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Integrating Ontologies and Streaming Machine Learning for Dynamic FinTech Competitiveness Evaluation

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ABSTRACT

The rapid evolution of the Financial Technology (FinTech) sector has intensified market competition and increased the need for enterprises to continuously evaluate and strengthen their competitive advantage. Traditional competitiveness assessment methods often rely on static historical data and subjective managerial judgment, limiting their effectiveness in highly dynamic digital environments. This study proposes a real-time ontology-based machine learning framework designed to evaluate FinTech competitiveness with enhanced accuracy, adaptability, semantic interpretability, and scalability. The proposed framework integrates three interconnected layers: (1) a semantic knowledge representation layer that employs FinTech-specific ontologies to model entities, relationships, KPIs, technologies, and regulatory concepts within the FinTech ecosystem; (2) a real-time data ingestion and preprocessing layer that collects and standardizes heterogeneous data streams from financial statements, digital transactions, customer interactions, APIs, and social media platforms; and (3) a machine learning layer that combines supervised, unsupervised, and streaming learning techniques to classify, predict, and monitor competitive positioning dynamically.

The framework is validated using KPI-driven datasets collected from Vietnamese FinTech enterprises between 2019 and 2024. Experimental results demonstrate that ontology integration improves semantic consistency, reduces data noise, enhances feature relevance, and increases model interpretability. The hybrid framework achieved high classification accuracy and effective real-time responsiveness, enabling stakeholders to identify emerging competitive opportunities, operational risks, and market trends. This study presents a scalable and intelligent competitiveness assessment framework that bridges semantic technologies and artificial intelligence to support strategic decision-making in digital financial ecosystems.

Subject Categories and Descriptors: **[I.2.11 Distributed Artificial Intelligence]:** Intelligent agents [**I.2.4 Knowledge Representation Formalisms and Methods**] Semantic networks

General Terms: Ontology, Machine Learning, Financial Technology, Machine Learning Framework

Keywords: FinTech, Ontology, Machine Learning, Real-Time Analytics, Competitive Advantage, Artificial Intelligence, Semantic Technologies, KPI Analytics

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1. Introduction

The Financial Technology (FinTech) industry has emerged as one of the most transformative sectors within the global digital economy. By leveraging advanced technologies such as artificial intelligence (AI), machine learning (ML), blockchain, cloud computing, and big data analytics, FinTech enterprises are redefining the delivery, accessibility, and personalization of financial services. These technologies have enabled innovative digital financial products including digital wallets, peer to peer lending platforms, robo advisory systems, decentralized finance applications, and algorithmic investment services. As digital transformation accelerates globally, FinTech firms face increasingly intense competition in both developed and emerging markets.

In highly volatile and technology driven markets, the ability to continuously evaluate competitive advantage has become essential for strategic sustainability and organizational growth. Conventional approaches to competitiveness evaluation, including SWOT analysis, Porter's Five Forces model, and Balanced Scorecard frameworks, provide useful managerial perspectives but suffer from several limitations in rapidly evolving digital ecosystems. Most traditional models rely heavily on static historical data, manual interpretation, and periodic evaluation processes that are insufficient for capturing real time market dynamics, customer behavior changes, technological disruptions, and regulatory developments.

Recent advances in artificial intelligence and real-time analytics offer promising alternatives for automated and adaptive competitiveness assessment. Machine learning algorithms can process large scale heterogeneous data streams, identify hidden patterns, detect anomalies, forecast market trends, and generate predictive insights that support dynamic strategic decision-making. However, many AI-driven systems lack semantic interpretability and domain specific contextual awareness, limiting their transparency and trustworthiness in organizational environments.

Semantic technologies, particularly ontology engineering, provide mechanisms for structured knowledge representation and semantic interoperability across diverse information sources. Ontologies formally define concepts, entities, relationships, and business rules within a domain, enabling machine readable understanding and contextual reasoning. In the FinTech domain, ontology-based systems can model relationships among financial products, regulatory requirements, technological infrastructures, market segments, customer behaviors, and organizational performance indicators.

This study proposes a novel real time ontology based machine learning framework for evaluating FinTech competitiveness. The proposed framework integrates semantic knowledge representation with streaming machine learning and KPI-driven analytics to create an adaptive, interpretable, and scalable competitiveness assessment system. The framework consists of three major layers:

1. A semantic ontology layer for representing FinTech entities, relationships, and KPIs;

2. A real-time data ingestion and preprocessing layer for integrating heterogeneous data streams; and

3. A machine learning layer for classification, prediction, anomaly detection, and competitive intelligence generation.

The framework is empirically validated using datasets collected from Vietnamese FinTech enterprises between 2019 and 2024, a period characterized by rapid digital transformation, increased financial inclusion, and regulatory innovation. By integrating ontology reasoning with machine learning analytics, the framework enables continuous monitoring of competitive performance and supports strategic decision making for regulators, investors, and FinTech executives.

The remainder of this paper is organized as follows. Section 2 reviews related literature on competitiveness assessment, ontology engineering, and machine learning applications in FinTech. Section 3 presents the conceptual framework and ontology architecture. Section 4 describes the methodology and experimental implementation. Section 5 discusses the results and findings. Finally, Section 6 concludes the study and outlines future research directions.

2. Related Works

2.1 Competitive Advantage in the FinTech Industry

Competitive advantage has long been recognized as a foundational concept in strategic management. Porter's competitive strategy framework identifies cost leadership, differentiation, and focus strategies as key mechanisms for achieving sustainable market leadership. [1] However, the emergence of FinTech ecosystems has transformed the nature of competition within the financial services sector.

Unlike traditional financial institutions, FinTech enterprises operate in highly dynamic digital environments characterized by rapid technological innovation, evolving customer expectations, platform based ecosystems, and regulatory uncertainty. Recent research indicates that agility, technological adaptability, customer centric product development, digital accessibility, and ecosystem integration have become primary determinants of competitive advantage in FinTech markets. [2, 3]

In emerging economies such as Vietnam, additional factors, including regulatory support, digital infrastructure maturity, financial inclusion initiatives, cybersecurity capabilities, and public trust significantly influence organizational competitiveness. These rapidly changing market conditions make traditional static evaluation models insufficient for capturing real time competitive positioning.

The advent of financial technology (fintech) has reconfigured financial institutions into a complex adaptive system where technology, data flows, and stakeholder interactions co-evolve [4] [Lóska]

Wang et al. [5] contribute to systems science by integrating complex adaptive systems (CAS) theory into competitiveness evaluation, shifting the focus from firm centric governance to ecosystem dynamics. In the fintech era, evaluating competitiveness solely from an internal corporate governance standpoint is insufficient [6, 7] [Najaf, Menicucci]. To bridge this gap, Wang [5] proposed a systems-based competitiveness evaluation framework that integrates Delphi and ANP methods to model the dynamics of fintech's ecosystem.

Recently, AI has been found to effectively counter the high costs of traditional advisory services and address the widespread lack of financial literacy among investors [8, 9, 10] [Hentzen, Shihembetsa, Königstorfer].

Consequently, recent studies increasingly advocate the use of AI-driven competitiveness assessment systems capable of processing dynamic, heterogeneous data streams in real time. Such systems enable organizations to continuously monitor operational performance, customer engagement, market trends, and innovation capabilities. [11, 12].

2.2 Ontology-Based Systems in FinTech

Ontology is formally defined as an explicit specification of a shared conceptualization within a particular domain. [13] In artificial intelligence and information systems, ontologies provide structured semantic representations that support interoperability, knowledge sharing, automated reasoning, and contextual interpretation.

Within the FinTech domain, ontologies can represent entities such as:

• Financial products and services;

• Regulatory policies and compliance requirements;

• Customer profiles and behavioral patterns;

• Technological infrastructures;

• Risk classifications;

• Business processes; and

• Strategic KPIs.

Ontology-based systems are particularly valuable in data rich and heterogeneous environments because they enable semantic integration across diverse data sources, including APIs, databases, customer relationship management systems, financial statements, and regulatory repositories. [14]

Previous studies have demonstrated the usefulness of ontology frameworks in areas such as:

• Regulatory technology (RegTech);

• Credit risk analysis;

• Financial knowledge graphs;

• Fraud detection;

• Financial service integration; and

• Semantic interoperability. [15 -21]

Nevertheless, the application of ontology engineering for competitiveness assessment remains relatively underexplored, particularly in real-time strategic analytics contexts.

2.3 Machine Learning and Real-Time Analytics in FinTech

Machine learning has become a critical technological enabler in the FinTech industry. Supervised learning algorithms such as Random Forest, Support Vector Machines (SVM), Gradient Boosting, and Neural Networks are widely used for fraud detection, customer segmentation, recommendation systems, and financial forecasting. [5, 9]

Unsupervised learning approaches, including clustering algorithms, Isolation Forests, and autoencoders, are increasingly utilised for anomaly detection and behavioural analysis. More recently, streaming machine learning and online learning techniques have gained attention for enabling continuous model adaptation in real-time environments. [4]

Natural Language Processing (NLP) methods further enhance competitiveness evaluation by enabling sentiment analysis, trend detection, and interpretation of customer feedback from unstructured textual data. Advancements in embedded finance, real-time analytics, and API-driven service models have propelled the emergence of intelligent financial platforms, profoundly reshaping digital financial ecosystems. [22]

Despite these advancements, existing machine learning systems often suffer from limited semantic interpretability and insufficient contextual awareness. Most models treat data as isolated numerical features without incorporating domain knowledge structures or semantic relationships.

2.4 Research Gaps

Based on the literature review, several important research gaps can be identified:

1. FinTech competitiveness has become increasingly dynamic, multidimensional, and data-intensive;

2. Existing competitiveness evaluation approaches are often static and lack real-time adaptability;

3. Ontology-based systems improve semantic interoperability but are rarely integrated into competitiveness assessment;

4. Machine learning models provide predictive capabilities but often lack explainability and domain-specific semantic interpretation;

5. Few studies integrate ontology engineering with real-time streaming machine learning for FinTech competitiveness evaluation.

To address these limitations, this study proposes a hybrid ontology-based machine learning framework that integrates semantic technologies, KPI analytics, and real-time AI-driven competitiveness monitoring.

3. Conceptual Framework

3.1 Overview of the Proposed Architecture

The proposed framework integrates ontology engineering, real-time data analytics, and machine learning into a unified, three-tier architecture designed for the continuous assessment of FinTech competitiveness. [23, 24]. As illustrated in Figure 1, the system is structured to ensure semantic interoperability, dynamic model adaptation, contextual reasoning, and agile strategic evaluation. The architecture comprises three interconnected layers: (1) the Ontology Input Layer, (2) the Data Processing and Machine Learning Layer, and (3) the Output and Decision Support Layer. Together, these components facilitate the continuous acquisition, semantic annotation, processing, and analytical evaluation of multi-source FinTech data streams, enabling real-time competitive intelligence generation.

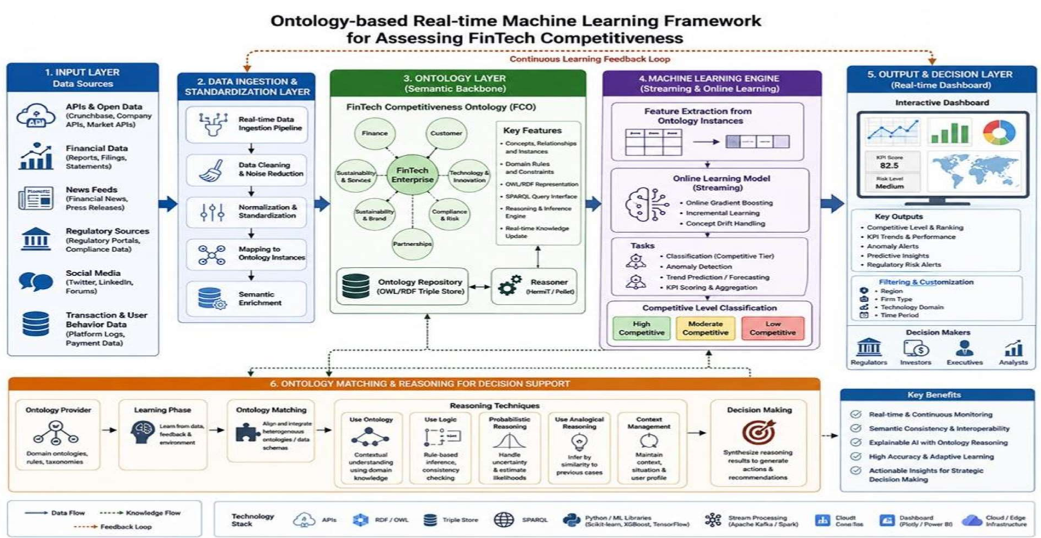

Figure 1. Schematic architecture of the proposed real-time ontology-based machine learning framework for FinTech competitiveness assessment

3.2 Ontology Input Layer

The ontology layer functions as the semantic backbone of the framework, providing a formalized knowledge representation of the FinTech ecosystem. A FinTech Competitive Ontology (FCO) was constructed using the Web Ontology Language (OWL2) within the Protégé environment. The FCO formally encodes core concepts, entities, key performance indicators (KPIs), relational structures, and domain-specific business rules pertinent to competitiveness evaluation. The ontology's class hierarchy encompasses nine principal categories: FinTechFirm, TechnologyCapability, MarketReach, CustomerEngagement, InnovationCapability, Risk Exposure, Regulatory Compliance, ESG Performance, and Strategic Partnership. Inter-entity relationships are formalized through object properties, including complies_with, provides_service, targets_market, collaborates_with, depends_on, processes_transaction, and adopts_technology.

This semantic layer fulfills four critical functions within the analytical pipeline. First, it ensures *semantic interoperability* by standardizing heterogeneous data originating from APIs, CRM systems, regulatory repositories, financial statements, transaction logs, and social media feeds. Second, it enables *data annotation and feature engineering* by semantically enriching incoming data streams with ontology-derived metadata, thereby enhancing machine learning interpretability and feature relevance. Third, it supports *real-time reasoning* through Description Logic and SPARQL-based queries, facilitating contextual inference, inconsistency detection, and automated knowledge discovery. Finally, the architecture is designed for *scalability and knowledge evolution*, allowing the ontology to dynamically incorporate emerging technologies, regulatory shifts, novel KPIs, and evolving market conditions without structural disruption.

3.3 Data Ingestion and Standardization Layer

The data ingestion layer orchestrates the continuous acquisition of real-time information from a diverse array of structured and unstructured sources. These include financial statements, regulatory filings, digital transaction systems, customer databases, news APIs, social media platforms, CRM systems, and market intelligence feeds. Upon ingestion, a dedicated preprocessing module executes a standardized pipeline comprising data cleaning, missing value imputation, normalization, timestamp synchronization, and noise reduction. Critically, this stage incorporates semantic mapping, wherein raw data instances are aligned with corresponding FCO entities. This ontology-driven standardization ensures semantic consistency and contextual coherence prior to data transmission into the machine learning pipeline, mitigating schema misalignment and enhancing downstream analytical fidelity.

3.4 Machine Learning Engine

The machine learning layer constitutes the analytical core of the framework, integrating supervised, unsupervised, streaming, and time series models to deliver a comprehensive assessment of competitiveness. Supervised learning algorithms, specifically Random Forest and Gradient Boosting, are used to classify FinTech enterprises into discrete tiers of competitiveness. Concurrently, unsupervised models including Isolation Forest and autoencoder based architectures detect anomalous KPI fluctuations and identify emerging operational risks. To accommodate the dynamic nature of digital financial markets, the framework employs Online Gradient Boosting for continuous, streaming model adaptation, enabling real time parameter updates without full retraining. Furthermore, Long Short Term Memory (LSTM) networks are utilized for temporal forecasting of critical KPI trajectories, including revenue growth rate, customer retention, transaction volume, fraud detection rate, and market share.

Leveraging semantically enriched input features, the classification module continuously categorizes FinTech enterprises into four strategic profiles: *Market Leaders*, *High-Potential Firms*, *Neutral Firms*, and *Declining Firms*. This multi-model ensemble ensures robust predictive accuracy, anomaly sensitivity, and adaptive responsiveness to shifting market dynamics.

3.5 Output and Decision Support Layer

The final layer translates machine learning outputs and semantic reasoning results into actionable strategic intelligence. An interactive, real-time dashboard synthesizes competitive trend analyses, KPI monitoring metrics, predictive alerts, anomaly indicators, strategic risk assessments, and regulatory exposure evaluations.

The visualization interface supports granular customization across multiple dimensions, including geographic regions, firm typologies, technology domains, KPI categories, and temporal windows. By transforming complex analytical outputs into intuitive, context-aware visualizations, this layer empowers investors, regulatory authorities, and organizational executives to make informed, data-driven strategic decisions in rapidly evolving FinTech markets.

4. Methodology and Research Experimentation

This study adopted a hybrid research methodology that integrates ontology engineering, real-time data analytics, and machine learning techniques to evaluate the competitive advantage of FinTech enterprises. The proposed framework was experimentally validated using KPI-driven datasets collected from Vietnamese FinTech organizations operating between 2019 and 2024. The methodology was designed to support semantic interoperability, real-time learning, predictive analytics, and explainable competitiveness assessment within highly dynamic financial ecosystems.

The experimental dataset was compiled from multiple heterogeneous sources, including Crunchbase APIs, financial reports, transaction systems, customer relationship management databases, regulatory portals, social media platforms, and financial news feeds. These sources provided both structured and unstructured information related to organisational performance, customer behaviour, innovation capability, compliance status, and market dynamics. More than fifty key performance indicators (KPIs) were collected and standardized to represent different dimensions of FinTech competitiveness.

To ensure a comprehensive assessment of competitiveness, the KPI framework incorporates financial, customer, technological, compliance, and sustainability indicators. Financial KPIs such as Revenue Growth Rate, Net Profit Margin, and Total Transaction Value were utilized to measure organizational profitability, operational scalability, and market expansion capacity. Customer oriented indicators including User Growth Rate, Customer Retention Rate, and Customer Satisfaction Score were incorporated to evaluate customer engagement, platform attractiveness, and long term loyalty. Technology and innovation metrics, such as Real-Time Transaction Processing Rate, Time to Market for New Products, and Process Automation Rate, were used to assess technological capability, innovation efficiency, and digital operational maturity.

In addition, compliance and risk-related KPIs were integrated into the framework to capture organizational resilience and regulatory preparedness. These indicators included Regulatory Compliance Rate, Number of Security Breaches, and Fraud Detection Rate. Sustainability oriented metrics such as ESG Score, Market Share, and Strategic Partnership indicators further enriched the competitiveness assessment by incorporating long-term organizational positioning, ecosystem integration, and corporate responsibility considerations. The integration of these multidimensional KPIs enabled the framework to provide a holistic and dynamic representation of FinTech competitiveness.

The framework's semantic foundation was established by constructing a FinTech Competitive Ontology (FCO). The ontology was developed using Protégé and formalized with OWL2 and RDF semantic technologies. The ontology defines domain-specific entities, hierarchical taxonomies, semantic relationships, and logical constraints associated with the FinTech ecosystem. Key ontology classes included FinTechFirm, TechnologyCapability, CustomerEngagement, InnovationCapability, RegulatoryCompliance, RiskExposure, ESGPerformance, and StrategicPartnership.

Semantic relationships among entities were modeled using ontology object properties such as complies_with, collaborates_with, targets_market, processes_transaction, and adopts_technology. These semantic structures enabled the ontology to function as a machine-readable and human-interpretable representation of organizational competitiveness. Furthermore, the ontology facilitated semantic interoperability by standardizing heterogeneous information originating from multiple digital sources.

Following ontology construction, the data ingestion and preprocessing phase was implemented to ensure consistency and quality across incoming data streams. The preprocessing module performed data cleaning, normalization, timestamp synchronization, missing value handling, and noise reduction. Incoming data instances were semantically mapped to ontology entities and enriched with contextual metadata. This semantic annotation process improved feature relevance and enhanced the interpretability of downstream machine learning models.

The machine learning component of the framework integrated supervised, unsupervised, and streaming learning techniques to support real-time competitiveness analysis. Random Forest and Gradient Boosting algorithms were employed for competitiveness classification tasks, enabling the system to categorize FinTech enterprises according to their competitive standing. To address temporal forecasting requirements, Long Short-Term Memory (LSTM) networks were utilized to model sequential KPI patterns and predict future organizational performance trends.

Unsupervised learning methods including Isolation Forest and Autoencoder models were incorporated to detect anomalies and identify abnormal KPI fluctuations associated with operational instability, cybersecurity incidents, or sudden market changes. These anomaly detection mechanisms enabled the framework to generate early warning alerts and support proactive managerial interventions.

To accommodate the dynamic nature of FinTech ecosystems, the framework employed streaming and online learning mechanisms through Online Gradient Boosting techniques. Unlike traditional batch-learning approaches, the streaming architecture continuously updates model parameters as new data arrives, eliminating the need for complete retraining. This adaptive capability allowed the framework to respond effectively to rapidly changing market conditions, technological innovations, and regulatory developments.

The experimental evaluation adopted a temporal validation strategy to preserve chronological consistency and prevent look-ahead bias. Historical KPI data were divided using time-series splits, ensuring that training and testing processes accurately reflected real-world forecasting conditions. Model performance was evaluated using multiple quantitative metrics, including accuracy, precision, recall, F1-score, Root Mean Square Error (RMSE), and coefficient of determination (R^2). These evaluation metrics enabled comprehensive assessment of classification performance, predictive accuracy, anomaly detection capability, and forecasting effectiveness.

The final stage of the framework involved real-time decision-support visualization through an interactive dashboard environment. Machine learning predictions, semantic reasoning outcomes, KPI trends, and anomaly alerts were transformed into actionable insights for regulators, investors, analysts, and organizational executives. The dashboard supported customizable filtering by region, firm type, technology domain, and KPI category, enabling flexible, context-aware strategic analysis.

Overall, the methodology establishes a unified and scalable research framework that integrates semantic technologies with machine-learning analytics to support intelligent, adaptive, and explainable competitiveness evaluation in modern FinTech ecosystems.

5. Results and Discussion

The experimental evaluation demonstrates that the proposed ontology-based machine learning framework provides an effective and scalable solution for real-time competitiveness assessment within FinTech ecosystems. By integrating semantic ontology engineering with streaming machine learning and KPI-driven analytics, the framework successfully captured dynamic organizational behavior, operational performance variations, and evolving market conditions across Vietnamese FinTech enterprises between 2019 and 2024.

The hybrid framework achieved an average F1-score of 0.83 and an overall competitiveness classification accuracy of 87%, indicating strong predictive capability in identifying and categorizing firms according to their competitive standing. The integration of ontology-based semantic enrichment significantly improved the consistency and interpretability of the underlying datasets. In particular, ontology-driven preprocessing reduced data noise by approximately 18%, enabling the machine learning models to focus more effectively on semantically meaningful features and relationships. This enhancement contributed to improved model stability and forecasting performance across multiple datasets and KPI categories.

The framework's real-time learning capability proved especially valuable in the highly dynamic FinTech environment. By implementing online gradient boosting and streaming learning mechanisms, the system continuously adapted to incoming data streams without requiring full retraining. The framework demonstrated the ability to process, analyze, and update competitiveness insights within a short response time of approximately five seconds, thereby supporting near real-time strategic decision making. Such responsiveness is essential in digital financial ecosystems where rapid technological change, market disruptions, and regulatory updates can significantly influence organizational competitiveness.

The ontology layer played a central role in enhancing semantic interoperability and contextual reasoning throughout the analytical pipeline. By standardizing heterogeneous information from APIs, financial reports, transaction systems, customer databases, and regulatory repositories, the ontology ensured consistency across data sources while preserving domain-specific meaning. Furthermore, semantic reasoning enabled the system to dynamically update relationships among KPIs, technologies, customer segments, regulatory requirements, and organizational entities. This capability substantially improved the explainability of machine learning outcomes by allowing predictions to be interpreted within a meaningful semantic context.

The competitiveness classification results revealed distinct performance distributions among Vietnamese FinTech enterprises. Approximately 30% of firms were classified as Market Leaders, indicating strong innovation capability, technological maturity, customer engagement, and operational stability. Another 28% of organizations were categorized as High Potential firms, demonstrating promising growth trajectories and emerging market influence despite some operational or strategic limitations. Neutral firms accounted for 29% of the dataset, reflecting moderate competitiveness and relatively stable market positioning, with no strong differentiation advantages. The remaining 13% were classified as Declining firms due to weaker KPI performance, lower innovation indicators, reduced customer retention, or higher operational and compliance risks.

The multi-KPI evaluation strategy significantly improved the quality of competitiveness assessment compared to traditional single metric approaches. Financial indicators such as Revenue Growth Rate and Net Profit Margin provided insight into organizational sustainability and profitability, while customer focused KPIs including User Growth Rate and Customer Retention Rate captured market engagement and brand attractiveness. Technology and innovation indicators such as Real Time Transaction Processing Rate and Time to Market for New Products effectively reflected operational efficiency and technological adaptability. Compliance and cybersecurity KPIs further strengthened the framework by incorporating risk-awareness and regulatory resilience into the competitiveness evaluation process.

The incorporation of LSTM forecasting models enabled the framework to identify temporal KPI patterns and anticipate future competitiveness trends. These forecasting capabilities proved particularly useful for monitoring transaction growth, customer behavior fluctuations, and emerging operational risks. Simultaneously, anomaly detection models such as Isolation Forest and Autoencoders successfully identified abnormal KPI fluctuations, enabling early warning generation and proactive managerial intervention. The combination of predictive analytics and semantic reasoning therefore enhanced both the accuracy and practical relevance of the proposed framework.

An important contribution of this study lies in the improved explainability of AI-driven competitiveness assessment. Unlike conventional black-box machine learning models, the proposed ontology based framework allows decision makers to trace predictive outcomes back to semantically defined concepts, relationships, and KPI structures. This transparency enhances stakeholder trust and supports more informed strategic decision making among regulators, investors, and organizational executives.

From a practical perspective, the framework demonstrates substantial applicability for multiple stakeholders within digital financial ecosystems. Regulators can utilize the system to monitor compliance trends, systemic risks, and market stability in real time. Investors can identify emerging market leaders and evaluate organizational resilience based on continuously updated competitiveness indicators. FinTech executives can leverage predictive alerts, KPI analytics, and anomaly detection insights to optimize strategic planning, operational efficiency, innovation management, and resource allocation.

The findings also highlight the scalability and adaptability of the proposed architecture. Although the experimental implementation focused on Vietnamese FinTech enterprises, the ontology structure can be extended to support multilingual semantic representations, additional ESG indicators, blockchain transaction analytics, and region-specific regulatory frameworks. This flexibility positions the framework as a promising foundation for broader deployment across ASEAN markets and other international digital financial ecosystems.

Overall, the results confirm that integrating ontology engineering with real time machine learning provides substantial advantages for competitiveness assessment in FinTech environments. The framework not only improves predictive performance and semantic consistency but also enhances interpretability, adaptability, and decision-support capabilities in rapidly evolving digital markets.

Market Leaders 30%

High Potential 28%

Neutral 29%

Declining 13%

The results indicate that the framework effectively captures variations in organizational performance, innovation capacity, operational efficiency, and market adaptability.

6. Conclusion and Future Work

This study proposed a real-time ontology-based machine learning framework for evaluating FinTech competitiveness using KPI-driven analytics, semantic technologies, and streaming AI models.

The framework integrates ontology engineering with machine learning to create a scalable, adaptive, interpretable, and semantically enriched competitiveness assessment system. By combining financial, customer, technological, compliance, ESG, and strategic partnership indicators into a unified ontology, the proposed approach enables real-time monitoring, predictive analysis, and strategic decision support.

Experimental results demonstrated that ontology integration improves semantic interoperability, enhances machine learning interpretability, reduces data noise, and supports more accurate classification of competitiveness. The hybrid AI framework achieved strong predictive performance while maintaining adaptability in dynamic market environments.

This research contributes both theoretical and practical value by bridging semantic technologies and artificial intelligence for strategic competitiveness analytics in FinTech ecosystems.

Future research directions include:

1. Integration of additional KPIs such as advanced ESG indicators and blockchain analytics;

2. Adaptive ontology evolution mechanisms;

3. Transformer-based and graph neural network models;

4. Real-world deployment and scalability evaluation;

5. Federated and privacy-preserving learning approaches;

6. Cross-border FinTech interoperability analysis;

7. Advanced explainable AI techniques; and

8. Integration with executive decision-support dashboards.

The proposed framework establishes a foundation for intelligent, real-time, and semantically aware competitiveness evaluation systems that support strategic decision-making in rapidly evolving digital financial environments.

References

[1] Porter, M. E. (1985). *Competitive Advantage: Creating and Sustaining Superior Performance. Free Press.*

[2] Gomber, P., Kauffman, R. J., Parker, C., Weber, B. W. (2018). On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems*, 35(1), 220–265.

[3] Puschmann, T. (2017). FinTech. *Business Information Systems Engineering*, 59(1), 69–76.

[4] Lóska, G., Uotila, J. (2024). Digital transformation in corporate banking: Toward a blended service model. Calif. Manag. Rev. 2024, 66, 93–115.

[5] Wang, X., Hu, W., Guan, N. (2025). A Systemic Approach to Evaluating Fintech-Driven Competitiveness in Commercial Banks: Integrating Delphi and ANP Methods. Systems, 13(5), 342. https://doi.org/10.3390/systems13050342

[6] Najaf, K., Chin, A., Fook, A. L.W., Dhiaf, M. M., Asiaei, K. (2024). Fintech and corporate governance: At times of financial crisis. Electron. Commer. Res. 24, 605–628.

[7] Menicucci, E., Paolucci, G. (2023). ESG dimensions and bank performance: An empirical investigation in Italy. *Corp. Gov. Int. J. Bus. Soc.* 2023, 23, 563–586.

[8] Hentzen, J. K., Hoffmann, A., Dolan, R., Pala, E. (2022). Artificial intelligence in customer-facing financial services: A systematic literature review and agenda for future research. *Int. J. Bank Mark.* 2022, 40, 1299–1336.

[9] Shihembetsa, E. (2021). Use of Artificial Intelligence Algorithms to Enhance Fraud Detection in the Banking Industry. Ph.D. thesis, *University of Nairobi, Nairobi, Kenya.*

[10] Königstorfer, F., Thalmann, S. (2020). Applications of Artificial Intelligence in commercial banks A research agenda for behavioral finance. *J. Behav. Exp. Financ.* 2020, 27, 100352.

[11] Nguyen, T. H., Cao, L. T. (2022). Real-time competitiveness monitoring using AI and financial indicators. *International Journal of FinTech Analytics*, 4(2), 123–138.

[12] Wang, Y., Li, H., Shen, J. (2021). Intelligent competitive analysis in FinTech using big data. *IEEE Access*, 9, 114356–114369.

[13] Gruber, T. R. (1993). A translation approach to portable ontology specifications. *Knowledge Acquisition*,

5(2), 199–220.

[14] Zhang, H., Sun, J., Wang, Y. (2020). A FinTech ontology for financial service integration. *Semantic Web Journal*, 11(3), 441–459.

[15] Ma, L., Xu, C., Hu, Y. (2023). Semantic technologies for financial compliance and risk management: A survey. *Journal of Financial Technology*, 5(1), 45–67.

[16] Kou, G., Yang, P., Xiao, F., Chen, Y. (2021). Evaluation of feature selection methods for financial risk prediction. *Decision Support Systems*, 139, 113124.

[17] Nguyen, A., et al. (2022). Semantic web technologies for financial regulation. *Journal of FinTech Studies*. [18] Crunchbase API Documentation. https://data.crunchbase.com/docs.

[19] Huang, H., et al. (2025). FinCaKGOnto: Constructing a financial causal ontology from text for semantic reasoning. *Applied Intelligence*.

[20] Chen, J., et al. (2023). Towards a FinTech knowledge graph: Ontology design and applications. *CEUR Workshop Proceedings*.

[21] State Bank of Vietnam. (2023). AI and machine learning impacts on Vietnamese digital banking efficiency.

[22] Sun, X, Yang, S. Cao, Y, . Zhao, Y, Z. Wang, Z. (2025). Standardized Interface Framework for Intelligent Financial Platforms: A Pre-Standardization Study," *In Journal of ICT Standardization,* vol. 13 (2), p. 181-210, June.