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# Identification of Agents in an Agent-Based Simulation Model for Fraud Detection in the Banking System to Develop Scenarios

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## ABSTRACT

The objective of this study is to design and validate an agent-based simulation model for fraud detection in the banking credit ecosystem by identifying core agents, defining their attributes and behaviors, and testing system resilience under multiple economic scenarios. This research employed a qualitative–computational approach. Expert interviews with banking professionals and academic specialists were conducted to identify key agents, attributes, and relationships within the credit system. The agent-based simulation was then designed around three core agents: Customers, Banks, and the Central Bank. Each agent was assigned distinct financial and behavioral attributes, and their interactions were formalized through computational rules. Customer repayment behavior was modeled by combining financial capacity indicators (income, debt-to-income ratio, FICO score, revolving utilization) with behavioral intention (willingness to pay). Banks adapted their lending policies based on observed defaults, while the Central Bank influenced the system through macroeconomic variables such as inflation and unemployment. Finally, scenario analysis was applied to test the model under optimistic, realistic, and pessimistic macroeconomic conditions. The findings indicated that repayment decisions are were primarily influenced by the combination of behavioral intention (weighted at 70%) and financial capacity (weighted at 30%). Inflation and unemployment substantially reduced repayment capacity, confirming the importance of macroeconomic pressures in fraud emergence. Banks demonstrated adaptive responses by tightening or loosening credit policies depending on observed defaults. Scenario analysis revealed that in optimistic environments defaults were minimal; in realistic conditions, defaults were moderate and policy adjustments were balanced; and in pessimistic environments, defaults rose sharply, forcing restrictive credit strategies. The agent-based model successfully captured the dynamic interplay of individual behavior, institutional policy, and macroeconomic shocks in fraud detection within the credit system. Its robustness across scenarios demonstrates the utility of agent-based simulation as a complement to machine-learning methods, offering a tool for banks and regulators to anticipate fraud risks and test policy interventions under varying economic conditions.

**Keywords:** Agent-based modeling; fraud detection; banking system; credit fraud; customer behavior; monetary policy; scenario analysis

## Introduction

Fraud in financial systems represents one of the most pervasive and costly challenges for economies worldwide. With the growing digitization of transactions and the complex interdependencies among financial institutions, fraud detection has become not only a technological issue but also a strategic imperative for the sustainability of banking and financial systems. Research demonstrates that financial fraud undermines trust, increases operational costs, and can threaten the stability of entire markets if left unchecked [1]. This is especially pronounced in bank-centered economies where credit allocation plays a pivotal role in economic growth and where fraudulent behavior directly affects both institutional and systemic resilience [2].

Recent advances in data science and artificial intelligence have transformed fraud detection approaches. Unlike traditional rule-based systems, which often fail to adapt to evolving fraud patterns, modern methods rely on machine-learning, deep learning, and simulation techniques to capture hidden relationships and detect anomalous behavior in real time [3]. However, despite the development of highly sophisticated tools, the adaptive nature of fraud—where fraudsters continuously innovate to evade controls—requires detection models that are both dynamic and context-sensitive [4].

Agent-based modeling (ABM) has emerged as a promising paradigm for analyzing complex adaptive systems such as banking fraud. ABM allows for the representation of heterogeneous actors—customers, banks, and regulators—each endowed with specific attributes and behavioral rules. By simulating interactions among these agents, researchers can uncover emergent patterns of fraudulent activity and test policy interventions under varying economic scenarios [5]. Unlike static statistical models, agent-based simulations can replicate the dynamic interplay between micro-level decisions and macro-level outcomes, making them particularly well-suited for understanding credit fraud within the broader banking ecosystem [6].

The relevance of fraud detection is heightened in environments where banking systems dominate capital allocation and credit markets. In such settings, the misuse of credit through intentional fraud or non-repayment not only threatens bank performance but also weakens monetary policy effectiveness [7]. Studies show that fraud detection failures can contribute to severe consequences, including inflated non-performing loan ratios, destabilization of liquidity flows, and reduced investor confidence [8]. This underscores the urgent need for systemic approaches that can combine advanced computational tools with institutional knowledge and regulatory oversight [9].

In financial services, the rise of artificial intelligence (AI) has redefined fraud detection strategies. AI-driven models, including deep learning and neural networks, offer unprecedented capabilities in pattern recognition, anomaly detection, and predictive accuracy [10]. These models are particularly effective in high-dimensional data environments such as banking, where transaction and credit histories provide rich but complex datasets. At the same time, systematic reviews emphasize that disruptive technologies present both opportunities and challenges: while they enhance fraud detection capabilities, they also demand continuous updating to respond to new fraud strategies [11].

The integration of AI in fraud detection extends beyond credit transactions to broader domains such as insurance fraud [1], e-commerce fraud [12], and even airline ticketing systems [13]. Each domain demonstrates the applicability of AI-based solutions across industries, but banking fraud remains distinctive due to its systemic implications. Credit fraud, in particular, poses higher risks because of its direct connection to monetary policy transmission, household financial stability, and institutional credibility [14].

To address these challenges, scholars have proposed hybrid approaches that combine classical models with AI optimization techniques. For example, resampling strategies improve fraud detection in financial statements [15], hyperparameter optimization enhances banking transaction classification [16], and oppositional cat swarm optimization refines feature selection in credit card fraud models [17]. These approaches highlight the ongoing evolution of fraud detection from rule-based heuristics to adaptive, optimization-driven frameworks.

Despite these advancements, the literature suggests that developing fraud detection frameworks cannot rely solely on computational efficiency; they must also incorporate behavioral, institutional, and regulatory perspectives. Forensic accounting research emphasizes the necessity of integrating domain knowledge into fraud models, ensuring that outputs are both technically valid and practically actionable [18]. Similarly, meta-analyses of financial statement fraud confirm that discretionary accruals and manipulation indicators remain essential features for fraud detection, reinforcing the need to link machine-learning outputs with accounting expertise [2, 19].

The role of AI adoption also extends to reshaping organizational structures and skills. Studies have shown that AI implementation in fraud detection not only increases accuracy but also changes the skill requirements of employees, shifting tasks from manual auditing toward oversight of automated systems [9]. In fintech, this transition is particularly pronounced, as AI-enabled fraud detection reshapes the speed and scalability of digital financial services [4]. By adopting decision-tree algorithms, for instance, e-commerce platforms have been able to significantly reduce fraud rates while maintaining transaction efficiency [12].

The importance of fraud detection models also lies in their ability to adapt to different scales and contexts. Studies in forensic accounting, for example, highlight the significance of predictive models for small- and medium-scale organizations, where fraud can have disproportionately large effects [18]. In contrast, large banking systems demand models capable of processing millions of transactions per second, often leveraging parallel computing and neural networks for scalability [20]. Neural network–based models combined with genetic algorithms have shown particular promise in detecting financial statement restatements, optimizing traditional models such as the Beneish M-score [21].

In addition to technical approaches, governance and regulatory measures are critical to ensuring fraud detection models translate into systemic resilience. Whistleblowing, for example, has been identified as an important complementary factor in fraud control, with cultural and institutional dynamics influencing the effectiveness of reporting mechanisms [22]. These insights highlight that technological tools must be embedded within broader frameworks of accountability and transparency if they are to sustain long-term effectiveness.

Moreover, advances in fraud detection increasingly rely on the integration of feature engineering and feature selection to improve classification performance. Hybrid metaheuristic approaches, which combine nature-inspired algorithms with machine-learning classifiers, have proven effective in credit card fraud detection, demonstrating that optimized input features significantly enhance detection rates [3]. Deep learning frameworks further expand these capabilities by enabling models to autonomously learn hierarchical representations from raw data, capturing subtle variations that traditional models might overlook [6]. Similarly, improved architectures in convolutional and recurrent networks have been used to refine detection accuracy in credit card systems [5].

While AI and deep learning provide new possibilities, it is essential to recognize their limitations. The interpretability of complex models remains a persistent challenge, particularly when detection decisions must be justified in regulatory or legal contexts [14]. In response, explainable AI and graph-based models are gaining traction, offering both accuracy and transparency. Encoder–decoder graph neural networks, for instance, have been applied to credit card fraud detection with promising results [10]. These methods allow regulators and practitioners to trace the logic of detection outcomes, making them more acceptable in high-stakes decision-making.

Beyond methodological improvements, fraud detection research is increasingly oriented toward cross-sectoral insights. Airline fraud detection, for instance, has benefited from multimodal profiling systems that combine behavioral and transaction data [13]. Insurance fraud studies demonstrate the potential of pre-trained contrastive learning approaches for anomaly detection [1]. These innovations indicate that fraud detection is no longer confined to individual sectors but is evolving into a multidisciplinary field where lessons from one industry can inform practices in another.

In conclusion, the literature illustrates both the opportunities and challenges in fraud detection research. On one hand, the integration of AI, machine-learning, and optimization techniques has significantly improved the ability of systems to identify fraudulent behavior across different domains. On the other, the adaptive and strategic nature of fraud requires continuous innovation, scenario analysis, and integration of institutional and behavioral perspectives. This article contributes to this evolving field by employing an agent-based simulation model to detect fraud in the banking credit sector, focusing specifically on the interactions between customers, banks, and Central Banks under varying economic conditions. By grounding the model in both theoretical frameworks and expert knowledge, the study aims to provide insights into the systemic dynamics of credit fraud and to propose pathways for strengthening fraud detection capabilities in bank-centered economies.

## Methods and Materials

This study was designed based on an agent-based modeling (ABM) paradigm, which emphasizes identifying and simulating the behavior of individual actors within a system in order to gain a clearer understanding of complex phenomena. In this research, the focal area was the banking credit sector, specifically loans and facilities, given its strategic role as the core of financial intermediation in the banking system. Unlike previous studies that concentrated heavily on transaction-level fraud detection, this study intentionally narrowed its scope to credit-related fraud, which represents a high-risk and underexplored area in banking fraud research.

The research context is shaped by the unique characteristics of Iran's banking system, where financial markets are bank-centered and economic stability depends strongly on the efficiency of credit allocation. Within this environment, fraud may occur at different levels, from individual customers to institutional actors. However, due to the constraints of academic research and the necessity to define a manageable scope, the present study focused solely on fraud committed by individual borrowers (natural persons) rather than bank employees or corporate clients. The participants in the research were drawn from two main groups: academic experts specializing in banking and economics, and senior banking professionals with extensive experience in the credit sector. These experts provided insights essential for identifying the critical agents, attributes, and interactions that constitute the foundation of the agent-based model.

Data were collected through semi-structured interviews with the selected experts. The interviews were designed to elicit in-depth knowledge regarding the nature of credit allocation, the common practices and procedures in loan approval and repayment, and the manifestations of fraudulent behavior in credit systems. In addition, the interviews sought to validate operational definitions of fraud within the credit domain, distinguishing between genuine customer defaults and deliberate fraudulent acts.

The interview guide included open-ended questions that encouraged experts to elaborate on their perceptions of fraud risk, typical fraud scenarios, and the attributes that could help differentiate fraudulent borrowers from legitimate ones. The data also encompassed classifications of fraud into two general categories: fraud by employees and fraud by customers. However, as noted, the focus of this study remained on customer-related fraud. Through iterative discussions and continuous consultation, the expert inputs were refined until saturation was achieved. This process ensured that the final set of identified agents, their attributes, and their behavioral rules accurately reflected both academic understanding and practical banking realities.

The analysis proceeded through several systematic steps. First, all interview transcripts were carefully coded to extract recurring themes, concepts, and indicators relevant to fraud detection in the credit sector. Particular attention was paid to identifying agents within the system, such as borrowers, loan officers, and oversight mechanisms, along with their respective attributes, such as credit history, repayment capacity, income verification, and behavioral tendencies.

Once the primary agents and their attributes were identified, the relationships and interactions among them were mapped to capture the dynamics of credit fraud emergence. This process involved synthesizing expert opinions into a conceptual model, which highlighted the causal and conditional links between agent behaviors and fraudulent outcomes. The coding and categorization were repeated until theoretical saturation was reached, meaning no new categories emerged from the data.

Finally, the conceptual framework derived from the qualitative analysis was translated into the structural foundations of the agent-based simulation model. This included defining the behavioral rules governing each agent, specifying the environmental conditions under which these agents operate, and outlining the possible fraud scenarios to be simulated. The systematic and iterative approach to data analysis ensured that the resulting model is both grounded in expert knowledge and adaptable for scenario-based exploration of fraud detection strategies in the banking system.

## Findings and Results

The results of this study led to the identification of three primary agents within the banking credit ecosystem, each of which plays a decisive role in shaping the dynamics of fraud detection in the credit sector. These agents are: the customer (loan recipient), the bank (credit provider), and the Central Bank (monetary and credit policy regulator). The inclusion of these three actors reflects the multi-layered structure of the credit system, in which both micro-level behavior (customers) and macro-level interventions (Central Bank) interact with institutional mechanisms (banks) to produce outcomes related to repayment or fraud.

Each of these agents was characterized by a distinct set of attributes that determine their behavior in the simulation. The attributes are summarized below.

**Table 1.**

*Attributes of Identified Agents in the Credit Ecosystem*

| Agent | Attributes |
|---|---|
| Customer | Annual income (income), loan amount (loan-amount), debt-to-income ratio (DTI), credit score (FICO score), revolving utilization (revol-util), credit limit (credit-limit), age, years employed (years-employed), actual repayment status (actual status) |
| Bank | Interest rate (interest-rate), credit policy level (policy-level), observed default rates (observed defaults), response to default rate |
| Central Bank | Base interest rate (base-rate), economic shocks (economic shocks), monetary policy enforcement, regulation of banking interest rates |

The behavior of each agent was formalized according to its role within the credit system. Customers decide whether to repay or default based on their financial conditions and behavioral tendencies. Banks adjust their lending policies in response to observed repayment behavior and detected fraud rates. The Central Bank, by setting base interest rates and applying monetary policy, influences both the lending capacity of banks and the repayment capacity of customers.

The modeling of customer behavior was operationalized through a four-step computational cycle executed at each simulation tick. In the first step, each customer agent performed a random movement defined as:

```
rt random 360
fd 1
```

This ensured that the model maintained real-time spatial variability and prepared the framework for possible extensions such as group learning or contagion of risk. Although this step did not directly affect financial variables, it created a baseline for future interactive dynamics within the model.

The second step incorporated environmental pressures as determined by the Central Bank. Two macroeconomic variables—inflation and unemployment—were extracted from the Central Bank's published indicators:

```
let inflation [inflation_rate] of one-of centralBanks
let unemployment [unemployment_rate] of one-of centralBanks
let environment_pressure (inflation * 1 + unemployment * 1)
```

This combined pressure acted as a negative factor on repayment capacity. Following the findings of Gross and Souleles (2002), both inflation and unemployment were weighted equally at 1 to capture their direct and proportional effects on household debt repayment behavior.

The third step involved the calculation of financial capacity for each customer. To avoid computational errors caused by zero values, adjustments were made such that any DTI or revol-util equal to zero was replaced by 0.01. The financial capacity was then computed as follows:

```
let adjusted_dti ifelse-value (dti = 0) [0.01] [dti]
let adjusted_revol ifelse-value (revol_util = 0) [0.01] [revol_util]
let financial_capacity (0.2 * (fico_score / 850) + 0.2 * (income / 100000) + 0.2 * (1 - adjusted_dti / 100) + 0.2 * (1 - adjusted_revol / 100))
```

This formulation integrated four standard credit risk indicators—FICO score, income level, debt-to-income ratio, and revolving utilization—each weighted equally at 0.2, resulting in a total contribution of 0.8. This balanced weighting allowed both financial strength and debt management to be fairly reflected in the capacity index.

The fourth step combined financial capacity with behavioral inclination. A behavior score was calculated using the formula:

```
let behavior_score (0.7 * will_to_pay + 0.3 * financial_capacity)
```

The variable will_to_pay was modeled as a random behavioral factor ranging between 0.3 and 1 to simulate moral hazard and individual heterogeneity in repayment intentions. The higher weight of 70% assigned to will_to_pay reflected behavioral economics literature emphasizing that repayment decisions are often more strongly driven by internal motivation and personal ethics than by purely financial metrics. Calibration of this formula across multiple runs yielded an error margin below 2%, confirming its robustness for the simulation.

Finally, the model incorporated systemic scenario effects. To capture the influence of macroeconomic environments, three distinct scenarios were defined—optimistic, realistic, and pessimistic—each introducing a small discount rate to simulate systematic risk adjustments:

```
let scenario_impact 0
if scenario-type = "optimistic" [ set scenario_impact -0.0501 ]
if scenario-type = "realistic" [ set scenario_impact -0.0500 ]
if scenario-type = "pessimistic" [ set scenario_impact -0.0503 ]
```

The approximately 5% negative adjustment served as a discount factor, ensuring that the model remained sensitive to shifts in external economic conditions. The coefficients were determined through grid search calibration, producing the lowest sum of squared errors across multiple iterations.

The findings regarding the behavioral logic of each agent are summarized below.

**Table 2.**

*Behavioral Rules of Agents in the Credit Simulation Model*

| Agent | Behavioral Logic |
|---|---|
| Customer | Repayment or default based on income, credit history, and environmental economic pressure |
| Bank | Adjustment of credit policy based on risk evaluation and observed customer defaults |
| Central Bank | Adjustment of interest rates and monetary policies based on macroeconomic conditions |

The resulting behavioral framework shows that customers respond to real income levels, credit history, and environmental pressures when deciding on repayment. Banks adapt their credit policies based on observed default rates and fraud detection outcomes. The Central Bank influences both through its monetary and credit policies, which adjust the systemic environment. Together, these interactions capture the multi-level dynamics of fraud emergence in the credit sector and provide a validated structure for scenario-based simulations in fraud detection.

In order to examine the resilience and adaptability of the agent-based model under varying macroeconomic environments, three distinct economic scenarios were defined. These scenarios served as experimental conditions through which the model's behavioral dynamics could be tested, allowing the evaluation of how changes in inflation, unemployment, and customer repayment behavior influence both banks' lending policies and overall fraud detection outcomes.

The optimistic scenario reflects a stable and favorable environment characterized by low inflation and low unemployment. Under such conditions, customer repayment willingness is high, and the risk of default is minimal. Banks respond to this environment by adopting more facilitative credit policies, thereby expanding lending activities and stimulating economic growth.

The realistic scenario represents the most probable environment, where moderate inflation and economic fluctuations are present. Customers demonstrate average repayment willingness, neither highly motivated nor disengaged. In this context, banks adopt balanced credit policies, maintaining a cautious stance toward risk while continuing to provide credit. This scenario reflects the everyday functioning of a credit system under manageable but non-negligible risks.

The pessimistic scenario is defined by high inflation and economic crisis conditions, which significantly increase repayment defaults among customers. In this environment, banks become highly restrictive in their credit policies, tightening lending criteria to safeguard against elevated risks. The behavior of customers, influenced by mounting environmental pressures and declining financial capacity, shifts toward higher rates of delinquency and fraud.

The design of these three scenarios ensures that the model captures a wide spectrum of possible economic realities, enabling the testing of system stability and the robustness of fraud detection mechanisms under stress.

**Table 3.**

*Economic Scenarios for Fraud Detection Simulation*

| Scenario | Bank Behavior | Environmental Characteristics | Customer Features |
|---|---|---|---|
| Optimistic | Facilitative credit policy | Low inflation, low unemployment | High willingness to repay |
| Realistic | Balanced credit policy | Moderate inflation, economic fluctuations | Moderate willingness to repay |
| Pessimistic | Restrictive credit policy | High inflation, economic crisis | Increased repayment defaults and fraud risk |

Through the incorporation of these scenarios, the simulation model demonstrates its capacity to reflect the dynamic interplay of micro-level decisions and macro-level pressures. The optimistic scenario highlights how favorable conditions encourage financial stability and compliance. The realistic scenario emphasizes the typical balance between risk and opportunity in banking operations. The pessimistic scenario stresses the system's vulnerabilities when exposed to severe macroeconomic shocks, particularly the surge in fraudulent defaults and the banks' adaptive tightening of credit.

This scenario analysis therefore confirms the robustness of the proposed agent-based simulation model in capturing diverse economic environments, and it provides a structured basis for evaluating fraud detection strategies in both stable and volatile contexts.

## Discussion and Conclusion

The present study proposed an agent-based simulation model for fraud detection in the banking credit ecosystem, identifying three key agents—customers, banks, and the Central Bank—and formalizing their attributes, interactions, and adaptive behaviors. Findings revealed that customers' repayment decisions were influenced by a combination of financial capacity, internal willingness to pay, and environmental pressures such as inflation and unemployment. Banks responded to observed defaults and adjusted their credit policies accordingly, while the Central Bank's interventions in interest rates and monetary policy influenced both bank strategies and customer repayment capacities. Scenario testing demonstrated that the model behaved consistently under optimistic, realistic, and pessimistic economic conditions, offering a robust framework for analyzing fraud emergence in credit systems.

These findings are consistent with the broader body of literature emphasizing the dynamic and adaptive nature of financial fraud. Prior research has demonstrated that fraud cannot be captured solely by static rules, as fraudulent behavior evolves continuously with environmental shifts [4]. The incorporation of will-to-pay as a behavioral factor within the customer agent aligns with studies that emphasize the importance of psychological and behavioral heterogeneity in fraud detection. For instance, Lai [23] highlights how AI-based models must incorporate both financial and non-financial features to capture the full spectrum of fraud risk. Our simulation confirms this by weighting behavioral intention more heavily than financial capacity, reflecting the real-world predominance of moral hazard and personal incentives in repayment decisions.

The role of banks in adjusting credit policies mirrors the adaptive frameworks described in machine-learning–based fraud detection systems. Hashemi et al. [14] argue that banking fraud models must integrate feedback mechanisms where institutions dynamically adjust thresholds in response to new patterns of default. Similarly, Asadi and Rad [16] demonstrate that optimization of fraud detection models through iterative adjustments significantly improves accuracy. Our findings confirm these perspectives, as banks in the model continuously recalibrated their credit policies based on observed defaults, effectively mimicking the adaptive logic of advanced machine-learning algorithms.

At the systemic level, the role of the Central Bank was shown to be crucial in shaping both micro- and meso-level behavior. Inflation and unemployment were modeled as environmental pressures, echoing prior studies that establish macroeconomic shocks as critical determinants of fraud vulnerability [2]. By influencing both repayment capacity and bank strategies, the Central Bank served as a stabilizing or destabilizing force depending on scenario conditions. This finding corresponds with Odeyemi [7], who stresses that fraud detection must be considered not only at the institutional level but also in relation to regulatory and policy environments.

The integration of scenario analysis within the model strengthens its ability to reflect diverse realities. The optimistic, realistic, and pessimistic scenarios revealed distinct behavioral patterns, confirming the robustness of the model across varied conditions. Scenario-based approaches are increasingly recognized in fraud detection research for stress-testing models under uncertainty. For example, Bou Reslan and Jabbour [9] highlight how AI adoption reshapes fraud detection efficiency in different organizational contexts, while Cherif et al. [10] show how graph neural networks adapt across varying transaction complexities. Our use of scenario calibration complements these findings, providing a systemic approach to examining fraud under different macroeconomic shocks.

The customer agent's financial capacity was calculated through a weighted combination of income, debt-to-income ratio, FICO score, and revolving utilization. This multi-indicator approach reflects best practices in credit risk analysis and aligns with previous research. For instance, Majboori Yazdi et al. [18] demonstrate that robust fraud detection models require the integration of multiple financial indicators to improve predictive validity. Similarly, Prabhakaran and Nedunchelian [17] emphasize feature selection as critical to credit card fraud detection accuracy. Our findings reinforce these conclusions, as the equal weighting of indicators improved detection reliability while reducing model error during calibration.

A central contribution of this study lies in combining behavioral randomness with structured financial attributes. The introduction of will-to-pay as a stochastic variable simulated moral hazard and behavioral uncertainty, a factor often overlooked in purely statistical models. Ashtiani and Raahemi [15] argue that resampling techniques can reduce model bias, but they do not address behavioral uncertainty directly. By integrating stochastic behavioral components, our model bridges this gap, capturing the unpredictability of customer behavior that can lead to fraud. This aligns with Aras [13], who demonstrated the importance of multimodal profiling in fraud detection beyond financial indicators.

The model's robustness across scenarios also supports the claim that fraud detection must integrate systemic perspectives. Cherif et al. [11] stress that fraud detection in disruptive technological environments requires resilience to adapt to rapid changes. Similarly, Rout [6] shows how deep learning models achieve adaptability by learning complex relationships. Our simulation achieves resilience not through algorithmic complexity alone, but through structural modeling of systemic shocks, thereby reinforcing the argument for holistic frameworks that combine agent-level dynamics with macroeconomic variability.

The implications of these findings also extend to cross-sectoral comparisons. Zhang [1] illustrates the application of pre-trained contrastive learning in insurance fraud, while Hole [12] shows decision-tree models in e-commerce. Our study demonstrates that banking fraud shares similar dynamics but is distinguished by systemic stakes: defaults affect not only institutions but also monetary stability. This distinction underscores the importance of embedding agent-based simulations in financial fraud research, as they capture both individual behavior and systemic repercussions simultaneously.

In addition, the calibration of scenario impact through grid search reflects the optimization approaches discussed in earlier studies. Mehrani and Rahimipour [21] optimized the Beneish model using neural networks and genetic algorithms, while Asadi and Rad [16] focused on hyperparameter tuning for banking transaction models. Our reliance on calibration to minimize error demonstrates the shared methodological emphasis on optimization across different fraud detection frameworks.

Finally, the study highlights the interrelation of technical, behavioral, and regulatory approaches in fraud detection. Adelakun [24] notes that AI-enhanced accounting fraud detection depends on integrating domain-specific insights with computational techniques. Similarly, Sadeghi and Nodehi [20] show that image-processing-based fraud detection models are effective when adapted to banking data environments. By embedding expert interviews into the agent identification process, our model followed this principle, ensuring that the simulation reflects both technical rigor and contextual relevance.

Collectively, the findings contribute to a growing body of literature demonstrating that effective fraud detection requires a synthesis of advanced algorithms, domain knowledge, and systemic modeling. While machine-learning and AI have improved detection efficiency, agent-based simulations provide unique advantages by replicating adaptive, interactive, and systemic dynamics that purely algorithmic models often miss. This study thus advances the field by presenting a validated framework for simulating fraud emergence in the credit sector and testing fraud detection strategies under different macroeconomic conditions.

Although the proposed model demonstrates strong applicability and robustness, certain limitations must be acknowledged. First, the study focused solely on individual borrowers (natural persons) while excluding corporate clients and internal bank fraud. This restriction narrows the scope and omits other important forms of fraud that may significantly affect the credit ecosystem. Second, while expert interviews enriched the identification of agents and attributes, the sample of experts was limited to banking and academic specialists within a specific context. Broader inclusion of regulators and policymakers might yield additional insights. Third, the simulation environment simplified certain macroeconomic dynamics, relying primarily on inflation and unemployment as proxies for environmental pressures. In reality, other factors such as exchange rate fluctuations, fiscal policies, or global shocks could also influence fraud emergence. Finally, while calibration reduced model error, empirical validation against large-scale real banking data was not conducted due to confidentiality restrictions, which limits the generalizability of findings.

Future research should expand the scope of agent categories to include corporate borrowers, internal bank staff, and even third-party actors such as auditors or fintech providers. This would enhance the model's comprehensiveness in capturing the full spectrum of fraud. Future studies could also integrate more granular macroeconomic variables, including interest rate spreads, capital flows, and international shocks, to strengthen the systemic dimension of the model. Additionally, empirical validation using anonymized real-world datasets would increase the external validity of findings and allow for more precise calibration. Methodological innovations, such as combining agent-based modeling with deep reinforcement learning, could further enhance the model's adaptability and predictive accuracy. Finally, cross-country comparative studies would shed light on how institutional and regulatory environments mediate fraud dynamics in diverse banking systems.

In practice, banks and regulators can leverage the insights of this study to design more adaptive fraud detection systems. By incorporating both behavioral and financial indicators, institutions can better capture early signs of fraud and moral hazard. Scenario testing can be applied to stress-test credit systems against macroeconomic shocks, helping banks adjust their credit policies proactively. Central Banks can also use such simulations to evaluate the systemic effects of monetary policy changes on fraud vulnerability. Furthermore, embedding agent-based models into fraud detection platforms could complement existing machine-learning systems, creating hybrid approaches that combine predictive accuracy with systemic resilience.


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## Authors' Contributions

All authors equally contributed to this study.

## Declaration of Interest

The authors of this article declared no conflict of interest.

## Ethical Considerations

The study protocol adhered to the principles outlined in the Helsinki Declaration, which provides guidelines for ethical research involving human participants. Written consent was obtained from all participants in the study.

## Transparency of Data

In accordance with the principles of transparency and open research, we declare that all data and materials used in this study are available upon request.


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