the experiment, as shown in Figure 7, these three graphs can assist in proving the performance of the FcLTA framework from

different dimensions. In the research on obtaining audit evidence at a high level of assurance, through the experimental process of training with the training set and validating with the test set, the validity of the proposed FcLTA framework was verified. Figure 7 presents the real value curve of audit risk and the prediction curve based on the FcLTA framework. Both of them fit well on the training set and the test set, and the lowest guarantee level of the obtained audit evidence reached 96.3%. In addition, the two model comparison graphs (NSE/RMSE/MAE/MSE comparison) from the perspective of model evaluation indicators further demonstrate the advantages of the FcLTA framework in terms of error control, prediction stability and other performance aspects. In summary, the FcLTA framework demonstrates precise fitting, high level of assurance and good model performance in tracking audit risk prediction and obtaining audit evidence. It effectively validates its application value in the scenario of obtaining audit evidence at a high level of assurance and provides reliable technical support for risk prediction and evidence acquisition in the auditing process.

Within the audit materiality level ($\varepsilon = 0.05$), the AUC of the proposed framework decreases by only 1.8%, which is significantly better than the comparison methods (transformer + GCN decreases by 4.7%). At the fraud risk threshold ($\varepsilon = 0.10$), the proposed framework still maintains an AUC of 0.862, while the comparison methods have dropped below 0.68. Robustness advantage: The adversarial training mechanism of the proposed framework reduces the performance degradation rate (slope) to only 1/3 of the comparison methods (as shown in Table 6).

5.2 | Performance Demonstration of Each Component of the FcLTA Framework

1. Overall performance display of each component

This section demonstrates the effectiveness of each module of the FcLTA framework in obtaining audit evidence at a high level of assurance. From the experimental data, it can be seen that each model shows significant differences in multiple indicators. The FcLTA model performs the best. Its assurance level reaches 96.3%, significantly higher than other models. The high-risk omission rate is only 3.7%, the lowest among all models, indicating that this model has extremely high accuracy in identifying high-risk situations. In terms of the average misstatement rate, the FcLTA is 8.2%, also superior to other models, indicating that it performs well in avoiding false alarms. In terms of the integrity of the evidence chain, the FcLTA score is 4.8, the highest among all models, demonstrating the model's advantage in forming a complete evidence chain. In contrast, the Baseline model is at the worst level in all indicators, with an assurance level of only 62.8%, a high-risk omission rate of 37.2%, an average misstatement rate of 29.5% and evidence chain integrity of only 1.5, significantly different from

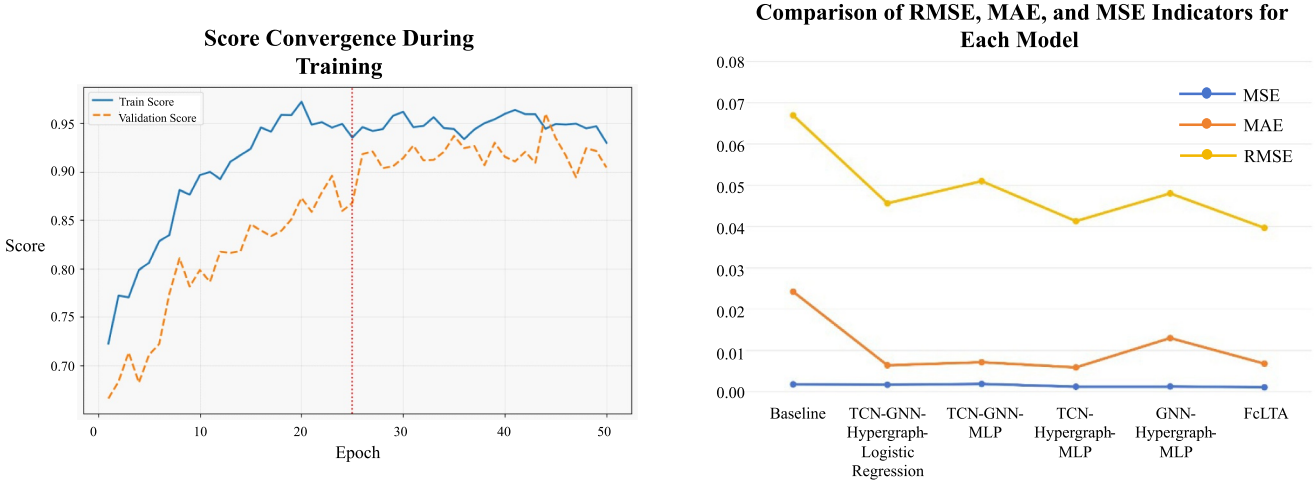


FIGURE 7 | FcLTA framework model training and testing results.

TABLE 6 | Performance comparison under different adversarial perturbation strengths.

ε	Proposed framework	Transformer + GCN	LSTM + FCN	Logistic regression	Performance degradation (proposed)
0.00	0.912	0.814	0.783	0.712	—
0.02	0.908	0.798	0.762	0.682	0.44%
0.04	0.901	0.775	0.734	0.643	1.21%
0.06	0.891	0.746	0.701	0.597	2.30%
0.08	0.878	0.712	0.663	0.548	3.73%
0.10	0.862	0.673	0.621	0.496	5.48%
0.15	0.823	0.581	0.518	0.387	9.76%
0.20	0.778	0.492	0.427	0.301	14.69%

the FcLTA model. Other models such as No Hypergraph, No MLP, No TCN, and No GNN, have indicators between FcLTA and Baseline, indicating that after removing different components, the model performance has declined to varying degrees (Tables 7–9).

2. The changes in the effectiveness of each module during the iterative process

From the above results, it can be seen that as the evidence chain becomes more complete, the importance of horizontally expanding evidence and combining evidence increases, and it also demonstrates the necessity of each module. In summary, the FcLTA model shows significant advantages in ensuring the (Assurance) level, reducing the high-risk omission rate, minimising false statements and enhancing the integrity of the evidence chain. It verifies its effectiveness and superiority in related tasks. Key findings: (1) The TCN module is the most crucial: Removing it leads to a 14.2% increase in high-risk omission rate, thus unable to capture the time pattern of financial embellishment. (2) The necessity of the hypergraph: the assurance level is reduced by 10.6%, and the ordinary graph is unable to express the multi-combination risks of 'equity–guarantee–transaction'. (3) The effectiveness of MLP pruning: Reducing overfitting, the false statement rate decreases by 10.7% (Figure 8).

TABLE 7 | Results of the abolition experiment on the audit assurance levels of each component.

Train	Guarantee level ≥ 90%	High risk of omission rate (%)	Average false alarm rate (%)
FcLTA	96.30	3.70	8.20
No TCN	82.10	17.90	14.60
No GNN	74.50	25.50	21.30
No hypergraph	85.70	14.30	12.10
No MLP	88.40	11.60	18.90
Baseline	62.80	37.20	29.50

TABLE 8 | The contribution ratios of each module in the first three iterations.

Iteration round	TCN contribution degree (%)	GNN contribution degree (%)	Hypergraph contribution degree (%)
1	42	25	18
2	37	31	23
3	35	33	25

TABLE 9 | Comparison of audit risk detection effects of the FcLTA framework in different iteration rounds.

Iteration round	Guarantee level	The number of newly added high risk	The proportion of key new evidence in this
1	0.832	62	0.32
2	0.917	29	0.41
3	0.963	8	0.67

5.3 | The Effect Display of the FcLTA Cycle Audit

This section demonstrates the effectiveness of iterative auditing in obtaining audit evidence at a high level of assurance. As shown in Figure 9, the level of assurance continuously increases with the advancement of the iterative rounds, and the number of newly identified high-risk enterprises significantly decreases. The proportion of key new evidence keeps rising. The three factors exhibit a favourable coordinated trend, indicating that the iterative process can effectively optimise the relevant mechanisms and enhance overall efficiency. It also verifies the importance of iterative tracking in obtaining audit evidence. The detailed analysis is as follows: Firstly, as the iterative process progresses, the overall level of assurance continuously rises, gradually approaching a higher stable state. The information shown in the figure only includes the average assurance levels from the 1st to the 3rd round. Additionally, the number of newly identified high-risk enterprises decreases significantly with the increase in the number of iterative rounds. This trend corresponds to the improvement in the level of assurance, indicating that as the level of assurance strengthens, the identification and control effects on high-risk enterprises gradually emerge, effectively suppressing the number of new high-risk enterprises. The proportion of key newly added evidence also shows an upward trend. It was 0.32 in the 1st round, rose to 0.41 in the 2nd round and significantly increased to 0.67 in the 3rd round. This indicates that as the iterative process deepens, the key newly added evidence obtained during the investigation becomes increasingly abundant, providing strong support for the improvement of the level of assurance and the reduction of the number of high-risk enterprises. This further verifies the positive role of the iterative process in enhancing the overall investigation quality and effectiveness.

6 | Conclusion

This paper proposes the Full-chain Loop Tracking Auditing framework (FcLTA framework), which addresses the limitations of traditional auditing in three key aspects: multimodal data processing, dynamic tracking of risk factors and control of assurance level. Through the business cycle process of 'obtaining evidence of internal sequential timing audit–obtaining evidence of horizontal expansion of audit matters–penetrating the multidimensional evidence association rules–achieving the anchor point at the reasonable assurance level', FcLTA resolves the shortcomings of traditional auditing. The main conclusions are as follows: Firstly, this paper constructs a dual-channel identification framework of internal time series evidence (TCN-Attention) and external expansion evidence (GNN attention), proving that the synergy effect of time series features and expansion features is statistically significant for the identification of high-risk audit evidence. Secondly, by binding multiple

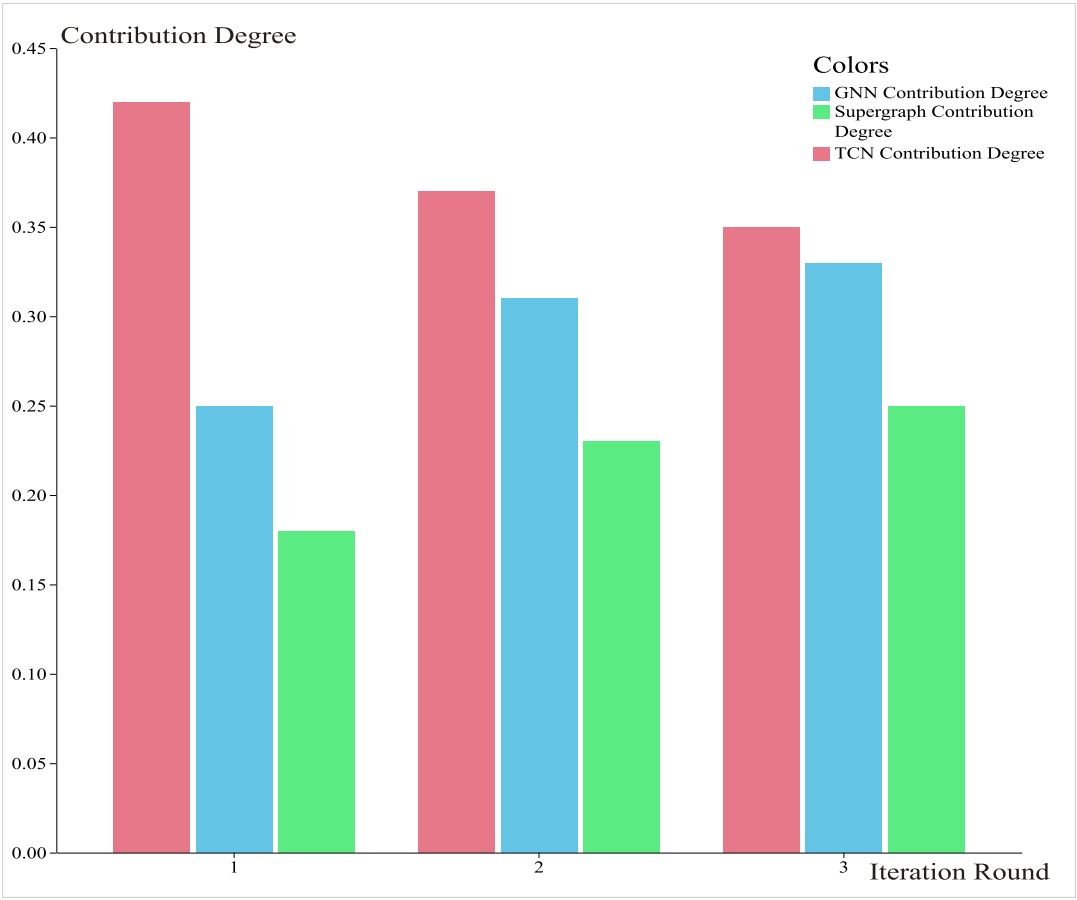


FIGURE 8 | FcLTA framework model training and testing results.

types of evidence such as financial indicators, text and external data into super-edges, it solves the modelling problem of multi-factor combinations such as 'guarantee circle–association transaction–public opinion mutation'. The ablation experiments show that the supergraph structure increases the proportion of assurance level ≥ 90% from 74.5% (ordinary graph) to 96.3%, verifying its irrelevance in high-order association mining. Finally, the proposed MLP adversarial pruning algorithm reduces the failure risk of auditing through iterative optimization of the evidence chain and achieves an improvement in auditing quality and efficiency. Overall, the FcLTA framework implemented Full-chain Loop Tracking Auditing, and the generated audit evidence can reach the reasonable assurance level required for assurance engagements. However, current models have insufficient coverage of relationship types in emerging auditing business models. In the future, it is planned to achieve dynamic relationship expansion through further learning; secondly, the legal validity determination of audit evidence (Assertions) still needs to be further connected with 'China Certified Public Accountants Audit Standard No. 1301'. This research provides a solution with both technical robustness and compliance with standards for intelligent auditing systems. Its methodology can be

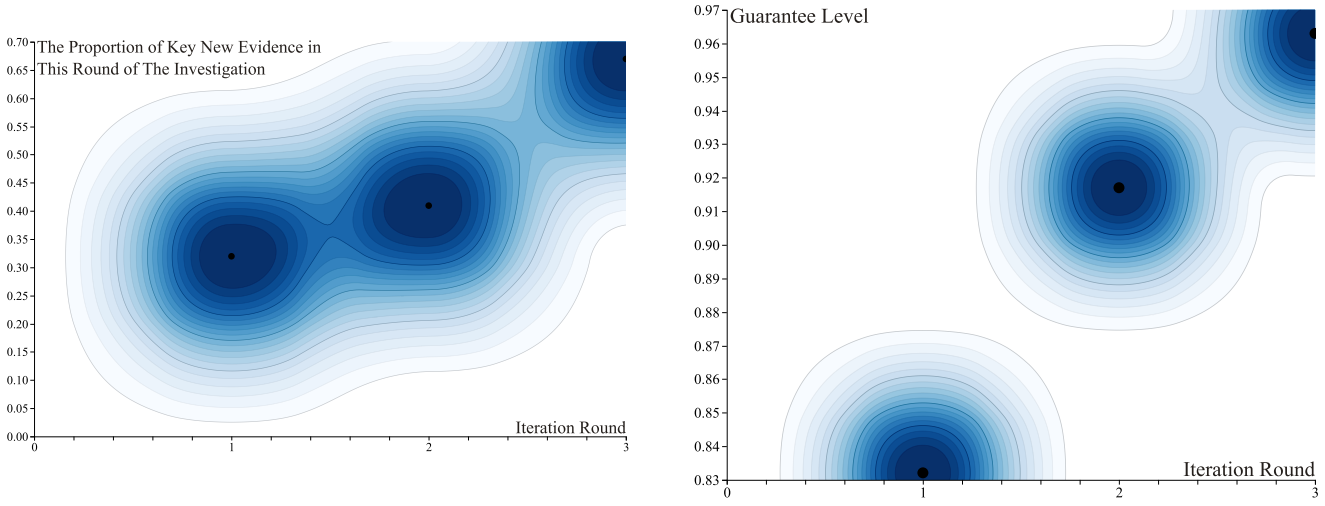


FIGURE 9 | FcLTA framework model training and testing results.

extended to other assurance business scenarios and promotes the transition of assurance business from 'reasonable assurance' to the 'high-precision assurance' paradigm.

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Conflicts of Interest

Chaoxu Mu is an Associate Editor for the journal, and was not involved in peer review process or the decision to publish this article. The authors declare that they have no conflict of interest.

Data Availability Statement

All data generated or analyzed during this study are included in the supplementary materials of this article, which can be accessed via the journal's online platform upon publication. If additional raw data are required for verification, they are available from the corresponding author upon reasonable request.

References

1. International Federation of Accountants, *ISA 200: Overall Objectives of the Independent Auditor and the Conduct of an Audit in Accordance with International Standards on Auditing*. (IFAC, 2009), https://www.iaasb.org/publications/basis-conclusions-isa-200-revised-and-redrafted.

2. PCAOB, AS 1105: Audit Evidence. Public Company Accounting Oversight Board (2010), https://pcaobus.org/oversight/standards/auditing-standards/details/AS1105.

3. W. Duan, N. Hu, and F. Xue, "The Information Content of Financial Statement Fraud Risk: An Ensemble Learning Approach," *Decision Support Systems* 182 (2024): 114231, https://doi.org/10.1016/j.dss.2024.114231.

4. T. C. Omer, M. K. Shelley, and F. M. Tice, "Do Director Networks Matter for Financial Reporting Quality? Evidence From Audit Committee Connectedness and Restatements," *Management Science* 66, no. 8 (2020): 3361–3388, https://doi.org/10.1287/mnsc.2019.3331.

5. M. Ashraf, P. Choudhary, and J. Jaggi, "Are Audit Committees Overloaded? Evidence From the Effect of Financial Risk Management Oversight on Financial Reporting Quality," *Management Science* 70, no. 12 (2024): 8414–8447, https://doi.org/10.1287/mnsc.2022.00360.

6. Y. Wang, B. Fang, S. Huang, K. Chen, Y. Jia, and A. Li, "Extrapolation Reasoning on Temporal Knowledge Graphs via Temporal Dependencies Learning," *CAAI Transactions on Intelligence Technology* 10, no. 3 (2025): 815–826, https://doi.org/10.1049/cit2.70013.

7. S. He, J. Shen, H. Yang, G. Xu, and L. T. Yang, "A Temporal Correlation Networks Based on Interactive Modelling for Remote Sensing Images Change Detection," *CAAI Transactions on Intelligence Technology* 10, no. 6 (2025): 1904–1918, https://doi.org/10.1049/cit2.70080.

8. X. Fang and S. H. Cho, "Cooperative Approaches to Managing Social Responsibility in a Market With Externalities," *Manufacturing & Service Operations Management* 22, no. 6 (2020): 1215–1233, https://doi.org/10.1287/msom.2019.0837.

9. C. Bockel-Rickermann, S. Verboven, T. Verdonck, and W. Verbeke, "Can Causal Machine Learning Reveal Individual Bid Responses of Bank Customers? –A Study on Mortgage Loan Applications in Belgium," *Decision Support Systems* 190 (2025): 114378, https://doi.org/10.1016/j.dss.2024.114378.

10. S. Liu, S. Wang, C. Sun, B. Li, S. Wang, and F. Li, "DeepGCN Based on Variable Multi-Graph and Multimodal Data for ASD Diagnosis," *CAAI Transactions on Intelligence Technology* 9, no. 4 (2024): 879–893, https://doi.org/10.1049/cit2.12340.

11. X. Wang, Z. Luo, and Y. Chen, "Automatic Generation of Critical Audit Matters (CAMs) Using LSTM-MacBert-Based Dual-Stream Transfer Learning," *IEEE Transactions on Computational Social Systems* 11, no. 5 (2024): 6435–6452, https://doi.org/10.1109/TCSS.2024.3385493.

12. Fan, Z., Yu, Z., Yang, K., et al., "Diverse Models, United Goal: A Comprehensive Survey of Ensemble Learning," *CAAI Transactions on Intelligence Technology*, 10, no. 4 (2025): 959–982, https://doi.org/10.1049/cit2.70030.

13. R. Xu, H. Chen, and J. L. Zhao, "Socio Link: Leveraging Relational Information in Knowledge Graphs for Startup Recommendations," *Journal of Management Information Systems* 40, no. 2 (2023): 655–682, https://doi.org/10.1080/07421222.2023.2196771.

14. L. Chen, S. Yao, and K. Zhu, "Responsible Sourcing Under Supplier-Auditor Collusion," *Manufacturing & Service Operations Management* 22, no. 6 (2020): 1234–1250, https://doi.org/10.1287/msom.2019.0861.

15. L. Hong, M. H. Modirrousta, N. M. Hossein, et al., "GAN-LSTM-3D: An Efficient Method for Lung Tumour 3D Reconstruction Enhanced by

Attention-Based LSTM," *CAAI Transactions on Intelligence Technology* 8, no. 3 (2020): 514–526, https://doi.org/10.1049/cit2.12223.

16. Y. Wang, R. Fang, A. Xie, H. Feng, and J. Lai, "Dynamic Anomaly Identification in Accounting Transactions via Multi-Head Self-Attention Networks," *Preprint asrXiv:2511.12122* (2025), https://arxiv.org/abs/2511.12122.

17. M. Bineid, N. Beloff, A. Khanina, and M. White, "CADM: An LSTM-Based Model for Detecting Creative Accounting in Time-Series Data From Saudi-Listed Companies," in *2025 20th Conference on Computer Science and Intelligence Systems (FedCSIS)* (2025), 99–109, https://doi.org/10.15439/2025F9424.

18. L. Huang, H. Chen, X. Wang, and G. Chen, "A Fast Algorithm for Mining Association Rules," *Journal of Computer Science and Technology* 15, no. 6 (2000): 619–624, https://doi.org/10.1007/BF02948845.

19. J. Han, J. Pei, and Y. Yin, "Mining Frequent Patterns Without Candidate Generation," *ACM Sigmod Record* 29, no. 2 (2000): 1–12, https://doi.org/10.1145/335191.335372.

20. B. Wu, K. M. Chao, and Y. Li, "Heterogeneous Graph Neural Networks for Fraud Detection and Explanation in Supply Chain Finance," *Information Systems* 121 (2024): 102335, https://doi.org/10.1016/j.is.2023.102335.

21. Y. Feng, J. Huang, S. Du, et al., "Hyper-Yolo: When Visual Object Detection Meets Hypergraph Computation," *IEEE Transactions on Pattern Analysis and Machine Intelligence* 47, no. 4 (2024): 2388–2401, https://doi.org/10.1109/TPAMI.2024.3524377.

22. Y. Zhao, H. Zhou, A. Zhang, R. Xie, Q. Li, and F. Zhuang, "Connecting Embeddings Based on Multiplex Relational Graph Attention Networks for Knowledge Graph Entity Typing," *IEEE Transactions on Knowledge and Data Engineering* 35, no. 5 (2022): 4608–4620, https://doi.org/10.1109/TKDE.2022.3142056.

23. H. Cheng, M. Zhang, and J. Q. Shi, "A Survey on Deep Neural Network Pruning: Taxonomy, Comparison, Analysis, and Recommendations," *IEEE Transactions on Pattern Analysis and Machine Intelligence* 46, no. 12 (2024): 10558–10578, https://doi.org/10.1109/TPAMI.2024.3447085.

24. P. C. Liao and S. Radhakrishnan, "Auditors' Liability to Lenders and Auditor Conservatism," *Management Science* 66, no. 8 (2020): 3788–3798, https://doi.org/10.1287/mnsc.2019.3302.

25. S. Cui, R. Gao, J. Kuang, L. Yang, H. Qiu, and X. Wei, "An Interpretable Imbalance Ensemble Classification Method for Readmission Risk Assessment Incorporating Multi-View Perturbation and SHAP Analysis," *Decision Support Systems* 190 (2025): 114404, https://doi.org/10.1016/j.dss.2025.114404.

26. K. Meredith, J. Blake, P. Baxter, and D. Kerr, "Drivers of and Barriers to Decision Support Technology Use by Financial Report Auditors," *Decision Support Systems* 139 (2020): 113402, https://doi.org/10.1016/j.dss.2020.113402.

27. H. Li, Y. Qian, Y. Jiang, Y. Liu, and F. Zhou, "A Novel Label-Based Multimodal Topic Model for Social Media Analysis," *Decision Support Systems* 164 (2023): 113863, https://doi.org/10.1016/j.dss.2022.113863.

28. Y. Zhao, H. Du, Y. Liu, et al., "Stock Movement Prediction Based on bi-Typed Hybrid-Relational Market Knowledge Graph via Dual Attention Networks," *IEEE Transactions on Knowledge and Data Engineering* 35, no. 8 (2022): 8559–8571, https://doi.org/10.1109/TKDE.2022.3220520.

29. K. Liang, L. Meng, M. Liu, et al., "A Survey of Knowledge Graph Reasoning on Graph Types: Static, Dynamic, and Multi-Modal," *IEEE Transactions on Pattern Analysis and Machine Intelligence* 46, no. 12 (2024): 9456–9478, https://doi.org/10.1109/TPAMI.2024.3417451.

30. L. Wu, H. Lin, Z. Gao, G. Zhao, and S. Z. Li, "A Teacher-Free Graph Knowledge Distillation Framework With Dual Self-Distillation," *IEEE Transactions on Knowledge and Data Engineering* 36, no. 9 (2024): 4375–4385, https://doi.org/10.1109/TKDE.2024.3374773.

31. X. Wang, Y. Chen, and H. Yao, "Revealing the Veil of Greenwashing in ESG Reports: Predicting the Degree of Corporate Greenwashing Based on Thematic and Sentiment Features of Text," *IEEE Transactions on Sustainable Computing* 10, no. 6 (2025): 1–18, https://doi.org/10.1109/tsusc.2025.3594401.

32. H. Chen, J. V. Chen, and F. Li, "The Number of Estimates in Footnotes and Accruals," *Management Science* 70, no. 1 (2024): 283–308, https://doi.org/10.1287/mnsc.2022.4659.

33. M. Z. Aslam, B. Raza, M. Faheem, and A. Raza, "AML-Net: Attention-Based Multi-Scale Lightweight Model for Brain Tumour Segmentation in Internet of Medical Things," *CAAI Transactions on Intelligence Technology* (2024): 1–17, https://doi.org/10.1049/cit2.12278.

34. A. A. Khan, R. K. Madendran, U. Thirunavukkarasu, and M. Faheem, "D2PAM: Epileptic Seizures Prediction Using Adversarial Deep Dual Patch Attention Mechanism," *CAAI Transactions on Intelligence Technology* 8, no. 3 (2023): 755–769, https://doi.org/10.1049/cit2.12261.

35. X. Wang, W. Bian, and X. Zhao, "Robust Unsupervised Anomaly Detection for Surface Defects Based on Stacked Broad Learning System," *IEEE/ASME Transactions on Mechatronics* 30, no. 5 (2024): 3676–3686, https://doi.org/10.1109/tmech.2024.3465563.

36. Q. Lu, W. Du, S. Yang, W. Xu, and J. L. Zhao, "Can Earnings Conference Calls Tell More Lies? A Contrastive Multimodal Dialogue Network for Advanced Financial Statement Fraud Detection," *Decision Support Systems* 189 (2025): 114381, https://doi.org/10.1016/j.dss.2024.114381.

37. H. Chen, T. Wang, and D. D. Yao, "Financial Network and Systemic Risk–A Dynamic Model," *Production and Operations Management* 30, no. 8 (2021): 2441–2466, https://doi.org/10.1111/poms.13384.

38. T. Guo, I. R. Bardhan, Y. Ding, and S. Zhang, "An Explainable Artificial Intelligence Approach Using Graph Learning to Predict Intensive Care Unit Length of Stay," *Information Systems Research* 36, no. 3 (2024): 1478–1501, https://doi.org/10.1287/isre.2023.0029.

39. C. Hu, B. Liu, Y. Ye, and X. Li, "Fine-Grained Classification of Drug Trafficking Based on Instagram Hashtags," *Decision Support Systems* 165 (2023): 113896, https://doi.org/10.1016/j.dss.2022.113896.

40. J. Chen, A. Qi, and M. Dawande, "Supplier Centrality and Auditing Priority in Socially Responsible Supply Chains," *Manufacturing & Service Operations Management* 22, no. 6 (2020): 1199–1214, https://doi.org/10.1287/msom.2019.0790.

41. G. C. Kane and S. Ransbotham, "Research Note-Content and Collaboration: An Affiliation Network Approach to Information Quality in Online Peer Production Communities," *Information Systems Research* 27, no. 2 (2016): 424–439, https://doi.org/10.1287/isre.2016.0622.

42. J. Kong, X. Ma,J.Wang, and X. Zhang, "Sample-Aware Adaptive Structured Pruning for Large Language Models," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 39, no. 17 (2025), 17938–17946, https://doi.org/10.1609/aaai.v39i17.33973.

43. D. Wu, X. Ma, and D. L. Olson, "Financial Distress Prediction Using Integrated Z-Score and Multilayer Perceptron Neural Networks," *Decision Support Systems* 159 (2022): 113814, https://doi.org/10.1016/j.dss.2022.113814.

44. K. C. Ng, P. F. Ke, M. K. So, and K. Y. Tam, "Augmenting Fake Content Detection in Online Platforms: A Domain Adaptive Transfer Learning via Adversarial Training Approach," *Production and Operations Management* 32, no. 7 (2023): 2101–2122, https://doi.org/10.1111/poms.13959.