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A Comprehensive Review of Financial Knowledge Graphs

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Knowledge Graphs (KGs) are increasingly used in finance to manage complex, interconnected data and support advanced analytics. This survey provides an overview of how KGs are applied across various financial areas, such as fraud detection, credit risk assessment, anti-money laundering, and regulatory compliance. We examine key techniques for building and using KGs in finance, including graph construction, embedding methods, and machine learning models. The survey also discusses challenges specific to finance, like handling private data, ensuring interpretability, and managing real-time data. Additionally, we explore the emerging combination of KGs with large language models and generative AI, which offers new possibilities for financial analysis and decision-making. By summarizing the latest developments, this paper aims to offer a clear view of how KGs are transforming finance and to highlight opportunities for future directions for KG research.

Keywords: Financial knowledge graphs; LLM; temporal knowledge graphs; fraud detection; market trend analysis; enterprise risk management; dynamic knowledge graphs.

1. Introduction

Knowledge graphs (KGs) have become increasingly valuable in the finance industry, where they facilitate the organization, analysis, and interpretation of complex interrelated data. These graphs provide a structured representation of entities and their relationships, facilitating advanced analytics in areas such as credit risk assessment, systemic risk analysis, compliance monitoring, and fraud detection. By capturing interdependencies within financial data, KGs offer actionable insights that support data-driven decision-making. For instance, prior research has highlighted the utility of KGs in visualizing systemic liquidity risks through the representation of interbank relationships,[1] as well as in enterprise risk management, where domain-specific KGs improve risk evaluation capabilities.[2]

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1.1. *Applications of knowledge graphs in finance*

KGs are instrumental in finance, addressing both operational and strategic challenges. They integrate diverse financial indicators for credit risk assessment, offering comprehensive evaluations of borrower creditworthiness.[18] Fraud detection benefits from KG-based anomaly detection systems, which identify hidden patterns in transaction networks.[3] KGs streamline regulatory compliance by structuring financial data for reporting and meeting legal requirements.[4] In market trend analysis, KGs combine metrics and event data to identify trends and mitigate risks.[5,6]

1.2. *Methods and advances in knowledge graph construction*

Robust methodologies are crucial for constructing financial KGs. Multi-source data integration unifies structured and unstructured datasets, enabling the discovery of complex relationships.[7] Graph embeddings convert KGs into machine-readable formats, retaining relational and semantic information critical for analytics. Advanced machine learning models, such as Graph Neural Networks (GNNs), facilitate tasks like link prediction, anomaly detection, and temporal forecasting.[8] Integration with explainable AI (XAI) and large language models (LLMs) enhances the interpretation of unstructured data and improves analytical explainability.[9]

1.3. *Taxonomy of financial knowledge graphs*

Financial KGs can be categorized into static, temporal, hybrid, and applicationspecific types. Static KGs capture stable relationships, ideal for compliance reporting and systemic risk analysis.[10] Temporal Knowledge Graphs (TKGs) incorporate time-dependent data, supporting dynamic applications such as trend forecasting.[11] Hybrid KGs combine static and temporal features, integrating multimodal data for tasks like fraud detection.[12] Application-specific KGs address targeted use cases like anti-money laundering (AML) and enterprise risk management, embedding domain-specific knowledge for precision and relevance.[18]

1.4. *Our contributions*

While prior research has explored applications of KGs in finance, many surveys focus narrowly on specific tasks or techniques, overlooking their integration with temporal, dynamic, and multimodal data.[10,13] This survey fills the gap by proposing a comprehensive taxonomy of financial KGs, systematically reviewing construction methodologies, and synthesizing advancements in LLMs and XAI.[14,15] We address challenges like data privacy, scalability, and interpretability while exploring opportunities in generative AI and temporal modeling.[5,16] Finally, we outline future research directions, emphasizing multi-modal integration and realtime dynamic updates.[12,17]

2. Taxonomy of Knowledge Graph Types in Finance

The taxonomy of KG types in finance categorizes KGs into four main types: Static, Temporal, Hybrid, and Application-Specific, each suited for different analytical needs in the financial sector, as shown in Fig. 1.

Static KGs maintain fixed structures, useful in stable data relationships like Entity-Relationship and Property Graphs. Vasiliu *et al.*[5] demonstrated these in modeling financial transactions and organizational hierarchies for consistent, indepth analysis.

The different types of KGs and application specific examples are shown in Fig. 2.

TKGs introduce a time dimension, capturing the evolving nature of financial data. Time-Series Graphs model changes in financial metrics, while Event-Based Graphs focus on the impact of discrete events. Ouyang *et al.*[9] illustrated TKGs for financial predictions, integrating multimodal data for enhanced trend analysis.

Hybrid KGs combine static and temporal features, often including multimodal data, enabling comprehensive analyses. Multimodal KGs blend text, images, and audio, while Dynamic KGs continuously update with real-time data changes. Li *et al.*[12] utilized multimodal KGs in phishing detection, an approach adaptable to complex fraud detection.

Application-Specific KGs are tailored to address specific financial challenges, embedding domain-specific knowledge to enhance relevance and precision. These graphs are critical in domains such as risk management, fraud detection, and market analysis. For example, Mitra *et al.*[18] demonstrated the utility of KGs in credit risk assessment by integrating diverse financial indicators to evaluate the creditworthiness of SMEs. Similarly, Cai and Xie[19] employed KGs in fraud detection to uncover hidden patterns in financial transactions, improving the precision and explainability of anomaly detection systems. Figure 2 shows the different types of application-specific KGs.

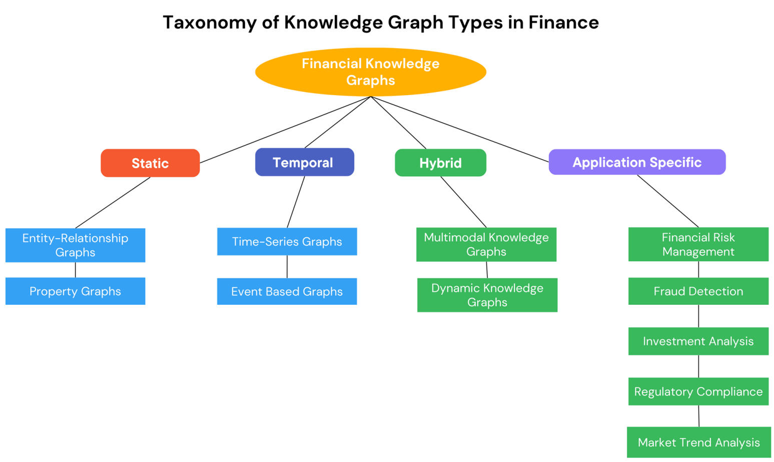

Fig. 1. Taxonomy of financial KGs.

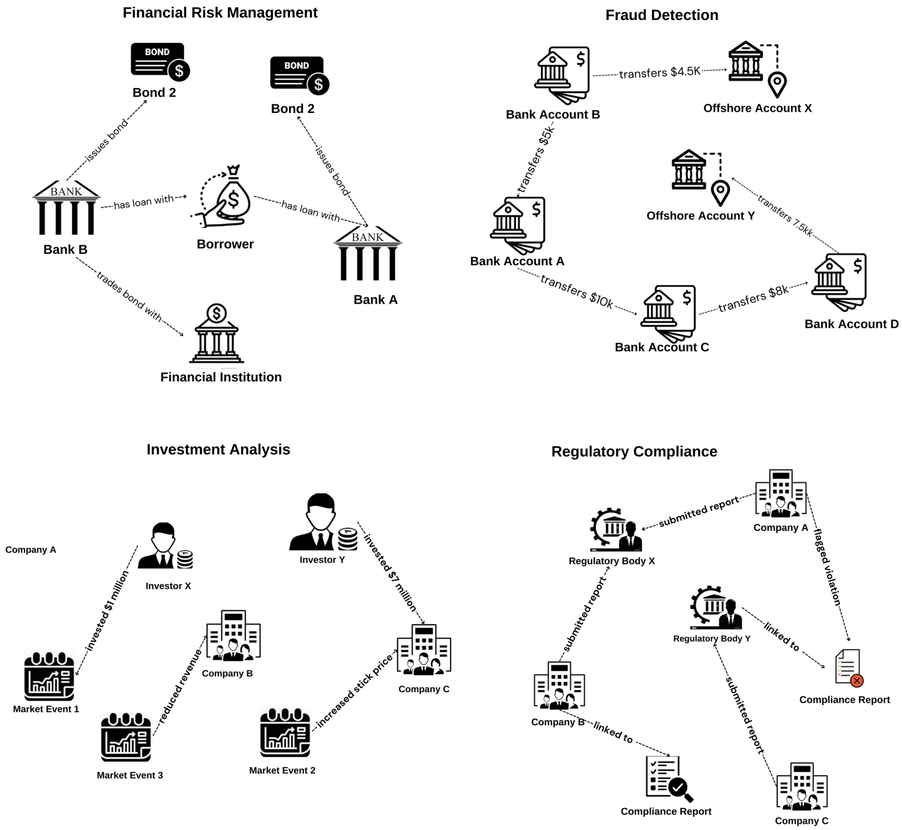

Fig. 2. Application-specific KGs examples.

Market trend analysis also benefits significantly from application-specific KGs. Ouyang *et al.*[9] showcased the use of modal-adaptive KGs, which integrate economic policy impacts and sentiment analysis, enabling nuanced insights into market dynamics. Furthermore, regulatory compliance applications use KGs to streamline reporting processes and ensure adherence to evolving financial regulations, as illustrated by Padmanaban.[4]

This taxonomy highlights the adaptability of KGs in finance, supporting diverse applications across both structured and evolving financial contexts.

3. Methodology for Financial Knowledge Graphs

The methodology for constructing and managing financial KGs involves systematic processes, including data collection, integration, representation, and advanced analytical techniques. These methods enable the effective modeling of financial data, which is often complex, heterogeneous, and dynamic.

Figure 3 shows the different types of KGs.

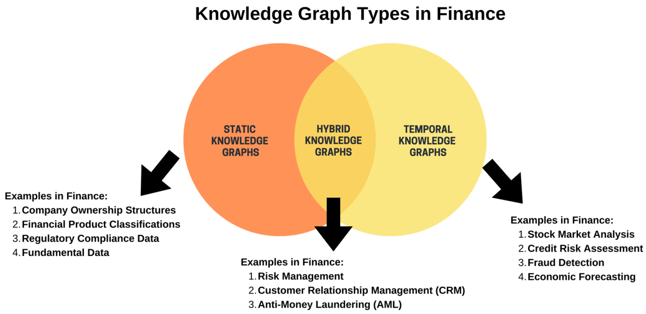

Fig. 3. Different types of financial KGs.

3.1. *Data collection and integration*

Data collection aggregates diverse sources such as corporate filings, transactions, and regulatory documents. Integration methodologies unify these data into cohesive graph structures, enabling cross-source analysis and the discovery of relationships. Automated extraction techniques are critical in this phase, as demonstrated by Mohsin *et al.* who populated static KGs with structured data extracted from financial reports.[7] Xu *et al.* extended this approach by developing frameworks to identify causative relationships between financial events, enriching TKGs with actionable insights.[8]

Multimodal integration further enhances the utility of KGs by incorporating diverse data formats, such as textual, visual, and numerical data. Li *et al.* emphasized the importance of robust data integration for enterprise risk assessment, linking disparate datasets for a unified analytical view.[2]

Static KGs capture stable relationships within financial data, offering a fixed structure suitable for compliance monitoring, systemic risk analysis, and reporting. These KGs are particularly effective in domains where relationships remain constant over time. Chen and Zhang used static KGs to visualize systemic risks in banking, mapping interdependencies among financial institutions.[20]

Property graphs, an extension of static KGs, incorporate attributes for nodes and edges, enabling more detailed analyses. For instance, Mohsin *et al.* utilized property graphs to automate financial reporting processes.[7] Relational Graph Convolutional Networks (RGCNs) are commonly employed to analyze entity relationships in static KGs, while rule-based systems provide an initial structuring framework. Despite their utility, static KGs are limited in handling dynamic or realtime financial data, necessitating more advanced methodologies. Table 1 compares static KG types, highlighting their application areas and key features.

3.2. *Temporal knowledge graphs*

TKGs introduce a time dimension to represent dynamic, time-sensitive relationships, making them essential for applications like stock trend analysis, economic forecasting,

Table 1. Comparison of static KG types in finance.

Paper	Focus area	Applications	Data type	Challenges	Key features
20	Systemic Risk in Banking	Visualizes interconnections in financial institutions	Financial relationships	Capturing systemic risk	Highlights connections and vulnerabilities
7	Information Extraction	Automates extraction from financial reports	Structured & unstructured data	Handling diverse formats	Enhances accessibility and interpretability
21	Text-Visualization Linkage	Links text to visualizations in reports	Text and visual elements	Synchronizing text with visuals	Enables integrated understanding of reports
17	KG Construction	Models static KGs for finance	Heterogeneous data	Data structuring & relationship definition	Initial structure for stability and scalability
22	KG Quality & Scalability	Enhances KG quality & scalability	Financial & economic data	Ensuring quality at scale	Supports complex inter-entity relationships

and event-driven market predictions. By incorporating temporal information, these graphs enable the modeling of evolving relationships and the identification of sequential patterns. Shi *et al*. applied hybrid GCN-LSTM models to capture temporal dependencies in stock price forecasting, combining graph structures with time-series data.[11]

Additionally, Xia *et al*. employed transformers to integrate historical financial contexts into temporal forecasting, enhancing the interpretability of TKGs.[23] Event-based TKGs focus on linking discrete financial events to their outcomes. For example, Xiong *et al*. introduced temporal rule learning to predict event impacts on financial outcomes.[24] Temporal GNNs further enhance these capabilities by capturing the evolving relationships embedded in time-sensitive data streams. Together, Time-Series and Event-Based Graphs enable comprehensive modeling of temporal data, supporting forecasting and risk management, as summarized in Table 3.

3.3. *Hybrid knowledge graphs*

Hybrid KGs combine features of static and temporal graphs, often integrating multimodal data and enabling real-time updates. These graphs are particularly wellsuited for complex financial applications, such as fraud detection and supply chain risk management. Liang *et al*. demonstrated the use of hybrid KGs for adaptive decision-making, employing pattern recognition and temporal analysis to model dynamic relationships.[10] Multimodal hybrid KGs integrate textual, visual, and numerical data, as shown by Li *et al*. in phishing detection, where the combination of textual and multimedia data significantly improved accuracy.[12] Dynamic KGs adapt to new information in real time, as demonstrated by Kosasih *et al*., who used dynamic GNNs to monitor supply chain risks and enable proactive decisionmaking.[27] Table 2 summarizes key applications of hybrid KGs in finance.

Table 2. Comparison of hybrid KGs in finance.

Reference	Multimodal KG	Dynamic KG	Applications	Methods
Mitra *et al*.[18]	×	✓	Credit Risk Assessment	Entity-Relationship Analysis
Li *et al*.[25]	✓	×	Enterprise Risk Management	Graph-Based Risk Modelling
Chen *et al*.[13]	×	✓	Privacy-Preserving KGs	Differential Privacy Techniques
Li *et al*.[12]	✓	✓	Phishing Detection	Large Language Models, Multimodal Graphs
Shi *et al*.[26]	×	✓	Stock Price Prediction	GCN-LSTM Model Integration
Kosasih *et al*.[27]	×	✓	Supply Chain Risk Management	Graph Neural Networks
Liang *et al*.[10]	✓	✓	KG Reasoning	Pattern Recognition, Temporal Analysis
Zhang *et al*.[28]	✓	×	Recommender Systems	KG Embedding Techniques
Cadeddu *et al*.[29]	✓	×	Tourism Data Analysis	Language Models, KG Integration
Chen *et al*.[30]	×	✓	Knowledge Development Prediction	Hybrid Learning Models

3.4. *Machine learning models for knowledge graphs*

Machine learning models, such as Relational Graph Convolutional Networks (RGCNs), Transformers, and LLMs, are tailored to address specific challenges and tasks within financial KGs.

RGCNs, introduced by Schlichtkrull *et al*., are designed to handle relational data within heterogeneous graphs.[35] These networks are effective in financial applications like credit risk assessment, where they analyze complex relationships between borrowers and lenders, and in systemic risk modeling, where they identify interconnections and vulnerabilities within financial systems.

Transformers are widely used for processing large and dynamic KGs. Tang and Liu applied Transformers in a distributed knowledge distillation framework to detect financial fraud, focusing on identifying anomalies in transaction patterns.[36] Similarly, Li and Passino developed the FindKG framework, which utilizes heterogeneous graph Transformers to dynamically construct KGs and detect global market trends.[31] These models integrate data from multiple sources, including numerical and textual inputs, for comprehensive financial analysis.

3.5. *Enhancing knowledge graphs with large language models*

The integration of LLMs with KGs has significantly expanded their utility by enhancing semantic depth, contextual understanding, and adaptability. Pan *et al*. emphasized the

Table 3. Comparison of TKGs in finance.

Paper	Focus area	Applications	Methods	Key features
Li and Passino[31]	Financial Trend Detection	Extracting TKGs	Large Language Models	Real-time trend detection pipeline
Xu *et al*.[8]	Financial Causality	Causality analysis	Text Mining	Links financial events temporally
Xiong *et al*.[24]	Temporal Rule Learning	Event prediction	Temporal Rules	Sequential financial pattern analysis
Vasiliu *et al*.[5]	Synthetic Data Generation	Financial time-series modeling	KGs	Generates synthetic financial data
Xia *et al*.[23]	Temporal Forecasting	Temporal KG forecasting	Chain-of-History Reasoning	Integrates historical context
Lin *et al*.[32]	Temporal Reasoning	Credit risk, investment	Temporal Embeddings	Multi-hop reasoning on financial data
Farghaly *et al*.[17]	Dynamic KG Construction	Structural and temporal integration	Temporal Modeling	Integrates structural and TKG features
Bai *et al*.[33]	Cross-lingual Alignment	Multi-language financial datasets	Embeddingbased Alignment	Expands TKGs to cross-lingual data
Shi *et al.*[11]	Stock Prediction	Stock movement forecasting	GCN-LSTM	Combines graph structure with temporal data
Dong *et al*.[34]	Temporal Path Reasoning	Time-sensitive prediction	Inductive Path Neural Network	Extracts time-sensitive prediction paths

reasoning capabilities of LLM-enhanced KGs, highlighting their ability to represent complex financial relationships accurately.[14] Retrieval-Augmented Transformers (RATs) have been used to create dynamic KGs capable of real-time trend detection, as demonstrated by Zhao *et al*.[16]

Transformers and LLMs like FinBERT, Open-finLLMs, respectively, are also instrumental in multimodal contexts, where they facilitate sentiment analysis, compliance monitoring, and fraud detection.[37] Zafar *et al*. addressed interpretability concerns by proposing methods for building trustworthy, explainable LLM-driven KGs, ensuring transparency in financial decision-making.[38]

3.6. *Graph embedding and machine learning*

Graph embedding techniques convert KG structures into machine-readable vector representations, enabling advanced analytics such as link prediction and clustering. These embeddings preserve relational and temporal information, supporting dynamic graph analysis. Explainable embeddings, such as those proposed by Shaikh *et al*. enhance interpretability through natural language queries.[15]

GNNs, including RGCNs and Graph Attention Networks (GATs), are widely used to analyze complex financial relationships. Zhu and Wu demonstrated the utility of KG-GNNs in peer-to-peer lending, identifying credit risk factors through relational analysis.[39] Cai and Xie employed GNNs in fraud detection, leveraging a two-layer KG structure to improve explainability and precision.[19]

4. Applications of Knowledge Graphs in Finance

In this section, we examine key applications of financial KGs, illustrating their role in diverse areas. KGs enhance credit risk assessment by integrating multiple financial indicators to evaluate creditworthiness; support fraud detection by analyzing graphbased relationships to spot anomalies; and aid market trend analysis by connecting and interpreting market data to forecast economic shifts. Additionally, KGs are critical in systemic risk management, identifying potential contagion across financial entities, and in regulatory compliance, where they streamline data processes to meet complex reporting requirements.

Financial KG research distinguishes between single-domain and multi-domain graphs. A single-domain KG, as shown in Fig. 4, focuses on specific areas like credit risk, integrating detailed financial histories and transaction data to provide deep insights into creditworthiness within lending frameworks.[18] In contrast, multidomain KGs, illustrated in Fig. 5, span various financial domains — combining data on market trends, corporate risks, and regulatory factors. This approach offers a holistic view for enterprise risk management, enabling analyses across financial areas, such as the impact of market changes on credit risk and compliance.[2,40]

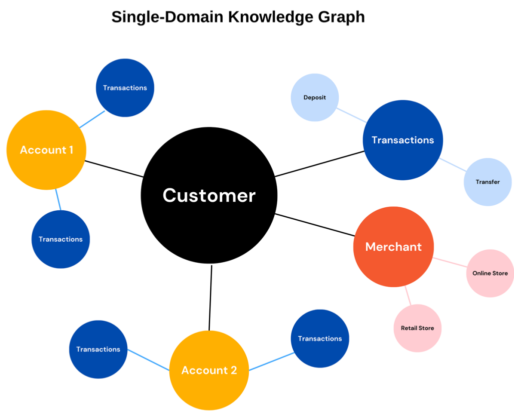

Fig. 4. Single domain financial KGs.

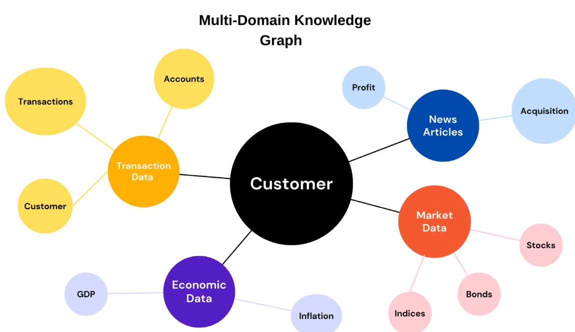

Fig. 5. Multi-domain financial KGs.

4.1. *Financial risk assessment*

Financial risk assessment leverages KGs and machine learning to evaluate credit, liquidity, and systemic risks. Mitra *et al*. developed a KG framework to assess MSME credit risk, enhancing lending decisions.[18] Song *et al*. used multi-level graphs to analyze enterprise credit risk.[41] Wang *et al*. proposed federated learning for privacy-preserving credit scoring.[42] Beyond credit, KGs aid liquidity and systemic risk analysis, as shown by Chen and Zhang,[20] and support bankruptcy predictions using graph neural networks.[43] Gambacorta *et al*. integrated non-traditional data, improving credit scoring and risk evaluation.[44]

4.2. *Fraud detection*

KGs play a crucial role in fraud detection, especially in Anti-Money Laundering (AML), by structuring and analyzing financial transactions to detect suspicious patterns. Karim *et al*. demonstrated how semi-supervised graph learning maps transactions to KGs for anomaly detection.[45] Transaction-based graph learning by Huong *et al*. revealed hidden connections in transactions, improving fraud detection.[46] Graph databases, as used by Muminovic and Halili, efficiently track and score suspicious activities.[47] Synthetic transaction data from Altman and Blanua improves model training for rare fraud cases.[48] Frameworks like GAMLNet integrate anomaly detection into graph structures to identify subtle money laundering patterns.[49]

4.3. *Investment analysis*

KGs are essential for investment analysis by structuring financial relationships for informed risk assessment. Mitra *et al*. proposed a KG framework for SME credit risk analysis, applicable to broader investment evaluations.[18] Song *et al*. introduced multi-level graphs to capture complex corporate structures for better investment decisions.[41] Wang *et al*. enhanced credit scoring across institutions through federated learning, ensuring data privacy.[42] Chen and Zhang used KGs to visualize systemic financial risks, mitigating contagion.[20] Expanding predictions, Wei *et al*. applied graph neural networks for bankruptcy prediction, while Gambacorta *et al*. leveraged non-traditional data in KGs for nuanced credit scoring and investment analysis.[43,44]

4.4. *Regulatory compliance*

KGs are instrumental in regulatory compliance by enhancing data transparency, interpretability, and efficiency. Padmanaban showed how integrating AI and ML with KGs streamlines regulatory reporting, reducing manual interventions.[4] Mkelburg *et al*. demonstrated their role in automating electronic invoice validation for adherence to regulations.[50] KGs also enhance fraud detection, with Cai and Xie using a two-layer KG to uncover fraudulent patterns in financial statements.[51] Shaikh *et al*. explored XAI with KGs to interpret complex datasets.[15] Additionally, KGs align enterprise risk management with compliance standards, as shown by Li *et al*. and support ESG transparency in regulatory frameworks.[2,52]

4.5. *Market trend analysis*

KGs enhance market trend analysis by identifying relationships in financial data for accurate predictions. Shi *et al*. used a KG framework combining graph convolutional networks (GCNs) and long short-term memory (LSTM) to predict stock prices.[11] Zheng *et al*. employed machine learning and time series models to analyze nonlinear financial behaviors.[53] KGs improve transparency, with Deng *et al.* applying causal inference to link financial events to stock trends and Chen and Zhang assessing systemic risk in banking.[40] Self-supervised models refine predictions using unstructured data.[54,55] Ouyang *et al.* enhanced trend analysis with modal-adaptive KGs integrating policy impacts and sentiment shifts.[9]

4.6. *Privacy and governance in knowledge graph construction*

Cross-border financial KGs face critical challenges in maintaining compliance with evolving privacy regulations such as GDPR, PDPA, and sector-specific banking guidelines. The complexity is amplified in temporal and dynamic KGs, where sensitive financial interactions and behaviors are continuously logged and inferred.

Recent studies have proposed frameworks that integrate privacy, utility, and explainability. He *et al*.[56] introduced a method for generating temporal heterogeneous graphs with controllable trade-offs between privacy and graph utility, enabling secure data use across distributed environments. Similarly, Long *et al*.[57] presented a federated learning approach to graph forecasting that prevents leakage of sensitive energy consumption patterns across entities.

Jeyaraman[58] emphasizes the necessity of embedding governance protocols directly into TRGCN-based financial KGs, supporting audit trails and permissioned access to entity relationships. Qiu *et al*.[59] further expand on this by applying TKG reasoning to secure data provenance within distributed systems.

These approaches advocate for the following:

- *Federated learning for KG updates* across borders without raw data movement
- *Anonymization and obfuscation* for individual-level features
- *Governance policies embedded as ontologies* within the KG structure
- *Auditability and lineage tracking* for all graph updates.

As KGs increasingly underpin mission-critical AI decisions in finance, integrating privacy-by-design and policy-aware infrastructure becomes foundational, not optional.

5. Open Challenges and Future Directions

Financial KGs have demonstrated immense potential in addressing complex financial tasks, yet several challenges impede their full adoption. Key issues revolve around data privacy, scalability, and interpretability, which must be resolved to unlock their broader applicability. Data privacy remains a significant concern as handling sensitive financial data must align with stringent regulations like GDPR. Automated frameworks are required to secure confidential information while ensuring usability for applications such as credit risk and systemic risk analysis, as emphasized by Mohsin *et al*.[7] and Mitra *et al*.[18]

Scalability poses another major challenge, as financial KGs must process massive and dynamic datasets in real time to meet the demands of high-frequency trading, fraud detection, and systemic monitoring. Farghaly *et al*. highlight the technical difficulties in managing dynamic data, while Sarmah *et al*. propose retrieval-augmented techniques to optimize performance in high-velocity environments.[6,17] Interpretability is equally crucial, as financial applications demand transparent and explainable systems to comply with regulatory standards and foster trust. Shaikh *et al*.[15] introduced explicable KGs (X-KGs) to improve transparency, with further contributions from Xu *et al*.[8] and Cai and Xie[3] in developing causal and layered models for fraud and risk analysis.

Emerging technologies offer promising solutions to these challenges. Generative AI can enrich KGs by synthesizing realistic financial data, addressing gaps in datasets, and improving predictive capabilities, as highlighted by Zhao *et al*.[16] and Kanaparthi *et al*.[60] TKGs enhance time-dependent modeling of financial entities, improving precision in dynamic markets, as demonstrated by Farghaly *et al*.[17] and Liang *et al*.[10] Furthermore, XAI integrated with KGs ensures transparency and compliance, with Shaikh *et al*.[17] advocating for natural language queryable models and Weber *et al*.[61] emphasizing XAIs role in regulatory alignment.[15,61] Addressing these challenges while leveraging advancements in generative AI, temporal modeling, and XAI positions financial KGs as transformative tools for decision-making, compliance, and systemic risk analysis.

6. Conclusion

This survey highlights the transformative potential of KGs in the financial sector, underscoring their utility in areas such as risk assessment, trend analysis, regulatory compliance, and investment decision-making. As financial data grow in volume, variety, and velocity, KGs offer a structured approach to model complex relationships and derive actionable insights. The integration of advanced techniques like LLMs, generative AI, temporal modeling, and XAI has driven significant advancements, enabling KGs to handle dynamic, multifaceted financial data with increased accuracy and interpretability.

While substantial progress has been made, challenges, such as data privacy, scalability, real-time processing, and the need for interpretable models, remain areas of active research. The demand for models that can manage high volumes of real-time data while preserving data security is critical in financial applications, where compliance and risk mitigation are paramount. Emerging trends, including the incorporation of generative AI for data enrichment, the development of TKGs to capture time-dependent insights, and the integration of XAI techniques to improve transparency, point to a future where KGs play a central role in intelligent financial systems.

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