While the current framework achieves robust results on benchmark datasets, there is significant potential to extend its real-world applicability. Future efforts can focus on evaluating the model using large-scale, real-time transactional data sourced from banking and financial institutions. Incorporating temporal dynamics and heterogeneous graph structures—representing interactions between users, merchants, and devices—may significantly improve the model’s ability to detect sophisticated and evolving fraud patterns. Moreover, adopting advanced architectures such as Graph Transformers and reinforcement-based GNNs could enhance the learning capability of the system on more complex graph representations.

In addition, model explainability is essential for real-world adoption. Integrating interpretability tools such as SHAP or LIME can help provide clear insights into model decisions, increasing trust among stakeholders. The framework could also be adapted for online learning environments to support real-time fraud detection. To ensure data privacy and security, future implementations should explore federated learning and differential privacy methods. These advancements will make the system more robust, scalable, and suitable for deployment in high-stakes financial settings.