Open Journal of Social Sciences, 2025, 13(9), 364-372
https://www.scirp.org/journal/jss
ISSN Online: 2327-5960
ISSN Print: 2327-5952

Combining Expert Knowledge Systems and AI Technology for Disseminating Anti-Fraud Knowledge in Rural Financial Contexts

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How to cite this paper: Zeng, Q. K. (2025). Combining Expert Knowledge Systems and AI Technology for Disseminating Anti-Fraud Knowledge in Rural Financial Contexts. *Open Journal of Social Sciences, 13,* 364-372.
https://doi.org/10.4236/jss.2025.139022

Received: August 21, 2025
Accepted: September 21, 2025
Published: September 24, 2025

Abstract

Over the past decade, financial fraud has emerged as a critical challenge in rural communities, where limited financial literacy, weak digital infrastructure, and social vulnerabilities make populations particularly susceptible to deception. Traditional awareness campaigns and regulatory efforts, while significant, have struggled to keep pace with the increasing sophistication of fraudulent schemes. Against this backdrop, this study explores the integration of Expert Knowledge Systems (EKS) and Artificial Intelligence (AI) technologies to enhance the dissemination of anti-fraud knowledge in rural financial contexts. A pilot implementation was conducted in three rural communities, employing survey-based evaluations, system performance testing, and user engagement monitoring to assess both technical and social impacts. The findings found the hybrid EKS-AI framework significantly outperforms traditional methods in terms of rural fraud detection accuracy, knowledge dissemination effectiveness, and user engagement.

Keywords

Expert Knowledge Systems (EKS), Artificial Intelligence (AI), Rural Financial Contexts, Financial Fraud

1. Introduction

Rural financial systems play a crucial role in promoting inclusive economic development and providing residents with essential financial services. However, over the past 5 - 10 years, rural communities have increasingly become targets of sophisticated financial fraud (Zhang & Loubere, 2013). Fraud schemes, ranging from phishing and Ponzi schemes to deceptive loan offers, have led to significant economic losses and heightened social vulnerability. Limited financial literacy, insufficient regulatory awareness, and weak digital infrastructure exacerbate the problem, making rural residents particularly susceptible (He et al., 2025).

Governments have recognized the severity of rural financial fraud and have implemented multiple measures to address it, including stricter regulations, fraud reporting mechanisms, awareness campaigns, and financial literacy programs. Local financial institutions and regulatory authorities have attempted to educate communities through workshops, leaflets, and mobile initiatives (McKee et al., 2022). Despite these efforts, traditional methods often lack scalability, adaptability, and personalization, limiting their effectiveness in rapidly changing digital environments.

In recent years, AI technologies have shown remarkable potential in enhancing fraud detection and knowledge dissemination (Binsawad, 2025). Through machine learning, natural language processing, and predictive analytics, AI can identify emerging fraud patterns, personalize educational content for different user groups, and provide real-time recommendations to prevent financial losses (Dimitrov, 2025). Meanwhile, Expert Knowledge Systems (EKS) capture institutional knowledge, regulatory rules, and best practices, ensuring that AI-driven recommendations remain compliant, accurate, and transparent.

This study investigates the combination of EKS and AI technologies to create a hybrid framework for disseminating anti-fraud knowledge in rural financial contexts. By integrating expert knowledge with AI adaptability, the proposed approach aims to improve both technical detection accuracy and social impact through effective education, awareness, and behavioral change.

2. Literature Review

2.1. Rural Financial Fraud and Knowledge Dissemination Challenges

Rural financial fraud has attracted significant research attention in recent years. Studies have shown that rural populations often lack formal financial education and are exposed to diverse fraud schemes (Li et al., 2024). Awareness campaigns, while effective in controlled trials, face difficulties in scalability and adaptability due to geographical, cultural, and technological constraints.

2.2. Applications of AI in Financial Fraud Detection and Prevention

Artificial intelligence has been widely adopted in urban financial contexts for fraud detection. Techniques such as anomaly detection, supervised learning, and deep learning have proven effective in identifying suspicious patterns and preventing losses (Khan et al., 2024). However, limited research has focused on AI-driven educational dissemination in rural areas, where contextual adaptation is critical.

2.3. Expert Knowledge Systems: Foundations and Applications

Expert Knowledge Systems are computer systems that encode domain expertise into decision rules. In financial contexts, EKS can encode regulatory guidelines, procedural knowledge, and historical fraud patterns. The integration of EKS with AI provides both interpretability and adaptability (Al-Daoud & Abu-AlSondos, 2025).

2.4. Integration of EKS and AI

Hybrid EKS-AI systems leverage the strengths of both approaches: EKS ensures transparency and compliance, while AI provides scalability and real-time adaptability. Recent studies suggest that such integration can enhance fraud detection and support personalized knowledge dissemination, although practical implementations in rural contexts remain limited. Existing literature highlights the technical potential of AI and the value of expert knowledge but lacks integrated solutions for rural financial education. This study addresses this gap by designing a hybrid framework that merges AI and EKS for anti-fraud knowledge dissemination.

3. Methodology

The methodology of this study is designed to investigate how the combination of Expert Knowledge Systems (EKS) and Artificial Intelligence (AI) technologies can effectively disseminate anti-fraud knowledge in rural financial contexts. Given the increasing sophistication of fraudulent schemes and the unique socio-economic conditions of rural populations, this research adopts a multi-layered methodological framework that integrates qualitative and quantitative approaches. The proposed methodology is structured around four core components: (1) research design, (2) data sources and collection, (3) hybrid EKS-AI framework development, and (4) evaluation metrics and validation strategies.

3.1. Research Design

This study employs a mixed-methods design that integrates both qualitative and quantitative analyses. The qualitative component focuses on gathering expert knowledge and contextual insights into rural financial fraud, while the quantitative component leverages AI models to analyze data patterns and test dissemination strategies. The design is iterative, emphasizing continuous feedback between expert knowledge and AI learning processes. The overall aim is not only to detect and interpret fraudulent patterns but also to enhance the effectiveness of anti-fraud education tailored to rural populations.

The research design follows three sequential stages:

- Stage 1: Knowledge Elicitation and Structuring

Domain experts in finance, law enforcement, and rural development are consulted to identify common types of fraud, their mechanisms, and appropriate preventive strategies. This knowledge is structured into an EKS framework with explicit rules and decision trees.

- Stage 2: AI Model Development and Integration

AI techniques are employed to learn from large-scale datasets of financial transactions and communication patterns, enabling the detection of fraud signals. These models are integrated with the EKS to create a hybrid system capable of delivering personalized, interpretable anti-fraud knowledge.

- Stage 3: Pilot Implementation and Evaluation

The hybrid system is tested in selected rural communities through mobile platforms and interactive applications, followed by an assessment of knowledge dissemination effectiveness and community-level behavioral change.

3.2. Data Sources, Collection and Preprocessing

The study relies on both primary and secondary data sources to ensure comprehensive coverage.

- Primary Data:

Expert Interviews: Semi-structured interviews with financial regulators, rural cooperative leaders, and cybersecurity specialists are conducted to collect domain knowledge regarding fraud schemes and countermeasures. Community Surveys: Questionnaires targeting rural households are administered to assess baseline financial literacy, exposure to fraud, and preferred communication channels for receiving educational content. Field Observations: Pilot workshops and mobile application trials are observed to capture user interactions with the system and gather qualitative feedback.

- Secondary Data:

Transaction Records: Anonymized datasets from rural financial institutions, including patterns of withdrawals, transfers, and loan applications, are analyzed for fraud detection. Fraud Case Reports: Official documentation from government agencies and media outlets is reviewed to identify fraud typologies and emerging trends. Educational Materials: Existing anti-fraud awareness materials, both traditional and digital, are collected to benchmark dissemination approaches. All data collection adheres to ethical guidelines, ensuring informed consent from participants, anonymization of sensitive data, and compliance with local regulations on financial privacy.

- Key Preprocessing Steps:

To ensure data quality and suitability for the EKS-AI framework, we implemented the following preprocessing steps, which will be illustrated with a workflow diagram in the revised manuscript:

Data cleaning (Removed 386 invalid records (e.g., transactions with missing key fields like transaction amount or timestamp, and amounts exceeding the reasonable range for rural daily transactions, defined as >10 times the local monthly average household income). Corrected 124 records with formatting errors (e.g., inconsistent date formats, typos in transaction type labels) by cross-referencing with auxiliary data from local financial service stations.), Feature normalization(Normalized continuous variables (e.g., transaction amount, time interval between consecutive transactions) using the min-max scaling method to eliminate the impact of magnitude differences on model training, transforming values to the range [0, 1]), Categorical variable encoding (Encoded discrete variables (e.g., transaction type: "subsidy consumption", "transfer"; transaction channel: "mobile payment", "counter service") using one-hot encoding, as these variables are critical for distinguishing fraud patterns (fraudulent transactions were overrepresented in unfamiliar third-party transfer channels).).

3.3. Hybrid EKS-AI Framework Development

The core methodological innovation of this study is the development of a hybrid EKS-AI framework. This framework is designed to harness the interpretability of expert systems and the adaptability of AI algorithms.

- Expert Knowledge System (EKS) Component:

The EKS encodes structured knowledge derived from expert interviews and regulatory guidelines. Knowledge representation takes the form of rule-based decision trees, ontology-based structures, and if-then reasoning rules. For example, a rule may state: If an individual receives a loan offer via unsolicited SMS and the lender requests an upfront payment, then the transaction is flagged as fraudulent. These rules provide baseline interpretability and domain alignment.

- AI Component:

The AI module is developed using machine learning algorithms such as Random Forest, Support Vector Machines (SVM), and deep learning architectures (e.g., Convolutional Neural Networks for text/image fraud detection, and Recurrent Neural Networks for sequential transaction analysis). Natural language processing (NLP) models are also applied to analyze SMS content, mobile application text, and social media messages for fraudulent indicators.

A rule-guided learning framework is employed, whereby expert rules serve as constraints or priors in AI training. This ensures that the AI model not only learns from data but also adheres to regulatory principles and contextual expertise. Conversely, AI outputs are validated and explained using expert rules to enhance transparency and user trust. The hybrid system is embedded in mobile-based applications designed for rural users. These applications deliver interactive content, including audio prompts in local dialects, gamified quizzes, and chatbot-based guidance. The system adapts the complexity and frequency of content delivery based on user profiles, literacy levels, and behavioral patterns.

3.4. Evaluation Metrics and Validation

To evaluate the effectiveness of the proposed system, a multi-dimensional assessment framework is adopted, combining technical, educational, and social indicators.

- Technical Performance Metrics:

Fraud Detection Accuracy: Precision, recall, and F1-score for detecting fraudulent transactions. Interpretability: The degree to which AI predictions can be explained by expert rules, measured through user comprehension tests.

- Educational Effectiveness Metrics:

Knowledge Gain: Pre- and post-intervention surveys to measure improvements in anti-fraud knowledge among rural users.

Engagement Rates: Frequency of interaction with the application, completion of learning modules, and user retention.

- Social Impact Metrics:

Behavioral Change: Reduction in reported fraud cases or increased reporting of suspicious activities by participants.

Trust and Adoption: User trust in digital financial services as assessed through follow-up surveys. Validation is conducted through a pilot study in three rural communities representing diverse socio-economic and cultural contexts. Financial fraud in rural communities is not limited to households with higher incomes; instead, it exhibits a cross-income prevalence. This is primarily attributed to the widespread gaps in financial literacy and insufficient access to anti-fraud resources across diverse economic groups in rural areas—rather than being constrained to specific income brackets. While core demographic characteristics (e.g., population scale, general economic structure) are referenced to contextualize the pilot's external validity, the exclusion of identifying and sensitive data ensures compliance with research ethics and the safety of the rural populations involved.

Statistical analysis, including paired t-tests and regression models, is applied to assess the significance of observed knowledge gains and behavioral outcomes. Qualitative feedback from focus groups supplements the quantitative findings, providing nuanced insights into system usability and cultural appropriateness.

The methodological framework outlined above integrates expert knowledge and AI technologies to create a hybrid system tailored to the needs of rural communities. By combining structured rule-based reasoning with data-driven adaptability, this study aims to enhance both the accuracy of fraud detection and the effectiveness of knowledge dissemination. The methodology ensures rigor through triangulation of data sources, innovation through hybrid system design, and relevance through real-world pilot testing. Ultimately, this approach provides a systematic pathway for addressing the urgent challenge of rural financial fraud while advancing the academic discourse on hybrid AI-expert knowledge applications.

4. Experimental Results and Discussion

This section presents the results of the pilot implementation of the proposed hybrid EKS and AI framework for disseminating anti-fraud knowledge in rural financial contexts. The results are reported along three dimensions: (1) technical performance in fraud detection, (2) educational effectiveness in disseminating anti-fraud knowledge, and (3) social impacts in terms of behavioral change and user trust. The findings are followed by a discussion that situates the outcomes within the broader literature and highlights both contributions and limitations.

The hybrid framework achieved an overall fraud detection accuracy of 94.3%, outperforming the Random Forest model (89.6%) and the rule-based expert system (82.1%). This improvement underscores the value of integrating structured expert rules with adaptive AI models.

The hybrid system achieved a precision of 92.7% and a recall of 95.1%, resulting in an F1-score of 93.9%. These results indicate not only a strong ability to correctly identify fraudulent activities but also a relatively low rate of false positives. A user comprehension test was conducted with 150 rural participants who interacted with system explanations of detected fraud cases. Approximately 78% of participants reported that the explanations were "clear and understandable," compared to only 43% in the AI-only model. This suggests that the integration of expert rules substantially enhances the transparency and usability of AI-driven outputs.

4.1. Educational Effectiveness

The dissemination component of the hybrid framework was evaluated through a mobile application deployed in three rural communities over a period of four months. The app delivered personalized anti-fraud knowledge modules, including voice-based lessons, interactive quizzes, and chatbot-assisted learning.

- Knowledge Gain:

Pre- and post-intervention surveys indicated a significant increase in anti-fraud knowledge scores. Average test scores improved from 41.2% before exposure to the system to 78.5% after four months of use, representing an improvement of more than 37 percentage points. Statistical analysis confirmed the significance of this change ($p < 0.01$).

- Engagement Rates:

User logs revealed that 73% of participants completed at least 80% of the assigned learning modules. On average, participants interacted with the app 2.4 times per week, suggesting sustained engagement. The use of local dialect audio prompts and gamified quizzes was cited as a key factor in maintaining user interest.

- Adaptive Learning:

The AI-driven personalization feature proved particularly effective. Users with lower initial literacy levels showed a larger relative improvement (average gain of 45 percentage points) compared to users with higher baseline literacy (average gain of 28 percentage points). This demonstrates the adaptability of the system in tailoring content to diverse user needs.

4.2. Social Impact

Beyond technical and educational outcomes, the pilot implementation also measured broader social impacts.

- Behavioral Change:

During the pilot period, reported fraud cases in the three communities decreased by 21%, while the number of suspicious activities reported to local authorities increased by 34%. These findings suggest that the system not only improved knowledge but also empowered users to apply that knowledge in real-life contexts.

- Trust in Financial Services:

Follow-up surveys revealed that 68% of participants expressed increased trust in digital financial services after using the application, compared to 45% before the intervention. This change is particularly significant, as lack of trust has historically been a major barrier to rural financial inclusion.

- Community Spillover Effects:

Informal interviews with community leaders indicated that users often shared anti-fraud knowledge with family members and neighbors, amplifying the system's reach beyond registered participants. This suggests the potential for positive spillover effects in broader rural networks.

5. Conclusion

This study set out to investigate how the integration of EKS and AI technologies can improve the dissemination of anti-fraud knowledge in rural financial contexts. The findings confirm several important contributions. First, the hybrid EKS-AI framework demonstrated strong technical performance in fraud-detection, achieving higher accuracy, precision, and interpretability compared to traditional AI or detection systems. This outcome underscores the complementary strengths of expert systems and AI: while expert rules provide transparency and regulatory alignment, AI algorithms contribute adaptability and data-driven insights. The combination effectively mitigates the limitations of each approach when used in isolation. Second, the research demonstrated that AI-enabled personalization significantly enhances financial literacy dissemination among rural populations. Taken together, the study contributes to the academic discourse on hybrid AI applications and provides practical implications for policymakers, financial institutions, and rural development organizations. It demonstrates that combining expert-driven transparency with AI-driven adaptability is a promising pathway for strengthening rural communities against financial fraud.

6. Future Work

Building on the findings and limitations of this study, several avenues for future research and development can be identified. Future studies should extend the pilot to larger samples across multiple regions, including diverse cultural and linguistic contexts. Comparative studies could examine how rural communities in different countries respond to hybrid EKS-AI systems, thereby contributing to a global understanding of financial fraud prevention. Fraudulent networks often operate across regional and institutional boundaries. Integrating datasets from multiple financial institutions and government agencies could improve the robustness of fraud detection. Research into federated learning techniques—where AI models are trained collaboratively without centralizing sensitive data—may offer a promising solution to privacy concerns. Although the hybrid framework improved interpretability compared to standalone AI, further work is required to advance explainable AI (XAI) techniques tailored to non-expert audiences. For rural populations with limited digital literacy, explanations must be not only technically accurate but also linguistically and culturally accessible. Incorporating visual storytelling, voice-based narratives, and localized metaphors may enhance comprehension and trust.

To maximize impact, future research should explore how hybrid systems can be aligned with government-led financial literacy programs. Embedding such systems into existing national strategies for rural development or digital inclusion could ensure sustainability and institutional support. Partnerships between financial regulators, local governments, and technology providers will be critical for scaling and governance.

Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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