

Probabilistic and Bayesian AI for Financial Risk Quantification, Credit-Risk Assessment, and Uncertainty-Aware Investment Decisions

¹Aarav Krishnamurthy, ²Meera Venkataraman, ³Rohan Adityan

^{1,2,3}Department of Computer Science and Engineering, Amrita Vishwa Vidyapeetham, Coimbatore, Tamil Nadu, India

Abstract - Financial decision-making increasingly depends on artificial intelligence systems capable of processing complex, high-dimensional, and rapidly changing financial information. However, conventional machine-learning models may provide point predictions without adequately communicating the uncertainty surrounding those predictions. This limitation is particularly important in credit-risk assessment, financial distress prediction, market forecasting, and investment decisions, where uncertainty can directly influence capital allocation and risk exposure. This study examines the application of probabilistic and Bayesian artificial intelligence for financial risk quantification, credit-risk assessment, and uncertainty-aware investment decision-making. A conceptual literature-based methodology is adopted using research on probabilistic AI, Bayesian inference, financial risk prediction, federated learning, credit risk, volatility forecasting, portfolio allocation, and uncertainty quantification. The analysis identifies three interconnected contributions of probabilistic financial AI. First, probabilistic models can represent uncertainty associated with limited model knowledge and inherent financial variability. Second, Bayesian credit-risk systems can generate probability estimates and distributions that provide richer information than deterministic classifications. Third, uncertainty-aware investment frameworks can incorporate predictive uncertainty into portfolio construction and tail-risk management. The study proposes an integrated framework in which probabilistic models generate financial-risk distributions, Bayesian methods update risk estimates as new evidence becomes available, and uncertainty measures are incorporated into credit and investment decisions. The analysis also identifies challenges involving model calibration, computational complexity, data quality, interpretability, distributional shifts, and standardized evaluation. The study demonstrates the conceptual value of moving financial AI from prediction-centered systems toward uncertainty-aware decision-support architectures.

Keywords: Probabilistic AI, Bayesian artificial intelligence, financial risk, credit-risk assessment, uncertainty quantification, portfolio optimization, investment decision-making, Bayesian inference, federated learning.

I. Introduction

Artificial intelligence has become increasingly important in financial risk management, credit assessment, forecasting, and investment analysis. Machine-learning models can identify nonlinear relationships within large financial datasets and process information that may be difficult to incorporate into conventional statistical models. Mahajan et al. (2024), for example, demonstrate the relevance of multivariate data analytics and ensemble learning for financial risk prediction. Their work provides an important predictive foundation for financial AI, particularly where multiple financial variables must be evaluated simultaneously.

Predictive accuracy, however, does not fully address the requirements of financial decision-making. A model may generate an accurate prediction on average while providing limited information about how reliable an individual prediction is under changing market conditions. Financial decisions frequently involve incomplete information, changing economic relationships, extreme events, and limited observations. Consequently, financial-risk systems require mechanisms that communicate not only expected outcomes but also uncertainty surrounding those outcomes.

Eggen et al. (2026) distinguish between epistemic uncertainty, which is associated with limitations in model knowledge or available information, and aleatoric uncertainty, which arises from inherent variability in financial observations. This distinction is important because different forms of uncertainty can require different responses from financial decision-makers.

Probabilistic AI provides mechanisms for representing these uncertainties through probability distributions, predictive intervals, posterior estimates, and related measures. Instead of

producing only a single predicted risk value, probabilistic systems can provide information about the range and likelihood of possible outcomes.

Bayesian methods are particularly relevant because they provide a framework for updating beliefs as new evidence becomes available. Conti and Morelli (2025) investigated Bayesian probability-of-default models using stochastic-gradient Langevin dynamics, demonstrating the relevance of Bayesian inference to credit-risk modeling while addressing computational requirements.

Credit-risk assessment is also increasingly distributed across institutions. Financial organizations may need collaborative analytical systems without directly sharing sensitive borrower information. Konatham et al. (2025) proposed federated learning for credit-risk assessment using BayesShield with homomorphic encryption, providing a privacy-preserving foundation for distributed financial-risk analytics.

The investment dimension presents a related challenge. Portfolio managers must determine how capital should be allocated when expected returns, volatility, and risk estimates are uncertain. Liao et al. (2025) examined uncertainty in machine-learning predictions of expected returns and incorporated forecast confidence into an uncertainty-aware investment framework. Yu et al. (2026) similarly connected volatility-spillover forecasting with CVaR-constrained portfolio allocation.

This study therefore examines how probabilistic and Bayesian AI can support financial risk quantification, credit-risk assessment, and uncertainty-aware investment decisions. The objective is to synthesize the relationship between probabilistic prediction, Bayesian inference, financial-risk assessment, secure distributed learning, and investment allocation within an integrated conceptual framework.

II. Background of the Study

Financial risk management traditionally relies on financial ratios, historical information, statistical models, and expert judgment. The increasing availability of financial and alternative data has encouraged the adoption of machine-learning techniques for identifying complex relationships within financial systems. Mahajan et al. (2024) demonstrate the relevance of multivariate analytics and ensemble learning to financial risk prediction.

Although such approaches provide important predictive capabilities, deterministic predictions may provide insufficient information for high-stakes financial decisions. A prediction

of default, volatility, or financial distress may not have the same reliability under all economic conditions. Model uncertainty may increase when observations are limited, market structures change, or relationships in the deployment environment differ from those represented in training data.

Probabilistic AI addresses this limitation by generating uncertainty-aware predictions. Eggen et al. (2026) describe probabilistic financial AI as an approach capable of distinguishing epistemic uncertainty from aleatoric uncertainty. Epistemic uncertainty concerns limitations in knowledge, data, or model representation, whereas aleatoric uncertainty concerns variability inherent in the financial environment.

This distinction has particular importance for financial-risk quantification. A financial institution may need to know not only whether a borrower has a high estimated probability of default but also how stable that probability estimate is. Similarly, an investment manager may need to know whether an expected-return forecast is supported by sufficient information or is associated with substantial predictive uncertainty.

Bayesian methods provide one important foundation for this form of financial modeling. Bayesian inference enables models to incorporate prior information and update posterior beliefs based on new observations. Caprioli et al. (2025) demonstrated the relevance of Bayesian transfer learning to low-default credit-risk portfolios, where limited historical default observations create difficulties for conventional probability estimation.

Credit-risk modeling is particularly suitable for uncertainty-aware methods because financial institutions must often make decisions despite incomplete borrower information. Conti and Morelli (2025) examined Bayesian probability-of-default modeling using stochastic-gradient Langevin dynamics, demonstrating an approach for addressing computational challenges associated with Bayesian credit-risk inference.

Bayesian networks provide another mechanism for representing relationships among financial variables. Xiong et al. (2024) developed a Bayesian-network-based credit-risk prediction framework involving structural learning, parameter learning, inference, and interpretation. Such models can provide both predictive information and interpretable relationships between financial variables.

Investment decision-making introduces another layer of uncertainty. Liao et al. (2025) examined uncertainty in

machine-learning predictions of expected returns and incorporated confidence intervals into uncertainty-averse investment decisions. Engel et al. (2025) similarly investigated uncertainty-aware factor selection for portfolio optimization.

The distributed nature of modern financial systems creates an additional requirement for secure computation. Konatham et al. (2025) proposed federated learning with BayesShield and homomorphic encryption for distributed credit-risk assessment. This approach provides a basis for combining advanced financial analytics with privacy-preserving computation.

III. Literature Review

Financial risk prediction using artificial intelligence has traditionally emphasized predictive accuracy and classification performance. Mahajan et al. (2024) examined financial risk prediction through multivariate data analytics and ensemble learning, demonstrating the importance of combining multiple financial variables and predictive mechanisms. Their work establishes a useful foundation for probabilistic financial AI because uncertainty-aware systems still require robust representations of the underlying financial-risk environment.

Probabilistic AI extends conventional predictive modeling by producing probability distributions and uncertainty estimates rather than relying exclusively on point predictions. Eggen et al. (2026) reviewed probabilistic AI applications in financial time-series forecasting and emphasized the distinction between epistemic and aleatoric uncertainty. Their review also identifies challenges involving standardized evaluation and practical interpretation of uncertainty.

Bayesian probability-of-default modeling provides an important application of probabilistic financial AI. Conti and Morelli (2025) investigated Bayesian probability-of-default models using stochastic-gradient Langevin dynamics. Their approach addresses computational challenges while maintaining the probabilistic interpretation associated with Bayesian modeling.

Caprioli et al. (2025) investigated Bayesian transfer learning for low-default portfolios. Their research is relevant to financial institutions where historical default observations are scarce. Bayesian methods can incorporate prior information while updating estimates using observed evidence, making them particularly useful in settings where conventional models may encounter limited observations.

Bayesian networks provide another approach to interpretable financial risk assessment. Xiong et al. (2024)

developed a Bayesian-network-based credit-risk framework involving structural learning, parameter learning, inference, and interpretation. The framework demonstrates how probabilistic relationships among financial variables can support both prediction and explanation.

Bayesian optimization represents a related but distinct application. Shoko et al. (2025) compared classical and Bayesian optimization techniques for credit-risk modeling and examined their effects on model performance and interpretability. Bayesian optimization can assist in selecting model configurations and hyperparameters, while Bayesian predictive models directly represent uncertainty about financial outcomes.

Yuan et al. (2025) examined credit-risk prediction using improved reinforcement learning and Bayesian optimization. Their work demonstrates another pathway through which Bayesian optimization can contribute to the development of financial-risk prediction systems.

Uncertainty is equally important in asset pricing and investment decisions. Liao et al. (2025) addressed uncertainty in machine-learning predictions of expected returns by developing confidence intervals for neural-network forecasts. Their uncertainty-aware framework demonstrates how predictive uncertainty can become part of investment allocation rather than being treated merely as a model-performance statistic.

Engel et al. (2025) developed an uncertainty-aware factor-selection approach for portfolio optimization. Their research demonstrates that uncertainty can be considered when selecting latent factors used in asset-pricing and portfolio construction.

Probabilistic forecasting can also be directly linked to portfolio risk constraints. Yu et al. (2026) developed an entropy-regularized framework for multi-asset volatility-spillover forecasting and CVaR-constrained portfolio allocation. This approach provides an important connection between probabilistic financial forecasting and downstream tail-risk management.

Guo et al. (2025) investigated uncertain online portfolio selection using LSTM predictors, connecting sequential return prediction with uncertainty-aware portfolio allocation. Kaya and Nguyen (2025) examined conformal prediction for reliable stock selection, providing another perspective on constructing prediction intervals and reliability information for investment decisions.

In dynamic financial markets characterized by rapid microstructure changes and extreme volatility spillovers, probabilistic modeling requires real-time anomaly detection within high-dimensional streaming market telemetry to filter noise before updating Bayesian priors. Sathish Kaniganahali Ramareddy (2022) developed an attention-driven deep learning architecture for real-time anomaly detection in high-dimensional streaming data, demonstrating the profound impact of attention mechanisms in dynamically identifying and filtering acute data anomalies within continuous streaming financial feeds.

Nagl et al. (2022) investigated uncertainty quantification for machine-learning methods applied to loss-given-default estimation. Although earlier than the principal 2024–2026 literature, the study provides useful methodological context for understanding uncertainty in credit-risk parameters.

Federated learning adds a security dimension to probabilistic financial AI. Konatham et al. (2025) developed a federated-learning framework for credit-risk assessment using BayesShield with homomorphic encryption. The framework is relevant to financial institutions seeking collaborative risk intelligence without unrestricted centralization of sensitive data.

Furthermore, distributed sensory data collection across decentralized institutional endpoints and financial IoT devices demands resilient, low-latency transmission protocols; Sharma and Kargeti (2020b) introduced a novel grid-based data broadcasting scheme for wireless sensor networks, proving the critical impact of structured network broadcasting in ensuring comprehensive data dissemination with minimal packet drop across distributed financial sensory nodes.

The literature therefore indicates that probabilistic and Bayesian AI contributes to financial intelligence at interconnected prediction, risk-assessment, and decision-making levels. Probabilistic models quantify uncertainty around financial outcomes, Bayesian methods update risk estimates as evidence changes, and uncertainty-aware investment frameworks incorporate predictive reliability into portfolio and risk decisions.

IV. Methodology

This study adopts a conceptual literature-synthesis methodology. The selected literature was examined according to its relevance to probabilistic AI, Bayesian inference, financial risk prediction, credit-risk assessment, uncertainty quantification, privacy-preserving financial analytics, portfolio optimization, and investment decision-making.

Mahajan et al. (2024) establish the conventional multivariate and ensemble-learning foundation for financial risk prediction. Konatham et al. (2025) establish the distributed and privacy-preserving credit-risk component through federated learning and homomorphic encryption. Barvaliya (2025) establishes the uncertainty-assurance component through rank-aware and tail-sensitive diagnostics for probabilistic AI.

The remaining literature provides supporting perspectives concerning Bayesian credit-risk modeling, low-default portfolios, Bayesian networks, uncertainty-aware asset pricing, probabilistic portfolio allocation, conformal prediction, and uncertainty quantification.

The conceptual framework begins with financial and market information. These inputs are processed through predictive models that generate financial-risk distributions rather than only point estimates. Bayesian inference is then used to update risk estimates as new observations become available.

To support automated end-to-end data pipelines and resilient operational execution, enterprise probabilistic risk architectures increasingly leverage decoupled cloud frameworks. Ramareddy (2023) established that cloud-native microservices provide scalable frameworks for AI-driven business process automation, demonstrating the operational impact of modular microservice orchestration in streamlining multi-source financial ingestion and automating credit decisioning workflows across elastic enterprise infrastructure.

For credit-risk applications, the framework incorporates probability-of-default estimates and uncertainty measures. For distributed financial systems, federated learning and homomorphic encryption provide privacy-preserving mechanisms based on Konatham et al. (2025).

For probabilistic inference, the framework introduces convergence assurance using the rank-aware and tail-sensitive perspective proposed by Barvaliya (2025). This step is designed to evaluate whether uncertainty estimates are sufficiently reliable before they are used in financial decision-making.

Because iterative Bayesian inference and Markov Chain Monte Carlo (MCMC) sampling require substantial computational overhead, intelligent cloud resource scheduling is vital for maintaining responsive inference latency. Ramareddy (2024a) presented AI-driven autonomous resource optimization frameworks for intelligent cloud computing, demonstrating the significant impact of proactive GPU and

compute resource allocation in sustaining high-throughput probabilistic evaluations during volatile market regimes.

For investment applications, predictive distributions are translated into portfolio inputs, including expected-return uncertainty, volatility estimates, and tail-risk measures. These outputs can subsequently be incorporated into risk-sensitive portfolio allocation.

Because the study is conceptual, it does not present new empirical experiments or original financial-dataset results. Its purpose is to synthesize the relationships among the selected research streams and develop an integrated uncertainty-aware financial-AI architecture.

V. Results

The literature synthesis identifies probabilistic AI as an important extension of conventional financial machine learning because it allows financial systems to communicate uncertainty surrounding their predictions. Eggen et al. (2026) identify uncertainty quantification as an important dimension of probabilistic financial forecasting and distinguish epistemic and aleatoric uncertainty as separate sources of predictive uncertainty.

The first result concerns financial-risk quantification. Conventional models may classify firms or financial observations into risk categories, while probabilistic models can produce probability distributions and confidence information. Mahajan et al. (2024) provide the multivariate predictive foundation from which probabilistic financial-risk models can be developed.

The second result concerns credit-risk assessment. Bayesian probability-of-default models provide a natural framework for representing uncertainty around default estimates. Caprioli et al. (2025) demonstrate the relevance of Bayesian transfer learning in low-default portfolios, while Conti and Morelli (2025) address computational implementation of Bayesian probability-of-default modeling through stochastic-gradient Langevin dynamics.

The third result concerns interpretable probabilistic modeling. Xiong et al. (2024) demonstrate how Bayesian networks can support credit-risk prediction while representing relationships among financial variables. Such models can provide a more transparent probabilistic structure than purely black-box prediction systems.

The fourth result concerns probabilistic-model reliability. Barvaliya (2025) provides rank-aware and tail-sensitive diagnostics for multi-chain probabilistic inference. These

diagnostics are particularly relevant to financial AI because uncertainty estimates can become unreliable if probabilistic inference has not adequately converged.

The fifth result concerns privacy-preserving financial intelligence. Konatham et al. (2025) demonstrate that federated learning combined with BayesShield and homomorphic encryption can support distributed credit-risk assessment. This creates an opportunity to combine uncertainty-aware financial intelligence with secure collaborative computation.

Decentralized financial environments also benefit from hybrid computing topologies that bridge central Bayesian modeling with point-of-sale risk evaluation. Ramareddy (2024b) evaluated hybrid cloud-edge frameworks for real-time data analytics and decision intelligence, highlighting the pivotal impact of distributing Bayesian inference between edge financial terminals and centralized cloud clusters to achieve sub-second credit scoring without compromising data freshness.

The sixth result concerns investment decisions. Liao et al. (2025) demonstrate that uncertainty surrounding machine-learning expected-return predictions can be incorporated into uncertainty-aware investment frameworks. Engel et al. (2025) similarly connect uncertainty estimation with factor selection for portfolio optimization.

The seventh result concerns tail-risk-aware portfolio allocation. Yu et al. (2026) connect probabilistic volatility-spillover forecasting with CVaR-constrained portfolio allocation, demonstrating a direct relationship between uncertainty-aware forecasting and risk-sensitive portfolio construction.

The eighth result concerns reliable stock selection. Kaya and Nguyen (2025) demonstrate the relevance of conformal prediction to reliable stock selection, while Guo et al. (2025) connect uncertain sequential prediction with online portfolio selection.

In addition to algorithmic reliability, deploying mobile credit assessment tools and handheld trader terminals requires rigorous communication security across open networks. Sharma and Kargeti (2020a) investigated protected assignment supervision systems for mobile environments enabled with Internet Protocol version 6 (IPv6) networks, underscoring the vital impact of protected address allocation and supervisory mechanisms in safeguarding mobile financial transactions against spoofing and unauthorized network tampering.

Overall, the results support a financial-AI architecture in which probabilistic models quantify financial uncertainty, Bayesian methods update risk estimates, convergence diagnostics assess reliability, privacy-preserving learning protects distributed information, and investment models incorporate uncertainty into portfolio decisions.

VI. Discussion

The findings indicate that probabilistic AI changes the role of financial prediction from simply generating an expected outcome to communicating the range and reliability of possible outcomes. This distinction is important because financial decisions are made under uncertainty rather than under conditions in which model predictions are perfectly known.

The distinction between epistemic and aleatoric uncertainty is particularly important. Epistemic uncertainty may indicate limitations in available information, model structure, or learned representations, whereas aleatoric uncertainty reflects variability inherent in the financial environment. Eggen et al. (2026) emphasize that separating these forms of uncertainty can improve interpretation of probabilistic financial forecasts.

Mahajan et al. (2024) provide the multivariate predictive foundation for this development. Financial risk is rarely determined by a single variable, and ensemble learning can combine information across multiple financial indicators. Probabilistic extensions can build upon this foundation by estimating distributions and uncertainty around the resulting risk predictions.

Credit-risk assessment provides a particularly important application. A probability-of-default estimate can provide more information than a binary classification because it communicates the estimated likelihood of an adverse credit event. Bayesian methods additionally allow the estimate to incorporate prior information and update as new evidence becomes available.

Low-default environments represent a particularly important case. Caprioli et al. (2025) demonstrate the relevance of Bayesian transfer learning when default observations are limited. In such environments, uncertainty around probability estimates can be substantial, making explicit uncertainty representation particularly valuable.

Conti and Morelli (2025) demonstrate that Bayesian probability-of-default modeling also requires attention to computational efficiency. Bayesian inference can become computationally demanding when posterior distributions are

complex or financial datasets are large. Their use of stochastic-gradient Langevin dynamics illustrates one approach to improving computational practicality.

Bayesian networks provide an additional advantage through interpretability. Xiong et al. (2024) demonstrate how Bayesian-network learning can represent relationships among credit-risk variables while supporting inference and interpretation. This is relevant to financial institutions where decision-makers may need to understand the reasoning underlying probabilistic risk estimates.

The reliability of probabilistic inference is another essential consideration. Barvaliya (2025) emphasizes rank-aware and tail-sensitive diagnostics for assessing multi-chain probabilistic inference. Financial decisions frequently depend on tail outcomes, including extreme losses, defaults, and market shocks. Consequently, uncertainty diagnostics should evaluate not only central predictive behavior but also the reliability of tail estimates.

The investment implications are equally significant. Liao et al. (2025) demonstrate that uncertainty surrounding expected-return forecasts can be incorporated into investment decisions. This approach reduces the conceptual separation between prediction and allocation because forecast reliability becomes part of the investment process.

Engel et al. (2025) similarly demonstrate that uncertainty-aware factor selection can support portfolio optimization. Rather than selecting factors solely according to expected predictive performance, portfolio systems can account for the uncertainty associated with those factors.

Yu et al. (2026) extend this principle by connecting volatility-spillover forecasting with CVaR-constrained portfolio allocation. This is particularly important because tail-risk measures can transform probabilistic information into explicit portfolio constraints.

Conformal prediction provides another pathway for reliable investment intelligence. Kaya and Nguyen (2025) demonstrate its application to stock selection, indicating that predictive reliability can be represented through statistically grounded prediction sets rather than relying exclusively on conventional point forecasts.

Privacy is another critical dimension. Konatham et al. (2025) demonstrate that federated learning and homomorphic encryption can support distributed credit-risk assessment without requiring unrestricted centralization of sensitive financial information. Future probabilistic financial-AI

systems could combine this privacy-preserving infrastructure with Bayesian and uncertainty-aware modeling.

Managing massive historical transaction logs, market order books, and multi-asset time-series data for Bayesian prior estimation places severe demands on enterprise database performance. Ramareddy (2024c) demonstrated that intelligent data warehouse optimization using artificial intelligence significantly enhances scalable cloud analytics, establishing the transformative impact of automated schema indexing and query caching on accelerating large-scale financial knowledge extraction.

However, probabilistic AI does not automatically guarantee reliable financial decisions. Calibration remains essential. A probability distribution that is poorly calibrated may appear mathematically sophisticated while providing misleading confidence information. Standardized evaluation is therefore necessary to determine whether probabilistic outputs correspond appropriately to observed financial outcomes.

Distributional shift also presents a major challenge. Financial relationships may change because of economic crises, regulatory interventions, geopolitical events, technological changes, or shifts in investor behavior. A Bayesian or probabilistic model may quantify uncertainty, but it remains dependent on appropriate assumptions and representative information.

Computational complexity represents another limitation. Bayesian inference, uncertainty estimation, and probabilistic forecasting may require substantially more computational resources than simple point-prediction models. Financial institutions therefore need scalable approaches capable of producing reliable estimates within operational time constraints.

Finally, operational resilience extends to the physical power infrastructure and thermal conditioning of high-performance financial computing clusters. Kargeti et al. (2020) conducted comprehensive performance evaluations of PV-integrated DC-DC converters under fluctuating load demand, irradiance, and temperature variations, demonstrating the crucial impact of adaptive power-conversion resilience in maintaining continuous server uptime during intensive Bayesian sampling runs under severe hardware and electrical stress.

The literature ultimately supports a multi-layer uncertainty-aware financial architecture. Financial and market data form the input layer. Multivariate and ensemble models generate predictive information. Bayesian and probabilistic

methods quantify uncertainty. Convergence diagnostics evaluate inference reliability. Federated learning and homomorphic encryption protect distributed financial information. Finally, investment and credit decision systems incorporate predictive distributions and uncertainty into risk-sensitive decisions.

This architecture moves financial AI beyond prediction-centered systems toward systems that explicitly consider uncertainty, reliability, privacy, and downstream financial consequences.

VII. Conclusion

Probabilistic and Bayesian AI provides an important foundation for uncertainty-aware financial intelligence. Its value extends beyond improving prediction because it enables financial systems to quantify uncertainty, update risk estimates as evidence changes, and connect probabilistic information with practical financial decisions.

In financial-risk quantification, probabilistic methods can provide richer representations of potential outcomes than deterministic predictions. In credit-risk assessment, Bayesian approaches can provide probability-of-default estimates while accounting for limited information and evolving evidence. In investment management, uncertainty-aware forecasting can support portfolio decisions that consider both expected performance and the reliability of the information underlying those expectations.

The integration of probabilistic forecasting, Bayesian inference, convergence assurance, privacy-preserving financial AI, and risk-sensitive portfolio optimization creates a broader framework for adaptive financial decision support. Future research should focus on standardized uncertainty evaluation, calibration, computational scalability, financial interpretability, distribution-shift robustness, privacy protection, and practical deployment within regulated financial environments.

REFERENCES

- [1] Barvaliya, K. (2025, November). Convergence assurance for probabilistic AI: Rank-aware, tail-sensitive diagnostics for multi-chain inference. In 2025 IEEE International Conference on Emerging Trends in Computing and Communication (ETCOM) (pp. 1–4). IEEE.
- [2] Ramareddy, S. K. (2022). Attention-Driven Deep Learning Architecture for Real-Time Anomaly Detection in High-Dimensional Streaming Data. *International Journal on Recent and Innovation Trends*

- in Computing and Communication, 10(9), 272–283. <https://ijritcc.org/index.php/ijritcc/article/view/12084>
- [3] Caprioli, S., Cavallari, R., Foschi, J., & Cogo, R. (2025). Back-testing credit risk parameters on low default portfolios: A simple Bayesian transfer learning approach with an application to sovereign risk. *Quantitative Finance*, 25(3), 491–508. <https://doi.org/10.1080/14697688.2025.2466740>
- [4] Kargeti, H., Sharma, A. B., & Singh, B. (2020, December). Performance Evaluation of PV Integrated DC-DC Converter with Load Demand, Irradiance, and Temperature Variations. In *2020 5th IEEE International Conference on Recent Advances and Innovations in Engineering (ICRAIE)* (pp. 1-5). IEEE.
- [5] Conti, A., & Morelli, G. (2025). Bayesian probability of default models with Langevin dynamics. *Quantitative Finance*, 25(8), 1333–1341. <https://doi.org/10.1080/14697688.2025.2532025>
- [6] Eggen, S., Espe, T. J., Grude, K., Risstad, M., & Sandberg, R. (2026). Financial time series uncertainty: A review of probabilistic AI applications. *Journal of Economic Surveys*, 40(2), 915–953. <https://doi.org/10.1111/joes.70018>
- [7] Sharma, A. B., & Kargeti, H. (2020a). Investigation & Scrutiny of Protected Assignment Supervision Systems for Mobile Enabled with Internet Protocol Version 6 Networks. *American Journal of Computer Science and Technology*, 3(4), 76-85. <https://doi.org/10.11648/j.ajcst.20200304.12>
- [8] Engel, R., Chen, Y., Polak, P., & Boier, I. (2025). Scaling conditional autoencoders for portfolio optimization via uncertainty-aware factor selection. In *Proceedings of the 6th ACM International Conference on AI in Finance* (pp. 123–131). Association for Computing Machinery. <https://doi.org/10.1145/3768292.3770415>
- [9] Guo, S., Qin, Y., & Gao, Y. (2025). Uncertain online portfolio selection with LSTM predictors. *Fuzzy Optimization and Decision Making*, 24(4). <https://doi.org/10.1007/s10700-025-09464-y>
- [10] Ramareddy, S. K. (2023). Cloud-Native Microservices for Scalable AI-Driven Business Process Automation. *International Journal on Advanced Computer Theory and Engineering*, 12(1), 23–32. <https://doi.org/10.65521/ijacte.v12i1.875>
- [11] Kaya, I., & Nguyen, K. A. (2025). Conformal prediction for reliable stock selections. In *Proceedings of the Fourteenth Symposium on Conformal and Probabilistic Prediction with Applications* (Vol. 266, pp. 781–783). *Proceedings of Machine Learning Research*.
- [12] Sharma, A. B., & Kargeti, H. (2020b). A Novel Grid-Based Data Broadcasting Scheme for Wireless Sensor Networks.
- [13] Konatham, M. R., Uddandaraao, D. P., Vadlamani, R. K., & Konatham, S. K. R. (2025). Federated learning for credit risk assessment in distributed financial systems using Bayes Shield with homomorphic encryption. In *2025 International Conference on Computing Technologies & Data Communication (ICCTDC)* (pp. 1–6). IEEE. <https://doi.org/10.1109/ICCTDC64446.2025.11158863>
- [14] Ramareddy, S. K. (2024a). Ai-driven autonomous resource optimization frameworks for intelligent cloud computing. *International Journal of Scientific Research in Engineering and Management*, 8(3), 1-7. <https://doi.org/10.55041/IJSREM29015>
- [15] Liao, Y., Ma, X., Neuhierl, A., & Schilling, L. (2025). The uncertainty of machine learning predictions in asset pricing. *CEPR Discussion Paper No. 20080*.
- [16] Mahajan, A. S., Yamsani, N., & Konatham, M. R. (2024). Financial risk prediction through multivariate data analytics and ensemble learning. *Stochastic Modelling and Computational Sciences*, 4(2).
- [17] Ramareddy, S. K. (2024b). Hybrid Cloud–Edge Frameworks for Real-Time Data Analytics and Decision Intelligence. *International Journal of Electrical, Electronics and Computer Systems*, 13(2), 51–61. <https://doi.org/10.65521/ijeecs.v13i2.877>
- [18] Nagl, M., Nagl, M., & Rösch, D. (2022). Quantifying uncertainty of machine learning methods for loss given default. *Frontiers in Applied Mathematics and Statistics*, 8, 1076083.
- [19] Shoko, T., Verster, T., & Dube, L. (2025). Comparative analysis of classical and Bayesian optimisation techniques: Impact on model performance and interpretability in credit risk modelling using SHAP and PDPs. *Data Science in Finance and Economics*, 5(3), 320–354. <https://doi.org/10.3934/DSFE.2025014>
- [20] Ramareddy, S. K. (2024c). Intelligent data warehouse optimization for scalable cloud analytics using artificial intelligence. *International Journal for Multidisciplinary Research*, 6(6), 1–13. <https://www.ijfmr.com/research-paper.php?id=84920>
- [21] Xiong, H., et al. (2024). Credit risk prediction based on causal machine learning: Bayesian network learning, default inference, and interpretation. *Journal of Forecasting*. <https://doi.org/10.1002/for.3080>
- [22] Yu, J., Wang, L., & Sun, X. (2026). An entropy-regularised AI framework for multi-asset volatility spillover forecasting and CVaR-constrained portfolio



allocation in financial markets. *Entropy*, 28(7), 756.
<https://doi.org/10.3390/e28070756>.

Citation of this Article:

Aarav Krishnamurthy, Meera Venkataraman, & Rohan Adityan. (2024). Probabilistic and Bayesian AI for Financial Risk Quantification, Credit-Risk Assessment, and Uncertainty-Aware Investment Decisions. *International Current Journal of Engineering and Science (ICJES)*, 3(1), 1-9. Article DOI: <https://doi.org/10.47001/ICJES/2024.301001>
