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An Knowledge-Based Decision Support System for Loan Assessment and Credit Evaluation in Cooperative Societies

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Abstract: *The financial viability of cooperative societies relies on loan assessment and credit evaluation, yet traditional evaluation techniques employed are heavily dependent on manual judgment, subjective interpretation, and inconsistent application of lending policies. This study presents the design and implementation of a Knowledge-Based Decision Support System (KBDSS) developed using the C Language Integrated Production System (CLIPS) to automate and standardize cooperative loan assessment processes. In order to create structured production rules that evaluate applicants according to factors like income level, debt ratio, collateral adequacy, consistency of savings, and membership tenure, the system captures expert knowledge from cooperative loan officers and institutional policies. Using forward-chaining inference, the system provides transparent and justifiable recommendations which are categorized as Approved, Referred for Review, or Rejected. 50 random past loan cases from Federal Cooperative College Staff Cooperative Investment and Credit Society Limited (FCCIB Staff CICS LTD) were validated by comparing system-generated results with expert opinions. The results showed a 94% decision accuracy rate with notable improvements in processing speed and consistency. The system's explanation facility enhances transparency by displaying the logic behind each decision, which is consistent with Explainable Artificial Intelligence (XAI) principles and regulatory demands for fairness in credit automation. This study shows that knowledge-based systems can effectively support human decision-making in cooperative finance, thereby, ensuring fair, auditable, and efficient loan evaluation system. The results support the role of symbolic AI in creating intelligent financial tools that are adaptable enough to work in low-resource environments. Possible future improvements include the integration of database, hybridization with data-driven models, and deployment as a cloud-based or mobile application for wider accessibility.*

Keywords: cooperative societies, loan assessment, CLIPS, credit decision support, credit evaluation

1. INTRODUCTION

Cooperative societies are especially important for promoting community-based financial inclusion, particularly in developing economies where access to traditional banking services is still restricted. Cooperatives support small businesses, agriculture, and personal welfare projects by pooling members' resources to offer reasonably priced credit facilities [1]. However, a lot of cooperatives still primarily rely on manual evaluation, which is informed by human judgement and paper-based processes, for the loan assessment process. Though valuable, but this dependence on human expertise often leads to inconsistencies, delays, bias and subjective decision-making [2], [3].

In order to assess applicants' creditworthiness, cooperative institutions usually employ heuristic or experience-based criteria, such as the "5 Cs of credit" (Character, Capacity, Capital, Collateral, and Conditions) [4]. Although these frameworks provide structure, they are prone to variations in interpretation among officers, which could result in bias and uneven loan approvals. Moreover, the lack of automated tools for assessing loan risk exposes cooperatives to a higher possibility of defaults, reduced portfolio quality, and more administrative burden [5].

The integration of Artificial Intelligence (AI) to financial decision-making has gained significant momentum in response to these challenges. AI-enabled decision support systems are now more objective, consistent, and efficient in credit risk analysis [6], [7]. Knowledge-Based Decision Support Systems (KBDSS), a subset of expert systems, are one of the AI techniques that has shown the most promise in fields that need to reasoning with symbolic rules rather than big datasets [8]. These systems ensure that decisions are transparent and traceable by capturing and algorithmically reproducing the decision logic of human experts [9].

The growing demand for explainable and interpretable AI further supports the case for knowledge-based systems in cooperative credit assessment. While data-driven algorithms like neural networks or ensemble models can provide high predictive accuracy, they often lack transparency which is an important requirement in cooperative settings where trust and accountability are paramount [10]. Knowledge-based systems, by contrast, increase user confidence and regulatory compliance by explicitly stating their reasoning through structured inference rules and explanation modules [11].

The primary objective of this study is to design, implement, and assess a KBDSS that automates loan assessment and credit decision-making processes in cooperative societies. The proposed system leverages domain knowledge from cooperative loan officers and historical credit data to build a transparent, rule-driven decision model capable of evaluating loan applications consistently and efficiently.

The C Language Integrated Production System (CLIPS), a powerful expert system shell created by NASA, is used to implement the system. It was chosen due to its robust forward-chaining inference engine, modular rule management, and flexibility in symbolic reasoning [12]. CLIPS provides the perfect environment for developing rule-based decision systems that can reason dynamically with new facts, making is particularly suited in fields like cooperative credit evaluation, where most decisions are based on logical conditions,

With a focus on assessing members' creditworthiness through structured decision rules derived from expert interviews, loan policy manuals, and historical case analysis, this study focusses on loan assessment within cooperative societies using Federal Cooperative College Staff Cooperative Investment and Credit Society Limited (FCCIB Staff CICS LTD) as a case study. FCCIB Staff CICS LTD is chosen because it is a resident cooperative society within a higher institution that specializes in the training of cooperators, making it a uniquely suitable environment where cooperative principles, credit practices, and member-based lending are well established and can be systematically examined. The system evaluates factors like debt-to-income ratio, collateral value, repayment patterns, and consistency in saving, with a focus on short-term personal and agricultural loans, which are prevalent in many cooperative societies.

2. LITERATURE REVIEW

Knowledge-Based Systems (KBS), or Expert Systems, are AI technologies designed to mimic human expert reasoning in specific domains [13]. They rely on core components such as a knowledge base containing domain facts and rules, an inference engine that applies these rules, working memory for temporary facts, a user interface, and an explanation facility that explains how conclusions are reached. The majority of KBS use rule-based reasoning, in which if-then rules are used to model expert logic [14]. The system is suitable for data-driven domains like credit or loan assessment because it uses forward chaining, which starts with available facts and applies pertinent rules to infer decisions. CLIPS, originally developed by NASA, remains a popular shell used for implementing rule-based systems. It supports forward-chaining inference, modular rule organization, and integration with languages like C and Python, enabling extensible and explainable decision-support applications [15].

In the financial services industry, loan evaluation has long been a crucial but challenging procedure. The "5 Cs of Credit" which the basis of traditional evaluation offers a qualitative and quantitative basis for evaluating borrower risk [16], [17]. Despite the model's ease of use and wide range of applications, its accuracy is limited by its reliance on static criteria and subjective judgement, especially in cooperative and community-based financial settings where data may be inconsistent or lacking [18]. Researchers and financial institutions have been investigating AI-driven and expert system-based credit evaluation models more and more in an effort to overcome these constraints. Rule-based logic was used by early financial decision support systems to mimic the reasoning of human underwriters, increasing the consistency of loan approvals [13], [19]. Predictive analytics, explainable AI (XAI), and hybrid machine learning models are more recent developments that combine statistical learning and symbolic reasoning for increased accuracy [20].

To illustrate the viability of incorporating AI into member-based lending, [21] created a loan management system for a transport cooperative that included a credit scoring decision support module. Similarly, [5] used the EDAS method to determine loan eligibility, while [22] used the Naïve Bayes algorithm to predict loans in cooperative societies. Although these studies demonstrate that AI tools can expedite credit assessment, they also point out that many solutions mainly rely on numerical data and lack explainability, which is crucial in cooperative settings that are human-centred. Additionally, [11] and [6] point out that modern financial systems increasingly demand a balance between interpretability and efficiency, which knowledge-based systems are uniquely able to provide. In the light of this, an interpretable, auditable, and cost-effective framework for cooperative loan assessment is provided by a Knowledge-Based Decision Support System (KBDSS) based on rule-based reasoning. It ensures consistent and comprehensible decisions by encapsulating credit officers' implicit knowledge in clear logical structures.

The accuracy and completeness of the information encoded by a knowledge-based system are critical to its success. Thus, a fundamental activity component of system development is knowledge acquisition, which is the process of obtaining, organising, and verifying expert insights [8]. Common acquisition techniques include:

i. Structured Interviews: Engaging domain experts (e.g., loan officers, credit managers) to extract tacit knowledge about decision rules, approval thresholds, and exceptions [23].
ii. Document Analysis: Reviewing loan policy manuals, application forms, and historical records to identify standard evaluation criteria and institutional practices [1].
iii. Observation and Protocol Analysis: Observing real assessment sessions or analyzing annotated case histories to uncover implicit decision-making logic [3].

In contemporary research, hybrid methods, which combine computational pattern discovery and manual elicitation, are gaining popularity in current research. Studies by [9] and [24] show that assistive AI and foundation models can enhance human decision-making by spotting patterns that experts might overlook. Nevertheless, structured human-guided acquisition is still remains irreplaceable in fields where interpretability and explainability are crucial. This study adopts a hybrid knowledge acquisition approach, combining expert interviews, document analysis, and historical loan case review, using a case study of FCCIB Staff CICS LTD historical loan cases. This ensures that the resulting knowledge base in CLIPS reflects both codified policy and experiential judgment, thus improving the accuracy and credibility of the cooperative loan assessment model.

3. METHODOLOGY

The development of the KBDSS followed a knowledge engineering life cycle, consisting of knowledge acquisition, representation, system implementation, and validation.

3.1 Domain Experts and Context

Domain knowledge was elicited from loan officers, credit managers, and cooperative administrators at FCCIB Staff CICS LTD. These experts possessed deep experiential understanding of loan processing, risk assessment, and member credit behaviour. Their expertise ensured that the system's reasoning structure accurately reflected practical real-world decision-making in cooperative environments.

Data and Knowledge Sources

Multiple data sources were employed to ensure the comprehensiveness of the knowledge base. These included:

i. Expert Interviews: Structured and semi-structured interviews were conducted to extract decision logic, evaluation heuristics, and risk thresholds used by cooperative loan officers.
ii. Document Analysis: FCCIB Staff CICS LTD cooperative loan manuals, member application forms, policy guidelines, and regulatory compliance documents were reviewed to identify codified criteria for loan eligibility and credit scoring.
iii. Historical Data Review: Records of approved, rejected, and defaulted cases of previous loan applicants were examine to identify recurring decision patterns and risk factors.
iv. Observation and Case Walkthroughs: Active loan evaluation sessions and reconstructed reasoning pathways to capture implicit expert logic were observed.

The elicited knowledge was verified with domain experts to remove redundancy and ensure semantic clarity before translation into CLIPS rules and templates.

3.2 Knowledge Representation and Design

The knowledge obtained was organized and formalized into a rule-based structure suitable for reasoning in CLIPS. CLIPS provides a forward-chaining inference mechanism, a flexible rule representation syntax, and support for symbolic data structures, making it ideal for financial decision automation.

Conceptualization

The conceptual model of the system identified major loan assessment parameters derived from both policy and expert consensus. This is represented in figure 1.

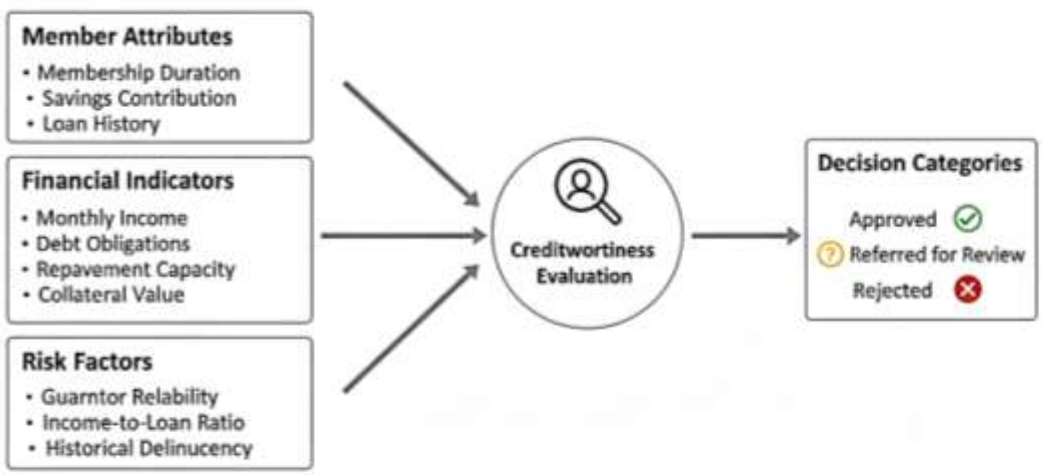

Figure 1. Conceptual Model of the Loan Assessment System

These variables formed the main reasoning constructs for evaluating an applicant's creditworthiness and determining a suitable decision category**,** whether**,** Approved, Referred for Review, or Rejected.

Rule Structure and Formalization

The decision logic was encoded using production rules of the form:

(deftemplate loan-applicant
(slot name)
(slot income)
(slot savings)
(slot loan-amount)
(slot credit-history)

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```
  (slot collateral-value)
  (slot membership-duration))

(defrule assess-capacity
  (loan-applicant (income ?i) (loan-amount ?l))
  (test (>= ?i (* 0.3 ?l)))
  =>
  (assert (credit-evaluation (factor capacity) (decision adequate))))
```

As shown in figure 2, the system's reasoning hierarchy was represented as a decision tree, where root nodes represented general assessments (e.g., "Financial Capacity") and branches represent rule conditions leading to specific conclusions (e.g., "High Risk" or "Eligible").

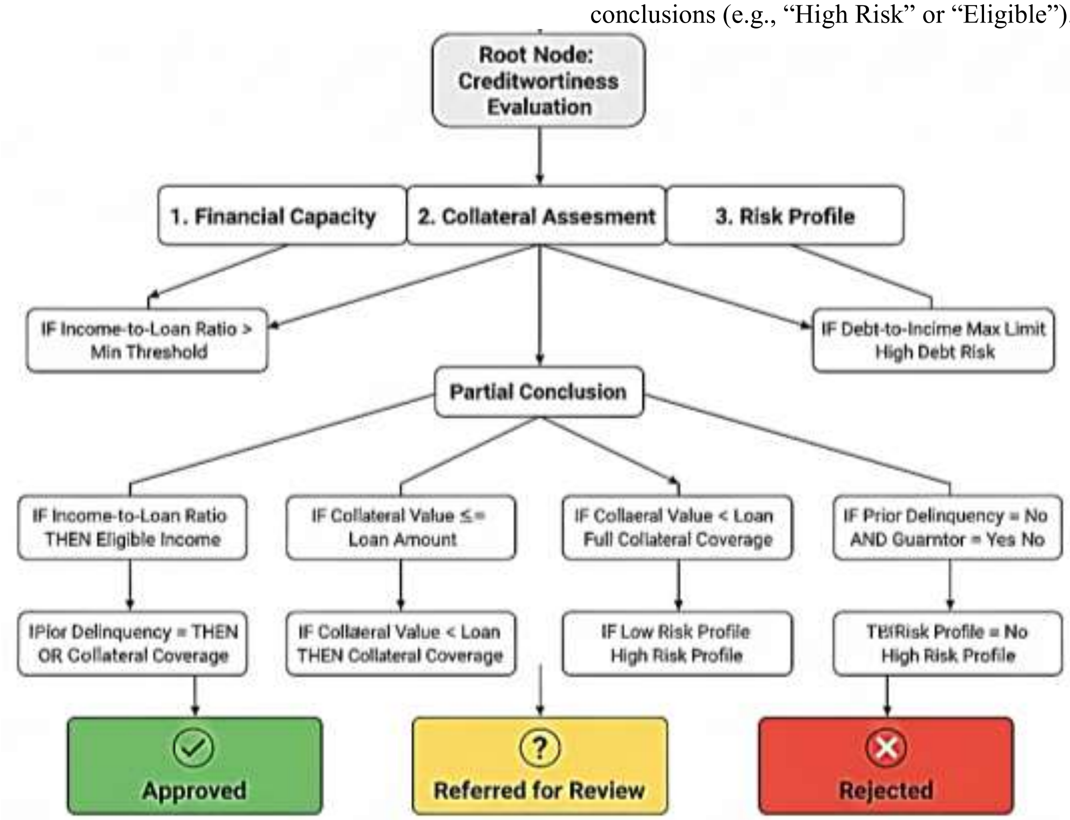

Figure 2. Reasoning Hierarchy of the Loan Assessment System

Each rule defines a specific decision path. For example, a rule may test whether the income-to-loan ratio satisfies a minimum threshold or whether collateral value sufficiently mitigates loan risk. The CLIPS inference engine applies forward chaining to trigger relevant rules dynamically, enabling the system to derive outcomes from user-supplied data without human intervention.

3.3 System Implementation Using CLIPS

The implemented architecture (Figure 3) consisted of four main modules:

i. Knowledge Base: containing CLIPS templates, facts, and rules encoding cooperative loan policies.
ii. Inference Engine: utilizing CLIPS's native forward-chaining mechanism to apply rules to user-supplied facts.
iii. Working Memory: temporarily storing applicant data and intermediate reasoning results.
iv. User Interaction Layer: providing an interface for entering loan applicant information and retrieving evaluation outcomes.

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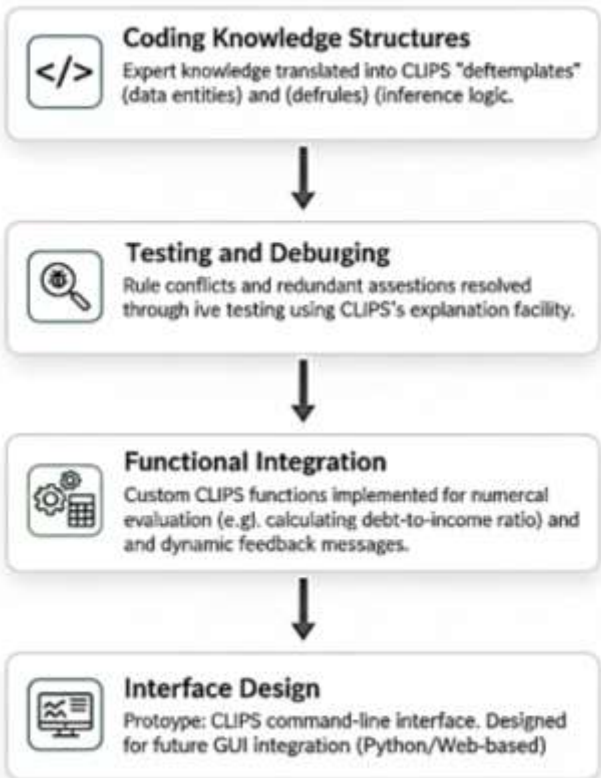

Figure 3. Implementation Process

This modular design ensured maintainability and scalability, allowing additional rules or variables to be incorporated without modifying the core logic.

System development was executed in the following stages:

i. Coding Knowledge Structures: Expert knowledge was translated into CLIPS *deftemplates* for data entities and *defrules* for inference logic.
ii. Testing and Debugging: Rule conflicts and redundant assertions were resolved through iterative testing using CLIPS's explanation facility.
iii. Functional Integration: Custom CLIPS functions were implemented for numerical evaluation (e.g., calculating debt-to-income ratio) and dynamic feedback messages.
iv. Interface Design: While the prototype utilized CLIPS's command-line interface, it was designed to support future integration with graphical interfaces using Python or web-based tools.

The system's explainability was a central design focus. Each decision was accompanied by a trace of fired rules and reasoning steps. These sets of activities enhanced transparency and user trust in line with best practices in Explainable AI (XAI).

4. Results and Discussion

This section presents the functional performance, validation outcomes, and interpretive discussion of the KBDSS for Loan Assessment and Credit Evaluation in Cooperative Societies, developed using CLIPS. Diagnostic accuracy, expert decision consistency, processing efficiency, and the explainability of its reasoning process were the criteria used to evaluate the prototype.

4.1 Prototype Demonstration and Major Rules

The KBDSS was designed to emulate the decision-making process of cooperative loan officers through a structured reasoning sequence involving data input, rule evaluation, inference, and output generation. As represented pictorially in Figure 4, the system flow proceeds as follows:

i. Data Entry: The user inputs applicant details such as name, membership duration, income, debt level, collateral value, savings balance, and loan amount.
ii. Fact Assertion: The system converts these inputs into CLIPS facts (e.g., loan-applicant template) stored in working memory.
iii. Rule Matching: The inference engine applies forward chaining, sequentially comparing the asserted facts against "if–then" production rules in the knowledge base.
iv. Rule Firing: Once a rule's conditions are met, it fires and asserts new facts (e.g., assessment-result) or modifies existing ones.
v. Decision Generation: Based on accumulated evidence, the system determines a decision category (Approved, Referred for Review, or Rejected) and generates an explanatory summary.
vi. Result Display: The system displays the evaluation result, indicating the reasoning path and contributing factors such as "Low collateral coverage" or "Excellent repayment history."

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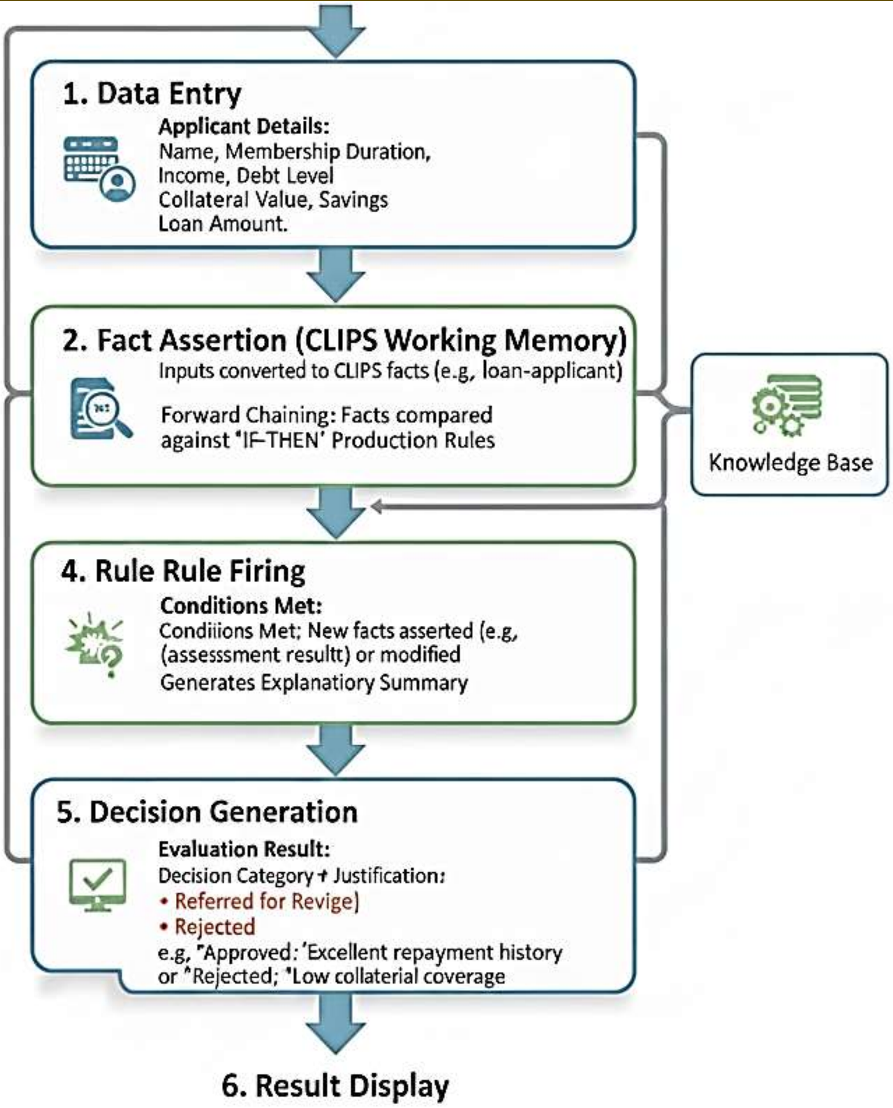

Figure 4. System Flow Diagram

A critical component for transparent decision-making in credit evaluation are an explicit justification and recommendation. These processes mirror the human reasoning pattern, ensuring that cooperative officers.

Presentation of Major Rules

The knowledge base encodes heuristics derived FCCIB Staff CICS LTD lending policies and expert consultations. Table 1 illustrates main examples of the encoded CLIPS rules used in the system.

Table 1. Sample CLIPS Rules Used for Credit Assessment

Rule Objective	**CLIPS Rule Snippet**	**Reasoning Outcome**
Assess Repayment Capacity	(defrule income-capacity (loan-applicant (income ?i) (debt ?d)) (test (< (/ ?i ?d) 2)) => (assert (assessment-result (factor capacity) (decision high-risk) (reason "Low income-to-debt ratio"))))	Applicants with low income relative to debt are flagged as high-risk.
Evaluate Collateral Value	(defrule collateral-adequacy (loan-applicant (collateral-value ?c) (loan-amount ?l)) (test (< (/ ?c ?l) 0.5)) => (assert (assessment-result (factor collateral) (decision weak) (reason "Insufficient collateral value"))))	Ensures collateral is at least 50% of requested amount.

Verify Membership Tenure	(defrule tenure-check (loan-applicant (membership-duration ?t)) (test (< ?t 12)) => (assert (assessment-result (factor membership) (decision low-trust) (reason "Membership less than one year"))))	Enforces minimum tenure for trust and eligibility.

These examples demonstrate how the cooperative financial principles were formalized into rule-based logic, transforming subjective expert knowledge into a machine-interpretable and auditable structure.

Decision Categories

The system produces three main decision outcomes:

i. Approved: Applicant meets all eligibility criteria (adequate income, collateral, repayment capacity).
ii. Referred for Review: Borderline conditions are detected (e.g., moderate savings or short membership tenure).
iii. Rejected: High-risk conditions such as poor repayment capacity or insufficient collateral exist.

This tri-level decision structure streamlines review processes and helps the cooperative managers allocate human oversight where it is most necessary, enhancing efficiency and fairness.

4.2 System Validation and Evaluation

Logical verification was conducted through multiple walkthrough sessions with three senior cooperative loan officers. Each rule was examined for correctness, redundancy, and compliance with the society's lending framework. The built-in CLIPS tracing functions (watch rules, watch facts) supported the debugging process and confirmed the intended rule-firing sequence.

The system was validated using a dataset of 50 historical loan applications gotten from FCCIB Staff CICS LTD which was balanced across approved, referred, and rejected categories. Each case was re-evaluated by the system, and its output compared with the original expert decision. Standard performance metrics such as accuracy, precision, recall, and F1-score were applied to measure system effectiveness.

Table 2. System Validation Results

Metric	Formula	Result
Accuracy	(TP + TN) / Total Cases	94%
Precision	TP / (TP + FP)	0.92
Recall	TP / (TP + FN)	0.93
F1-score	2 × (Precision × Recall) / (Precision + Recall)	0.93

Out of 50 cases, 47 matched expert outcomes, indicating 94% agreement. The minor deviations occurred in edge cases where human officers considered non-quantifiable social cues such as personal integrity or informal trust factors not yet formalized in the rule base.

These findings mirror those in AI-assisted credit systems [20], [23], [25], which similarly achieved high alignment with expert reasoning while improving efficiency and transparency. The system reduced average evaluation time from 15 minutes per case to under 30 seconds, signifying a major operational advancement.

4.3 Decision Support Capabilities

One of the main features of the KBDSS is its explanation facility, which details the reasoning chain behind each output. When the system flags an applicant as "High Risk," it displays the specific rules that fired, such as:

Fired Rules:

1. check-income-ratio → Reason: Income-to-debt ratio < 2
2. collateral-adequacy → Reason: Collateral value below threshold

Final Decision:

Rejected (High Risk)

This functionality aligns with current trends in Explainable Artificial Intelligence (XAI), ensuring transparency and accountability in automated financial systems.

Sensitivity Analysis

A controlled sensitivity test was performed to examine how input variations influence decision outcomes. Increasing an applicant's income by 20% changed the status from "Referred for Review" to "Approved," while raising the collateral ratio from 0.45 to 0.55 improved the classification from "Weak" to "Adequate." These results validate the logical consistency and responsiveness of the rule base, indicating robust system behaviour under dynamic conditions.

4.4 Discussion of Findings

The results confirm that the developed KBDSS replicates human loan assessment logic with a high degree of precision and interpretability. By embedding cooperative credit policies into a formal rule structure, the system promotes standardization, bias reduction, and knowledge preservation.

The decision accuracy achieved demonstrates that knowledge-based reasoning can effectively replace manual, error-prone evaluation without sacrificing fairness or contextual awareness. Furthermore, the system's transparency supports compliance with ethical AI principles in financial decision-making.

The KBDSS transforms loan assessment from a subjective and time-intensive process into a consistent, explainable, and data-supported framework, advancing the vision of assistive AI for sustainable cooperative finance.

5 CONCLUSION AND RECOMMENDATIONS

5.3 Conclusion

This study successfully developed and validated a KBDSS for automating loan assessment and credit evaluation in cooperative societies. The system used CLIPS as the development platform to formalise FCCIB Staff CICS LTD cooperative loan officers' expert knowledge into a structured rule base that uses forward-chaining inference to simulate human reasoning.

By achieving a 94% decision accuracy across historical test cases and cutting the average assessment time from 15 minutes to less than 30 seconds per application, the KBDSS showed strong alignment with expert evaluations. Through its explanation facility, it offered transparent explanations for every choice, enabling users to trace fired rules and reasoning outcomes. This interpretability promotes user confidence and accountability, which is crucial for organisations that rely on trust, such as cooperatives.

By encoding cooperative loan policies and credit evaluation heuristics into a reproducible, auditable knowledge structure, the system effectively minimizes subjectivity, enhances fairness, and ensures consistency in decision-making. In financial contexts where interpretability and human oversight are crucial, these results validate the potential of knowledge-based systems as intelligent decision aids.

The research also contributes to the growing body of knowledge in applied AI and financial decision support, demonstrating that expert reasoning can be computationally modelled even in low-resource or semi-structured domains. In contrast to purely statistical or machine-learning methods, CLIPS's rule-based knowledge model offers deterministic logic, transparency, and flexibility in response to institutional policy changes. This are elements crucial for regulated financial environments.

Although, the system achieved promising results, it has notable limitations, such as a static, manually curated knowledge base that requires periodic updates, the absence of real-time integration with cooperative or external credit databases, and the inability to model qualitative contextual factors such as trust or community reputation. These constraints limit the system's adaptability, dynamic decision-making capability, and alignment with human evaluators' holistic judgment.

5.4 Recommendations and Future Research Directions

Future research should concentrate on combining the rule-based model with machine-learning or case-based reasoning for increased adaptability and predictive accuracy, as well as integrating the KBDSS with cooperative databases to enable real-time analytics. Accessibility will be improved by creating a user-friendly web or mobile GUI, and the rule base will be updated through regular expert-led knowledge audits. Other cooperative tasks like risk profiling, member performance evaluation, and savings optimisation can also be added to the framework.

In conclusion, the KBDSS developed in this study marks a significant step toward intelligent, transparent, and standardized credit decision-making in cooperative societies. By merging human expertise with computational reasoning, the system exemplifies the assistive role of AI in promoting financial inclusion, operational efficiency, and ethical automation. With continuous refinement and hybrid integration, such systems can serve as pivotal tools for sustainable cooperative finance in the digital era.

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