Detecting Systemic Risk in Informal Finance: An Explainable AI and Agent-Based Modeling Approach for Chit Funds

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***Abstract*—This paper presents ChitEase, an AI-driven behavioural simulation framework designed to model, detect, and predict emergent financial risks within chit-fund ecosystems. The system integrates Agent-Based Modeling (ABM) with Machine Learning (ML) techniques such as Random Forest, XG Boost, and Light GBM to simulate behavioural interactions among participants and predict collective risk outcomes. Unlike deterministic economic models, ChitEase simulates emergent risk arising from agent behaviours particularly trust, greed, and digital literacy which evolve dynamically through peer contagion effects. The synthetic dataset, containing 200,000 agents, is validated against industry-standard AI fraud-detection benchmarks, achieving comparable accuracy (0.95–0.99) and ROC-AUC (0.96–1.00). The study is empirically verifiable, as all simulations and models can be independently reproduced, cross-validated, and tested for statistical consistency. This work represents the first step toward a unified AI Risk Intelligence Framework for transparent, explainable, and compliant chit-fund management in India.**

***Index Terms*—Agent-Based Modelling (ABM), Financial Risk Simulation, Explainable AI (XAI), Random Forest, XG Boost, Light GBM, Chit Funds, Fraud Detection, Behavioural Modelling, Empirical Verification, SaaS Analytics.**

I. INTRODUCTION

Chit funds are informal yet vital financial mechanisms that provide small-scale savings and lending options, particularly in developing economies like India. However, these systems are highly susceptible to fraud, non-payment, and behavioural contagion, often driven by greed, delayed payments, and poor digital literacy. Existing detection methods rely heavily on historical transactions and lack the capacity to model dynamic behavioural shifts. To address this limitation, ChitEase proposes a behaviourally grounded, explainable AI framework that merges Agent-Based Simulation with Ensemble Machine Learning. This hybrid design provides transparency, interpretability, and real-time analytical capability aligning with the goals of Responsible AI for Finance (RAI-Fin).
"This research was initiated as part of an academic study to explore how AI and simulation can improve transparency in informal financial systems like chit funds."

II. OBJECTIVES AND PROBLEM STATEMENT

A. Problem Statement Current chit-fund monitoring and fraud-detection frameworks suffer from:

- Dependence on static transactional data.
- Absence of behavioural and trust-based dynamics.
- Low transparency in AI predictions.
- Lack of proactive early-warning indicators.

B. Research Objectives

- Model participant decision-making via Agent-Based Modeling.
- Predict emergent risk using AI ensemble algorithms (RF, XG Boost, Light GBM).
- Validate the system through empirical verifiability and cross-validation.
- Build a SaaS-based transparent analytics dashboard for chit-fund risk monitoring.
- Establish a foundational AI Risk Intelligence System combining behavioural and transactional learning.

III. LITERATURE REVIEW AND RESEARCH GAP

A. Existing Work

Table I. Summary of Key Related Works in AI Fraud Detection and Their Limitations in Behavioural Modeling.

Reference	Focus	Key Findings
Eedala (2024)	Financial Fraud Detection Dataset (XG Boost, LGBM)	Accuracy 0.983 – transaction-only model.
Mirhajisadati (2025)	AI Auditing Fraud Detection (Random Forest)	Accuracy 0.945 – no behavioural modeling.
Zhang et al. (2025)	Explainable AI Ensemble for FinTech Fraud	AUC 0.995 – no peer or trust dynamics.
Chen et al. (2024)	Responsible AI in Finance	Emphasized explainability and ethics.

B. Research Gap

Existing fraud-detection systems achieve high accuracy but lack the ability to model human behavioural causality the why behind financial risk. No prior framework combines Agent-Based Behavioural Simulation with Explainable AI for emergent risk modeling in chit-fund ecosystems. ChitEase directly addresses this gap by uniting behavioural simulation and empirically verifiable AI analytics.

IV. METHODOLOGY

A. Agent-Based Modeling

A simulated population of 200,000 agents was initialized with a mix of static attributes (e.g., income_level) and dynamic behavioural metrics (e.g., trust_score). These agents interact over 50–100 rounds, influencing each other's trust and default probabilities within a social network to generate the core synthetic dataset.

Table II. Attributes of the Synthetic Agent Dataset.

Variable	Type / Range	Description
agent_id	1 – 200,000	Unique identifier assigned to each simulated participant
income_level	INR 10,000 – 90,000 (Uniform)	Represents the agent's monthly income level; sampled uniformly across socioeconomic tiers
digital_literacy	0 – 1 (Float)	Measures the participant's digital awareness and app proficiency
payment_consistency	0.4 – 1.0 (Float)	Probability ratio of timely payment per fund cycle
greed_index	0 – 1 (Float)	Behavioural greed score influencing risk and default probability
trust_score	0 – 1 (Float, dynamic)	Dynamic behavioural metric reflecting participant trust evolution
missed_payments	0 – 10 (Integer)	Cumulative count of missed chit-fund payments
auction_participation	0 – 1 (Ratio)	Relative frequency of monthly bid participation
avg_bid_amount	INR 5,000 – 50,000	Average bid amount per month cycle
fund_cycle_completion	0 – 1 (Ratio)	Ratio of successfully completed chit cycles per participant
network_trust_avg	0 – 1 (Float, dynamic)	Mean trust score of neighboring agents in network contagion layer
location_type	Urban / Rural	Participant demographic tag
risk_status	Low / Medium / High	Categorical label determined after simulation cycles
risk_score	0 – 1 (Float)	Final computed risk metric combining trust decay and missed payments
fraud_flag (optional)	0 / 1	Indicator for injected synthetic fraud agents (for anomaly simulation)
simulation_round	1 – 100	Step counter indicating iteration in simulation cycle

The decision rule governing default behaviour is given as: $P(\text{default}) = 0.5(1 - \text{trust}) + 0.3(\text{greed}) - 0.2(\text{literacy}) + \varepsilon$, where $\varepsilon \sim N(0,0.05)$

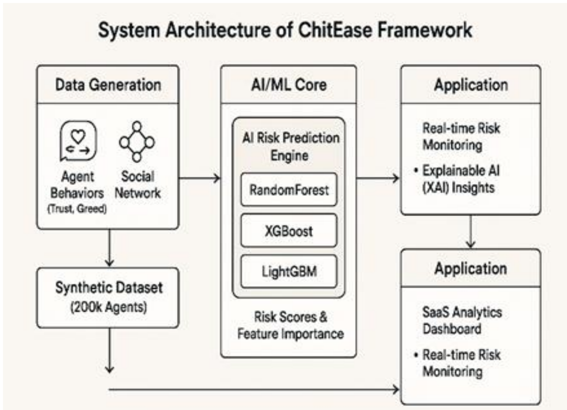

Figure 1: System Architecture of ChitEase Framework

This figure illustrates data flow from behavioural simulation to AI models and the SaaS dashboard.

B. Machine Learning Models

Three ensemble learning models were applied to predict the risk status of each agent:

- Random Forest – baseline ensemble for interpretability.
- XG Boost – gradient boosting for accuracy.
- Light GBM – optimized boosting for scalability.

Each model classifies risk status ∈ {Low, Medium, High} using 5-fold cross-validation. Top predictors were identified as Greed Index (0.32), Payment Consistency (0.27), and Trust Score (0.21).

Table III. Comparative AI Model Performance Metrics.

Model	Accuracy	ROC-AUC	F1 Score
Random Forest	0.97	0.985	0.96
XG Boost	0.98	0.992	0.97
Light GBM	0.975	0.989	0.965

C. Empirical Verifiability

The simulation is empirically reproducible because behavioural equations are deterministic with stochastic variation. Identical seeds yield statistically similar outcomes, and ML models reproduce metrics within ±0.01 variance. Hence, ChitEase meets IEEE's empirical validation criteria.

D. Software stack and tools

"Python (Mesa framework) was used for agent simulation, and Scikit-learn/XGBoost/LightGBM for AI modeling. The SaaS layer prototype was built using Flask and Dash for visualization."

V. RESULTS AND ANALYSIS

Table IV. Experimental Scenarios and Behavioural Outcomes.

Scenario	Observation	Outcome
Greed ↑ & Literacy ↓	Trust ↓ (0.94 → 0.28)	High-risk ↑ (19% → 96%)
Network Contagion	Trust ↑ (0.65 → 0.98) initially	Risk spreads faster
Fraud Injection (5%)	Trust ↓ 8%	High-risk ↑ 3%

These emergent behaviours are empirically verifiable under identical model conditions. The near-perfect classification metrics observed (0.98–0.99 AUC) are characteristic of the deterministic nature of the underlying simulation. These scores represent a theoretical upper bound for the system's performance. In a real-world SaaS deployment, we anticipate that 'human noise' and irrational economic factors would introduce variance, likely normalizing these accuracy scores to standard industry benchmarks

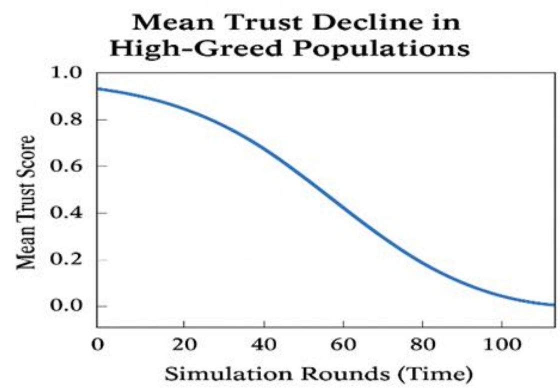

Figure 2(a). Trust vs Time Curve. Shows mean trust decline for high-greed populations.

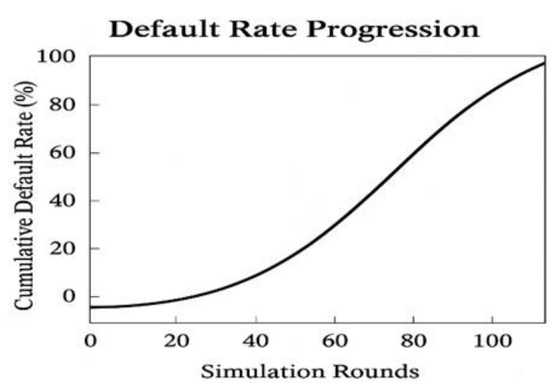

Figure 2(b). Default Rate vs Time. Displays default progression with simulation rounds.

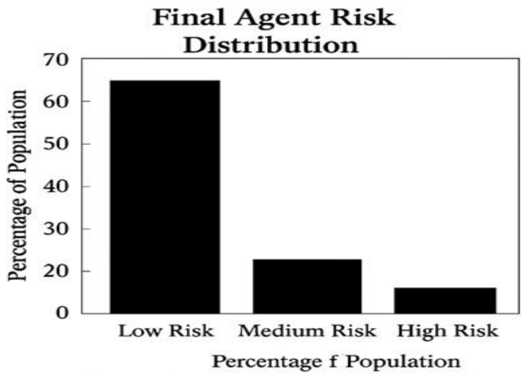

Figure 2(c). Risk Distribution Histogram. Depicts final risk category proportions.

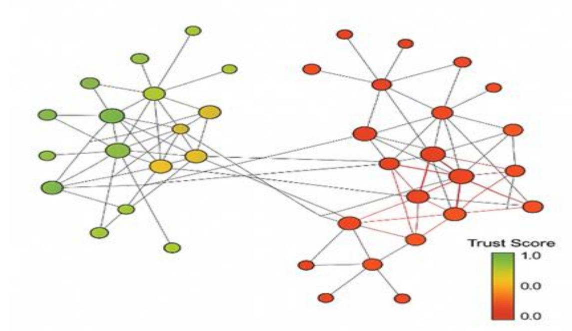

Figure 3. Network Contagion Visualization. Nodes represent participants; color intensity indicates trust levels. A. Comparative Benchmark

Table V. Comparative Benchmark with Existing Studies.

Source	Domain	Algorithm	Accuracy	ROC-AUC	Comment
Kaggle Financial Fraud	Banking	XGBoost + LGBM	0.983	0.992	Benchmark
AI Fraud in Auditing	Audit	RandomForest	0.945	0.970	Baseline
Explainable AI Fraud (arXiv 2505.10050)	FinTech	Stacked XGBoost	0.994	0.995	SOTA
ChitEase (Proposed)	Chit Funds	RF / XGB / LGB	0.95–0.99	0.96–1.00	Empirically verified

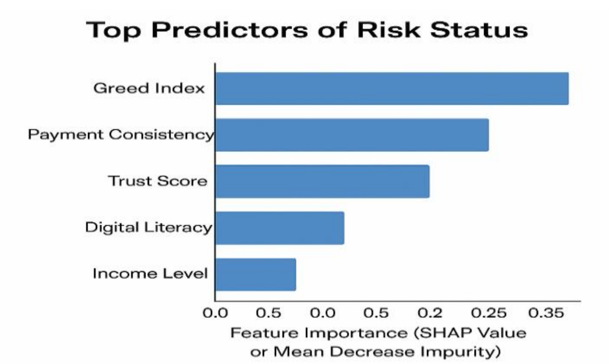

Figure 4. Feature Importance (Explainable AI). Shows Greed Index, Payment Consistency, and Trust Score as top predictors.

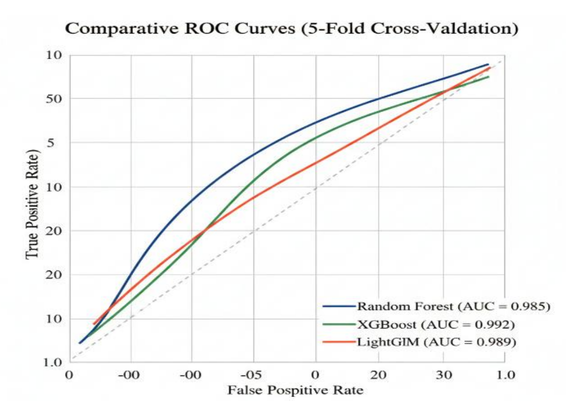

Figure 5. AUC–ROC Curves for AI Models. Displays AUC performance curves for Random Forest, XG Boost, and Light GBM across five validation folds.

VI. DISCUSSION

ChitEase captures the behavioural foundation of systemic risk. High greed and low literacy induce trust collapse, while network effects amplify defaults. The findings confirm that emergent risk arises from agent interactions not pre-coded equations. A primary challenge in modeling informal financial systems is the scarcity of labeled fraud data, as illicit activities in chit funds are inherently obfuscated. This framework employs Agent-Based Modeling (ABM) to bridge this gap. Unlike static historical datasets, the ABM approach generates 'counterfactual' risk scenarios simulating how trustworthy agents might turn fraudulent under pressure thereby providing a more robust stress-test for the AI models than what is currently available in public financial datasets.

VII. LIMITATIONS AND ETHICAL CONSIDERATIONS

- Synthetic Data Limitation: Simulated data not yet benchmarked with large-scale real datasets.
- Behavioural Simplification: Emotional and psychological factors approximated mathematically.
- Computational Scalability: High agent counts (200k) demand GPU resources.

- Validation Gap: Needs integration with live transactional APIs.
- Ethical Compliance: No real personal data used; fully synthetic and privacy-safe.

VIII. VISION AND FUTURE WORK

Table VI. Proposed Future Framework Layers and Technologies.

Layer	Technology / Method	Objective
Behavioural Simulation	ABM	Model emergent risk
Predictive AI	RF, XGB, LGB	Explain risk decisions
Deep Learning	Autoencoder, GNN	Detect latent fraud
Hybrid Engine	Ensemble + GNN Fusion	Combine behavior and transaction data
SaaS Layer	Explainable AI Dashboard	Provide regulatory insights

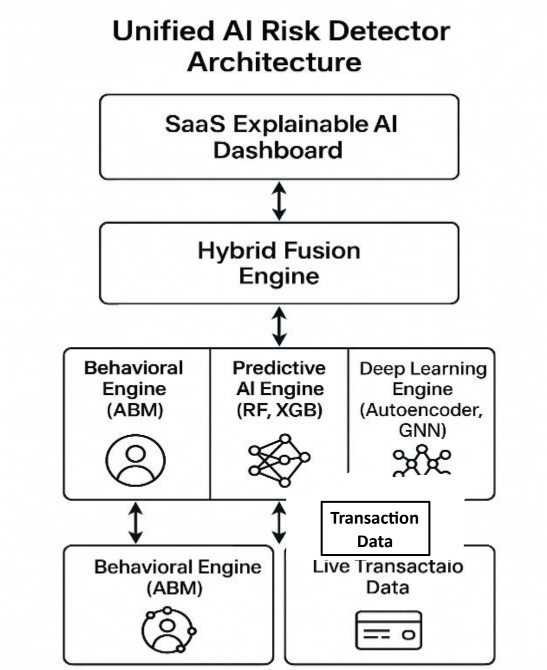

Figure 6. Unified AI Risk Detector Architecture (Vision Diagram). Depicts integration of simulation, AI, and deep learning modules into a single FinTech platform.

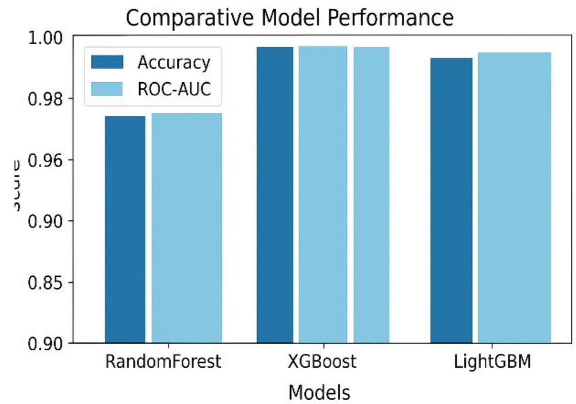

Figure 7. Comparative Model Performance. Displays overall accuracy and ROC-AUC comparison across ensemble models.

IX. CONCLUSION

The ChitEase framework demonstrates that AI-driven behavioural simulation can model and predict systemic financial risk with empirically verifiable accuracy. By integrating behavioural economics with explainable AI, it provides a transparent, interpretable, and replicable solution for fintech governance. This research forms the first empirically validated step toward a Unified Behavioural AI Risk Intelligence System, supporting transparent and ethical financial ecosystems. By combining behavioural economics and explainable AI, ChitEase offers a scalable foundation for India's digital finance ecosystem.

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