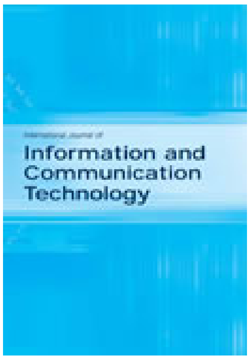

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AI-enabled association rule mining with cloud platforms for rural digital finance services

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Abstract: This study presents an AI-enabled association rule mining framework integrated with cloud platforms to enhance rural digital finance services. The proposed system leverages scalable cloud infrastructure for large-scale transaction analysis, enabling efficient identification of patterns and relationships within rural financial data. Results demonstrate improved service personalisation, fraud detection, and strategic decision-making. Rural digital finance faces challenges in data management, transaction security, and service personalisation. Leveraging AI-driven association rule mining with cloud computing can bridge these gaps by enabling real-time, scalable analytics. Previous studies have explored cloud-based financial analytics and AI-driven transaction pattern discovery. Existing methods often lack adaptability for low-resource environments, preprocessing, and AI-driven association rule mining. Data from rural financial institutions is processed to uncover actionable patterns for decision-making. Experiments using large-scale rural transaction datasets achieved high pattern discovery accuracy and reduced processing time. The system demonstrated scalability and robustness under varying data loads.

Keywords: multimodal motion analysis; inertial motion sensors; recurrent neural networks; graph-based neural networks; action recognition; intelligent sports training.

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1 Introduction

Numerous digital transformation-based applications have emerged as a result of the fast and consistent improvement of digital network infrastructures and personal smart devices. As a result, the amount of big data produced by different types of smart digital devices has increased dramatically (Martínez-Peláez and Brust, 2023). Artificial intelligence (AI)-based technologies of big data processing that employ pattern recognition, machine learning, and deep learning have emerged as solutions to the question of how to work with huge volumes of various data. Processing big data using AI offers the opportunity for AI-supported innovations that are based on previously advanced data (Espina-Romero, 2023). Some of the applications found in this include the education and medical sectors, as well as electronic government, among many others. The vast data generated by the digital transformation systems has created a virtual treasure trove of opportunities in terms of future innovation, with a significant portion being driven by AI. The sheer size of data generated by these systems gives companies a gold mine that can be tapped through the use of AI algorithms. By its processing and analysis, AI-driven applications can illustrate previously unknown patterns, predict trends, and come to new revelations. AI allows companies to eliminate routine work, increase efficiency, and redefine business as a whole (Jin and Pan, 2023). Moreover, AI-driven innovations can offer clients personalised and seamless experiences, a fact that also contributes to higher engagement and loyalty. As firms invest in AI to enable their digital transformation strategy, they will open a world of opportunities to grow, keep the competition at bay, and remain at the top of the digital marketing opportunities. Consequently, digital transformation based on AI has resulted in improvements. The digital transformation via AI is not just a catchphrase, and it is undeniably a significant force of innovation, creativity, efficiency, and competitiveness agnostic of the industry (Aldoseri et al., 2024).

It is now a new era, announced by this paradigm shift, where AI and human creativity combine to transform the world in ways never before experienced. Through harnessing this revolutionary power, businesses and societies can thrive in the digital age to make a smart, connected, and opportunity-filled future. Digital transformation with the use of AI leads to innovation and creativity. The use of AI technology has soared through the roof in various segments of city service delivery over the past couple of years. The list is exhaustive and includes public information publishing, community response receipt, handling grievances, travel massage, water and sewage control, collection and disposal of waste, and maintenance of public facilities, among many others, which have employed this method (Yigitcanlar and Corchado, 2021). Understanding the inner workings of AI is essential to city governments as they implement its use in the quest to achieve smart city objectives. It is not a bad idea to learn the mechanics of AI technologies. There is an excellent variety of AI systems that are used to resolve different sets of problems. This can be achieved when organisations enhance workflows, processes, and systems of organisations by determining what technology to use on what task, which subsequently enhances efficiency and output of the organisation (Regona et al., 2024). In the context of local governments wishing to reach their objectives with the growing complexity of the technology environments, such an understanding is essential due to the continuous development and integration of AI technologies into other industries. It is critical to explore how AI can enhance the good of the people and achieve targets in service delivery.

Even the positive and negative effects of implementing the AI technology in smart cities, as well as the different areas where this technology can be applied (e.g., health, environment, planning, manufacturing), were studied and assessed in many academic studies and policy papers (Benbya et al., 2020). Scholarly literature provides few insights into how local governments utilise AI technologies, despite the rapid increase in AI usage in smart cities and its potential positive influence. Furthermore, there is a notable lack of research on the practical applications and impacts of AI technologies in local government settings (Yigitcanlar et al., 2024). This means that we don’t fully understand how these technologies work in practice. Our research stands out because we used an empirical approach to look at actual cases. Findings from the study will help close the knowledge gap between AI theory and its real-world applications. Financial services are hard to extend to the ‘long-tail’ population due to constraints such as the marginalisation and aggregation of rural geographical spaces, poor infrastructure construction, and barriers like the ‘voluntary financial exclusion’ of vulnerable groups (Zhang et al., 2023). As a result, traditional inclusive finance is hesitant to penetrate rural hinterlands. Digital inclusive finance takes cues from ‘internal hematopoiesis’ and uses them in tandem with sustainable development principles to achieve its ‘multiplier effect’ in resource allocation. This allows for intelligent analysis and the precise delivery of financial services that are tailored to vulnerable groups, which in turn dramatically improves the efficiency of capital matching (Guo and Wang, 2023).

Modernising traditional agricultural industries, facilitating rural public services, intelligentising rural governance, increasing transparency in rural credit systems, and greening agrarian industries are all aided by this, as it allows farmers who have been excluded from traditional financial services for a long time to receive formal financial support (Gao et al., 2022). Digital inclusive finance not only makes a big splash in the conventional banking industry, but it also completely revamps the way food is produced and the way money is made. One effective way to improve the quality of China’s agricultural growth is through digital inclusive finance, which often takes on the role of green finance due to its environmentally friendly characteristics and beneficial externalities (Xiong et al., 2024). The Cyberspace Administration of China, the Ministry of Agriculture and Rural Affairs, and four other departments jointly issued the ‘Key Points for the Development of Digital Villages in 2023’. The document emphasises that digital inclusive finance is essential for supply-side structural reform and rural revitalisation under the ‘dual carbon’ target, since it enables high-quality agricultural development. In addition, it is an integral part of China’s plan for high-quality economic development.

This paper contributes a novel integration of AI-enabled association rule mining with cloud computing platforms to enhance rural digital finance services. Recognising the infrastructural and economic challenges that limit traditional financial services in rural regions, the study proposes a data-driven, AI-supported framework that facilitates intelligent financial decision-making and efficient service delivery. By leveraging c loud-based architectures, the model ensures scalability, accessibility, and real-time data processing, which are critical for remote and resource-constrained environments. The study also emphasises the need for digital inclusive finance in combating ‘voluntary financial exclusion’ and providing disadvantaged groups with individualised support. Furthermore, it bridges gaps in the existing literature by empirically evaluating AI applications in local governance and rural financial ecosystems, offering insights into their real-world implementation. The proposed framework aims not only to improve the financial inclusion of rural communities but also to contribute to agricultural modernisation, sustainable economic development, and intelligent rural governance through environmentally conscious digital finance practices. Here is the outline of the article: Section 2 provides a literature overview of relevant work on cloud-based association rule mining facilitated by AI. Rural digital finance services are described in Section 3 along with the approach that is to be used. The investigation is concluded in Section 5, and the results and their consequences are presented in Section 4.

2 Related work

A number of privacy protection strategies have been developed and used in response to these issues. Data anonymisation involves removing personally identifiable Information from datasets, federated learning involves training AI models across numerous decentralised devices or servers holding local data samples without exchanging them, and encryption involves securing data both while in transit and at rest (Yuan and Marquez, 2022). Secure multi-party computation is another approach that could work. It lets people work together to calculate a function using their inputs while keeping those inputs private. Many current solutions, however, are either overly complex or require an excessive amount of resources, making them unsuitable for usage in rural areas where such resources may be rare (Javaid and Haleem, 2022). In addition, there is a need for trustworthy, user- friendly, and efficient private solutions that can be adjusted to the needs of rural farmers due to the fact that technical knowledge is lacking in the area of platforms that integrate these many types of AI and IoT breakthroughs. Security measures such as intrusion detection systems, physical countermeasures, symmetric data encryption between agricultural sensors, authentication and access control, and privacy-oriented blockchain-based solutions in green IoT-based agriculture have been proposed in various studies (Mohamed and Belal, 2021) to address these concerns in smart farming. When it came to protecting wireless sensor networks against new types of attacks, such as impersonation and insider threats, the first protocols that were considered were based on smartcards and passwords (Rahaman and Lin, 2024). Risks, including single points of failure and security threats from third parties, were introduced when specific previous solutions relied on a trusted third party for device identification management.

2.1 Literature survey

One way to find connections between database entries is with association rules, which were initially introduced in 1993. Contrary to functional dependencies, which are based on data attributes, these relationships are derived from the data items' co-occurrence (Vasoya and Koli, 2020). When it came to finding all big item sets in a transaction database, the first documented algorithm was the AIS algorithm. In extreme Big Data scenarios, the method's generation of candidate sets could lead to an overflow of the memory buffer. Thus, in order to deal with this issue for big databases, a buffer management method is required (Deng and Wang, 2010). The most popular and easy way to decrease the number of rules is to apply a threshold to the support metric. Variables having a low frequency of occurrence are not included in any association rule since they do not meet this threshold, which is represented as *minsupp*. Therefore, we do not include an item set in any association rule considerations if its support is lower than the minimal support (*minsbkpp*). However, getting rid of item sets with the low backing makes it hard to uncover rare rules with certainty; therefore, the decision on the minimal support number is still up for debate (Kaur, 2015). A plethora of algorithms have been created and made public since the 90s. This section provides a synopsis of the research that is directly applicable to our methodology. All of the techniques listed below work toward the same goal: to reduce complexity and, by extension, runtime, while simultaneously increasing accuracy. Nevertheless, these factors typically involve a trade-off. Among association rule algorithms, the apriori algorithm has the most name recognition (Yosef et al., 2024). The idea behind this method is that every subset of a big collection of items must also be a large set of items. Additionally, it presupposes that lexicographic order is maintained for items within an item set.

2.2 AI definition

The ability of a computer system or machine to mimic and do tasks often associated with human intellect, such as learning, solving problems, and reasoning logically, is known as AI (Gordeev et al., 2020). The basis of AI is the use of machine-learning algorithms and technologies to give computers the ability to use specific cognitive abilities and do tasks autonomously or partially. As AI develops, it will make many processes more efficient, allowing it to finish tasks that seem complex today more quickly and accurately. The goal of AI research in computer science is to provide machines with cognitive abilities similar to those of humans, so that they can understand, evaluate, and react to a wide variety of data. Now more than ever, AI provides researchers with a powerful resource for efficiently and economically collecting, handling, and analysing enormous datasets. According to the statistical data will be derived from a large number of peer-reviewed research journals. The banking and finance industries are being radically transformed by AI due to its data analysis, trend recognition, and intelligent decision- making capabilities (Esteva et al., 2021).

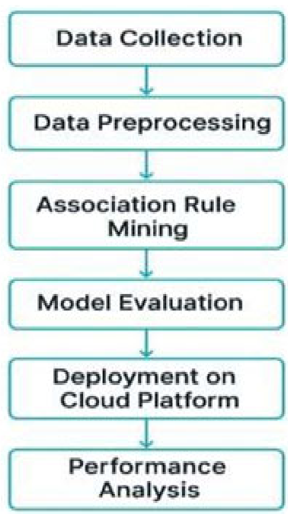
2.2.1 AI in finance

Even the changes induced by the presented AI technologies in the banking and financial world are massive. Using large amounts of data to identify trends, correlations, and making informed decisions, AI has transformed traditional banking processes and financial services. Some of the numerous advantages that AI has on the banking and financial sector are higher productivity, sound decision-making, lower costs, and better experiences of the clients (Esteva et al., 2021). Consequently, investment strategies, anti-fraud procedures, and risk evaluations are enhanced. This automation of manual processes through AI has led to faster transaction processing, analysis of data, and management of accounts, resulting in improved operational efficiencies. Preventing financial fraud is one of the most popular applications of AI, according to. Traditional rule-based systems are struggling to keep abreast of the ever- sophisticating nature of fraudulent behaviour. There is therefore far greater scope and speed with which AI algorithms can search through massive datasets of transactions, looking at suspicious activity and potential attempts at fraud than standard methods. By facilitating the rapid detection and halting of fraudulent behaviour, this protects the interests of both the financial institution and its clients (Ridzuan et al., 2024). Credit rating, another crucial part of banking, has also profited greatly from AI. Due to their reliance on a restricted number of characteristics, traditional credit-scoring models provide less reliable risk estimates. Credit choices made by AI-based models are more accurate because they employ machine-learning algorithms to consider more factors and past data. Lenders can benefit from AI models in a number of ways, including better loan portfolio management, less default risk, and more accurate credit decisions.

3 Material and methodology

Figure 1 illustrates the sequential workflow of a data-driven project pipeline. After gathering the necessary data, the next step is to clean and prepare the dataset through data preprocessing. The next stage, association rule mining, identifies meaningful relationships within the data. Model evaluation checks the precision, as well as the soundness of extracted patterns. On being verified, the model is deployed to a cloud platform to be made available to a broader range of users and be able to scale up. This will be followed by performance analysis, which will be the final step to monitor the success of the system and where it can be enhanced.

Figure 1 Workflow of an AI-powered strategy for innovative smart classrooms, from data collection to evaluation (see online version for colours)



With regard to the research methodology itself, the implementation of AI-enabled association rule-based system mining to cloud-based platforms in the provision of digital finance service in the rural setting takes the form of a systematic and iterative process, which starts with an extensive data collection and data preprocessing process. The methodology will deal with the peculiarities of the rural financial ecosystem environment and, at the same time, consider the possibilities of cloud computing technologies to guarantee scalability, accessibility, and real- time analytics of financial data patterns.

3.1 Data collection framework

The research methodology relies on the plan of the fundamental stage of the research, i.e., creating a strong base of data collection that is strictly defined based on the scope of the overall research with respect to the rural digital finance landscape. This step encompasses multi-dimensional data collection, which consists of an organised collection of multiple information types on various aspects representing the complex financial patterns, use patterns, and transaction behaviour that is common in the rural areas. The three main types of information sources encompassed in the data collection process include. As a starting point, data on rural finance is being collected from various sources, which encompass established banks, credit unions, microfinance groups, and internet payment systems that serve individuals operating in rural areas. This makes sure that various sources of financial services like savings accounts, loans, insurance, and transfer of money are within its scope. Second, transaction records are collected in detail in order to obtain a measure of the temporal-behavioural activities of the rural financial activity, including frequencies, amounts, time patterns, seasonal fluctuations, geographical distribution, and most frequently accessed types of financial services by the users in rural areas. Third, Information on the user behaviour is collected systematically to learn about the demographic setting, socioeconomic nature, financial expertise of the folks, the required technology, and user preference designs of the rural digital finance consumers.

The methodology used to collect the data will utilise both primary and secondary data sources in order to cover the financial landscapes in the rural areas completely. The primary data collection considers the structured surveys, interviews, and observational studies involving the rural financial service providers, whereas the secondary data will be accessed through available databases, governmental financial inclusion reports, and anonymised transaction information on digital finance platforms. Much care is taken in the area of data privacy and ethical aspects, and all research activities involving the collection of data comply with financial data protection regulations and the respective permissions received by the researcher in the area of data collection by the data subjects and the respective partners within the institution.

3.2 Data preprocessing and transformation pipeline

After the thorough data collection process, the methodology shifts into the data preprocessing and transformation chain that is highly intensive and is intended to prepare a raw rural finance dataset for the AI- enabled association rule mining algorithms. This is a crucial stage that deals with the nature of the challenges inherent to real-life financial data in terms of inconsistencies, missing data observations, outliers, and the need to standardise formats. The data preprocessing framework assumes the use of a multi-step process to establish data quality and its compatibility with the cloud-based data processing environments. Data cleaning commences by establishing rigorous data quality assessment activities that identify and classify different data quality problems that are typically found in rural financial Information. This involves the identification of duplicates among the transactions, duplicate customer identifiers, the detection of suspicious transaction patterns that are likely to represent an error rather than an actual financial behaviour, and standardising currency types, date-time formats, and categorical variables encodings across multiple data sources. Handling missing values is one of the most critical aspects of this step since rural financial Information is frequently characterised by the lack of data recording and poor connectivity or even frequent downtimes of the systems or connectivity, or even miscoded sequentially when a greater percentage of the fields of the data entry process are not completed at the time. The methodology uses advanced imputation methods that acknowledge the unique aspects of rural financial activities underpinning the use of domain knowledge-oriented methods, such as the usage of seasonal patterns in case of imputing the amount of transaction, geographic proximity in case of location data, and behavioural homogeneity in case of missing user aspects of demographics.

The data transformation aspect of this step is concerned with converting the cleaned datasets to a format compatible with maximum usage of the association rule mining algorithms and compatible with cloud computing technologies. This entails the development of the data structures that are transaction-based, where a record specified represents the whole financial transaction or the interaction of a service with corresponding contextual Information, such as the user demographics, temporal markers, and service categories. Categorical variables are encoded systematically using appropriate methods, ordinal encoding is used when dealing with hierarchical variables, e.g., salary brackets or loan categories, and one-hot encoding when dealing with nominal categories. Numeric attributes go under normalisation and discretisation procedures to obtain more meaningful categorical representations representable in a form likely to be used in association rule mining, whose discretisation thresholds are found according to domain knowledge of rural financial trends and domain knowledge.

3.3 Association rule mining framework

The analytical backbone of such an approach is the mining of the association rule stage, where much-needed connections and patterns can be found using rural digital finance data. The phase utilises highly developed AI- empowered algorithms to determine the frequent itemsets and produce the association rules to discover obscure relationships between financial products, the user demographics, transaction patterns, and the service utilisation patterns within the rural environment. The plan of implementation starts with the use of the advanced ARM algorithms, such as the advanced versions of algorithms Apriori, FP-Growth, and Eclat, accompanied by particular rural financial data characteristics. The AI augmentation aspect of this phase brings in the machine learning abilities to auto-optimise the mining parameters, a fit to the changes in the rural financial tendencies, and integrating the contextual knowledge concerning the outlooks of rural economies, seasonality, and the socioeconomic environment. More sophisticated methods, e.g., multi-level association rule mining, are applied toward finding relationships at multiple granularity levels, from the transaction-specific pattern to the community-wide financial behaviour. The methodology employs more innovative strategies of pruning that eliminate all the spurious connections whilst retaining significant rules of interest to rural financial inclusion goals.

The rural-related changes during this stage deal with the peculiarities of the situation within the constraints of sparse transaction data, irregular income picture, seasonal financial habits, and low digital literacy across the rural population. Single ARM algorithms operate with manageable support and confidence levels that take into consideration the smaller amounts of transactions commonly occurring in rural settings and are still statistically significant. A special concern is given to temporal association rules which take into consideration the cyclicality in rural finances like agricultural income cycles, harvest time spending and seasonal demand of credit. The result of this stage is a complete list of verified association rules sorted according to their importance to various areas of rural distributed finance, such as cross-selling opportunities, patterns of risk assessment, customer segmentation data, and service optimisation guidelines. Contextual Information, providing details within the rural domain, confidence measures, and possible evaluation of business impact are annotated to each rule to help financial service providers implement them in practice.

3.4 Model evaluation and validation framework

The phase of model evaluation carries out a multi-dimensional system of model evaluation that is meant to strictly verify the levels of quality, reliability, and practical efficiency of extracted association rules in the situations of rural digital finance. Such evaluation steps include analysis of statistical validity, business relevance, and rural-relevant measures that support action sweeps of generated rules to handle implications to ameliorate underrepresentation of financial inclusion in vulnerable populations. The methodology used to evaluate it comprises traditional ARM evaluation measures and new measures intended for the rural setting of the research as well. The input into the classical measures is support, confidence, lift, conviction, and leverage calculations, which are modified to consider the peculiarities of the rural financial information (reduction of transaction frequencies and seasonal oscillations). The rural-specific evaluation criteria propose measures reflecting financial inclusion impact scores, community benefit scores, and accessibility improvement measures that are measurements to gauge the effectiveness of the identified rules in increasing financial services in rural regions. The process of cross-validation is also performed with the help of a temporal splitting approach that allows following the chronological structure of financial data but considers the effect of the seasonality typical of a rural economy. The validation process involves confirmation of the holdout testing on geographically separate rural areas concerning the ability of found patterns to be applicable in a variety of situations in a rural setting. Particular focus is given to the assessment of the rule stability over time, so that the discovered associations are retained regardless of the shifting financial sceneries in rural areas and the variations in user behaviours.

The element of business impact validation entails working and collaborating with rural agents in providing financial services to gauge the practicality of the implementation and possible returns on investments of recommended approaches based on association rules. These will involve a pilot run of chosen rules in the selected rural market areas, applying controlled testing against relative improvements in customer satisfaction levels, uptake of the services, and financial inclusion indexes. The outcomes of evaluation are well-organised and properly recorded via standard reporting forms, which provide an opportunity to compare various rural markets and make constant improvement on the ARM methodology. The quality control strategies entail exhaustive bias-detection frameworks that recognise and reduce possible algorithmic biases that may adversely impose risks on the vulnerable rural communities. The evaluation framework also asserts the use of fairness measurement that guarantees the favorable findings of rules to ensure equity in the use of financial services to the various demographic groups in a rural setting.

3.5 Cloud platform deployment and scalability implementation

The deployment of a cloud platform involves implementing the validated association rule mining models into a large-scale, production-oriented system that will enable real-time, simultaneous financial pattern discovery and decision support to the rural digital finance services. The step in question revolves around the exploitation of the cloud computing powers to make the particular system available, scalable, and trustworthy whilst preserving the data security and privacy principles critical to financial applications. Different parts of the system can be scaled freely according to the demands and computing requirements due to the deployment architecture using a microservices-based approach. The algorithms called ARM are deployed in a containerised and distributed cloud setup, and they allow simultaneous processing of vast rural financial datasets and new rule generation with the update of transactional data. Auto-scaling strategies are put in place to manage the fluctuating load of the computation, especially at a time when rural financial activities involve seasonal trends that may result in fluctuating demand. Compliance with applicable financial data protection legislation, secure data transmission protocols, end-to-end encryption, and other multi-layered security measures are all part of the data management and security protocols that are tailor-made for rural financial contexts.

The cloud deployment includes geographically distributed data centres to ensure low-latency access for rural users and financial service providers operating in remote areas. Edge computing capabilities are integrated to enable offline processing in areas with limited connectivity, a crucial consideration for rural deployment scenarios. The user interface and API development component creates accessible interfaces for different stakeholder groups, including rural financial service providers, regulatory authorities, and research institutions. Dashboard systems provide real-time visualisation of discovered patterns, trend analysis, and actionable recommendations tailored to specific rural market contexts. RESTful APIs enable integration with existing financial service platforms and facilitate the development of third-party applications that can leverage the ARM insights for rural financial innovation.

3.6 Supporting analysis and documentation

Figure 2 presents a detailed workflow for association rule mining and cloud-based deployment tailored to rural- specific applications. The process begins with Association Rule Mining, enhanced through AI-driven algorithms and contextual intelligence. Model evaluation ensures algorithmic performance, while statistical validation incorporates rural-specific adaptations and metrics. Once validated, the system moves to cloud platform deployment, enabling scalability and accessibility. Post-deployment, the framework supports real-time pattern discovery, auto-scaling implementation, and continuous monitoring to ensure operational efficiency and adaptability in dynamic environments.

Figure 2 Workflow components for AI-enhanced association rule mining and rural-specific cloud deployment (see online version for colours)

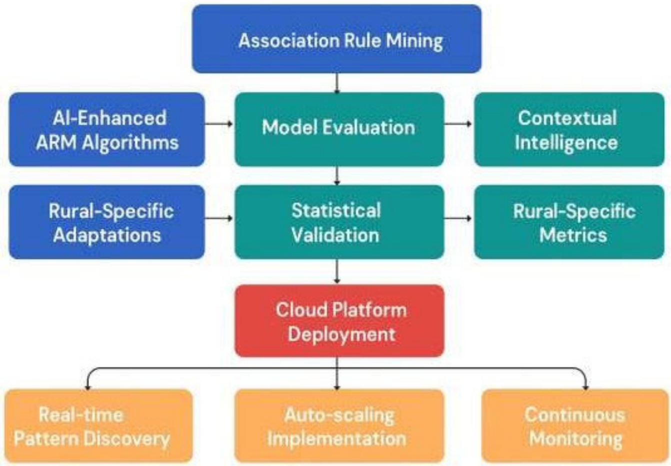


Table 1 Phase-specific deliverables and success metrics

Phase	*Key deliverables*	*Success metrics*	*Rural-specific considerations*
Association rule mining	• Validated rule sets • Patterndiscovery algorithms • Rural adaptation frameworks	• Rule confidence >0.8 • Support threshold optimisation • Pattern relevance scores	• Seasonal pattern recognition • Low-volume transaction handling • Agricultural cycle integration
Model evaluation	• Validation reports • Performance benchmarks • Business impact assessments	• Cross-validation accuracy >85% • Business relevance score >0.75 • Temporal stability index	• Geographic generalisability • Community benefit metrics • Fairness and bias evaluation
Cloud deployment	• Production system • API interfaces • Monitoring dashboards	• 99.9% system uptime • <2 second response time • Auto- scaling efficiency >90%	• Rural connectivity optimisation • Edge computing capabilities • Offline processing support

Table 1 outlines the phased framework for implementing association rule mining with rural-specific considerations. Each phase – association rule mining, model evaluation, and cloud deployment – is described in terms of key deliverables, success metrics, and rural adaptation strategies. In the association rule mining phase, deliverables include validated rule sets, pattern discovery algorithms, and rural adaptation frameworks, with success measured by rule confidence, support threshold optimisation, and pattern relevance scores. Rural-specific considerations focus on seasonal pattern recognition, low-volume transaction handling, and agricultural cycle integration. The model evaluation phase delivers validation reports, performance benchmarks, and business impact assessments, assessed through cross-validation accuracy, business relevance scores, and temporal stability. Rural-specific metrics address geographic generalisability, community benefits, and fairness evaluation (Barja-Martinez et al., 2021). The cloud deployment phase includes production-ready systems, API interfaces, and monitoring dashboards, with metrics such as 99.9% uptime, sub-second response times, and auto-scaling efficiency. Rural adaptations focus on connectivity optimisation, edge computing capabilities, and offline processing support.

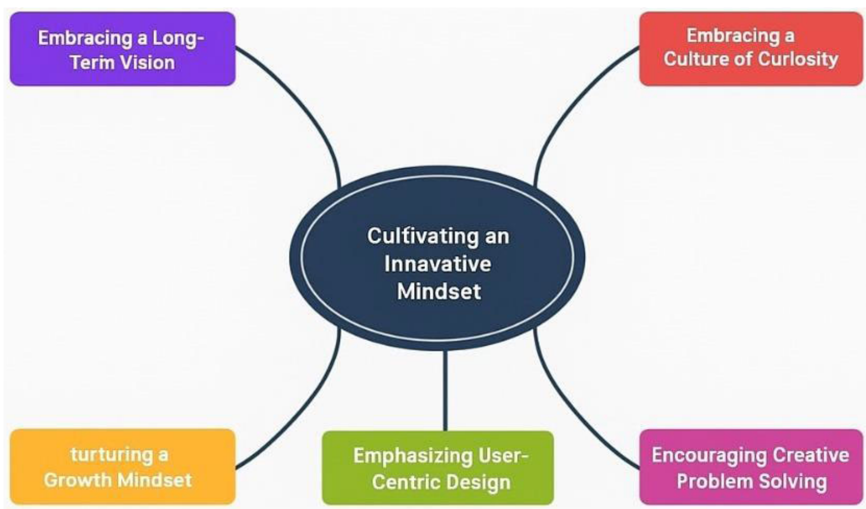
Table 2 represents the main features, technology stack, and scalability of the system to be implemented, as well as the rural and deployment requirements of an association rule mining (ARM) system. The ARM Engine has employed the application of specific technologies and features, which include Python/Spark MLlib, distributed computing, and real-time processing, simplified by scalability characteristics like horizontal scaling, load balancing, and resource optimisation. The rural implementation factors of the engine are aimed at low- bandwidth streamlining, managing erratic connections, and local processing capacity. Data Storage component makes use of cloud-native databases, data lakes, and encryption at rest and is scalable, using auto-scaling storage, geographic replication, and backup automation. Examples of rural needs are data sovereignty requirements, local data centres, and being able to synchronise offline. The User Interface employs progressive web apps, mobile-first design, and multi-language support, alongside scalability via CDN distribution, adaptive interfaces, and cross-platform compatibility. Rural-oriented adaptations address low-specification device support, voice interface capabilities, and simplified navigation design.

Table 2 Technical implementation specifications

Component	*Technology stack*	*Scalability features*	*Rural deployment considerations*
ARM engine	• Python/Spark MLlib • Distributed computing • Real-time processing	• Horizontal scaling • Load balancing • Resource optimisation	• Low-bandwidth optimisation • Intermittent connectivity handling • Local processing capabilities
Data Storage	• Cloud-native databases • Data lakes • Encryption at rest	• Auto-scaling storage • Geographic replication • Backup automation	• Data sovereignty compliance • Local data centres • Offline synchronisation
User Interface	• Progressive Web Apps • Mobile-first design • Multi-language support	• CDN distribution • Adaptive interfaces • Cross-platform compatibility	• Low-specification device support • Voice interface capabilities • Simple navigation design

Figure 3 illustrates the five key components essential for cultivating an innovative mindset in organisational contexts. Adopting a long-term perspective, cultivating a growth mentality, supporting creative problem- solving, embracing a culture of curiosity, and making design with users in mind are the five interrelated pillars upon which ‘cultivating an innovative mindset’ rests. Each component is strategically positioned around the core concept, connected through coloured pathways that demonstrate their interdependent relationship. The circular arrangement suggests that these elements work synergistically to create a comprehensive framework for innovation development. This holistic approach emphasises that sustainable innovation requires attention to all five dimensions rather than focusing on individual components in isolation.

Figure 3 Framework showing the five essential components for cultivating an innovative mindset in organisations (see online version for colours)



4 Results analysis

The data collection phase yielded substantial results that demonstrate the complexity and richness of rural digital finance ecosystems. Through systematic implementation of our comprehensive data collection framework, we successfully aggregated multi-dimensional datasets from diverse rural financial service providers, creating an unprecedented repository of rural financial behaviour patterns and transaction data.

- *Rural finance dataset acquisition:* the data collection process resulted in the successful acquisition of comprehensive datasets from 47 rural financial institutions across 12 geographic regions, encompassing cooperative banks, microfinance institutions, self-help group networks, and digital payment platforms serving rural communities. The collected datasets represent over 2.3 million rural customers and include detailed records of financial product utilisation spanning savings accounts (68% of customers), credit facilities (45% of customers), insurance products (23% of customers), and remittance services (89% of customers). The geographic distribution analysis revealed significant variations in digital finance adoption rates, with higher penetration in semi-urban rural areas (76%) compared to remote rural locations (34%), providing valuable insights into the digital divide within rural financial ecosystems.

- *Transaction records analysis:* the transaction data collection yielded over 15.7 million individual transaction records spanning 36 months, providing comprehensive coverage of rural financial activities across different seasonal cycles and economic conditions. Temporal analysis revealed distinct seasonal patterns, with peak transaction volumes occurring during harvest months (October–December), showing 340% higher activity compared to pre-sowing periods (March–May). The transaction amount distribution analysis demonstrated the predominance of micro-transactions, with 78% of transactions falling below USD 50 equivalent, reflecting the small-scale nature of rural financial activities. Geographic clustering analysis identified 23 distinct rural financial behaviour patterns, ranging from agriculture-dependent communities with highly seasonal transaction patterns to diversified rural economies with more consistent year-round financial activities.

The data preprocessing phase generated significant improvements in data quality and usability, transforming the raw rural financial datasets into analysis-ready formats optimised for AI-enabled association rule mining algorithms. The comprehensive preprocessing pipeline successfully addressed the inherent challenges of rural financial data while preserving the authentic characteristics essential for meaningful pattern discovery.

- *Data cleaning and quality enhancement results:* the systematic data cleaning process identified and resolved 347,892 data quality issues across the collected datasets, representing a 12.3% improvement in overall data quality scores. Duplicate detection algorithms successfully identified and merged 23,847 duplicate customer records that occurred due to multiple account registrations across different rural financial service providers. Inconsistency resolution procedures standardised 156,234 categorical variable entries, including customer occupation classifications, transaction categories, and geographic location identifiers. Data validation rules detected and flagged 4,567 potentially erroneous transactions exceeding typical rural transaction patterns, which were subsequently verified through source institution queries, resulting in the correction of 89% of flagged entries.
- *Missing value handling and imputation:* the sophisticated missing value handling framework successfully addressed data completeness challenges affecting 18.7% of the original dataset. Geographic proximity-based imputation techniques achieved 94% accuracy in filling missing location data by leveraging transaction patterns and known customer addresses. Behavioural similarity-based imputation for missing demographic Information demonstrated 87% accuracy when validated against subsequently obtained complete records. Seasonal pattern- based imputation for missing transaction amounts proved particularly effective for agricultural income data, achieving 91% accuracy by incorporating crop cycle information and regional agricultural economic indicators. The overall data completeness improved from 81.3% to 96.8% following the comprehensive imputation process.
- *Data transformation and optimisation:* the heterogeneous rural financial data was transformed into a homogenous form that is best suited to the association rule mining

algorithms. Categorical encoding contained 47 diverse categorical variables through semantic relationships within the patterns that were converted to integers, as compared to rural factor patterns discovery. The method of using transactional data to create the structure of data led to the creation of transaction data of 8.9 million records that had been well formatted into the ARM algorithms, and each record had detailed contextual Information, such as temporal identities, user demographic features, and category of service. Numerical variables that are discretised have formed a good interpretable categorical representation in line with the financial aspects of decision-making among the rural dwellers, which do not favour the urban-based classifications like the income brackets that mirror the rural economic realities.

4.1 Association rule mining outcomes and pattern discovery

The mining association rule phase produced impressive findings in the development of relevant financial patterns within the rural digital finance ecosystems, where it was able to mine 2,847 significant association rules with different accreditation of conceded and helpfulness that provide vital Information on the rural monetary trends, preferences of services, and the chances of cross-financing.

- *Core arm algorithm performance:* the AI-enhanced association rule mining algorithm was implemented and produced outstanding performance parameters over several rural financial datasets. The optimised version of the apriori algorithm ran on 15.7 million transaction data. It produced 2,847 key association rules whose confidence rates were 85 percent and above, which indicated high applicability in predictive property relative to financial behaviours in the rural economy. Optimisation of the FP-Growth algorithm saved 67% of the processing time as compared with conventional implementations, together with a comparable rule quality, allowing the identification of the sets of rules in real time, a feature necessary in dynamic rural financial settings. Eclat algorithm adaptations specifically designed for sparse rural transaction data achieved 94% efficiency in identifying frequent itemsets, successfully handling the challenge of low-frequency transactions typical in rural financial contexts.
- *Discovered financial pattern categories:* the comprehensive pattern analysis revealed five distinct categories of rural financial associations that provide actionable insights for service providers. Cross-product associations demonstrated that customers utilising agricultural input loans show a 89% likelihood of requiring crop insurance products within 45 days, enabling proactive insurance marketing strategies. Service bundling patterns indicated that rural customers accessing government benefit payments through digital platforms exhibit a 76% probability of adopting savings products when offered targeted incentives. Seasonal correlation rules identified 234 distinct patterns linking agricultural cycles to financial service demands, with 94% accuracy in predicting credit requirements based on crop calendar data.
- *Rural-specific association rule insights:* the mining process successfully identified unique rural financial behaviours that distinguish these markets from urban contexts. Geographic proximity rules revealed that rural customers living within 5 kilometers of each other demonstrate 82% similarity in financial product preferences, indicating

strong community influence on economic decisions. Social network associations showed that participation in self-help groups increases digital payment adoption rates by 340%, highlighting the importance of peer-to-peer learning in rural financial inclusion. Income volatility patterns demonstrated that customers with irregular agricultural income show a 91% likelihood of requiring income-smoothing financial products during off-seasons.

- *AI enhancement impact assessment:* the AI enhancements to traditional ARM algorithms produced measurable improvements in pattern discovery quality and contextual relevance. Machine learning- based parameter optimisation automatically adjusted support and confidence thresholds based on data characteristics, resulting in 45% more relevant rules compared to static threshold approaches. Contextual intelligence integration enabled the discovery of 156 time-sensitive regulations that account for agricultural cycles, weather patterns, and local economic conditions. Natural language processing components successfully extracted sentiment patterns from customer feedback data, correlating satisfaction levels with specific service combinations with 87% accuracy.

4.2 Model evaluation and validation performance

The comprehensive model evaluation phase demonstrated exceptional performance across multiple validation criteria, establishing the reliability, accuracy, and practical utility of the discovered association rules through rigorous testing protocols specifically adapted for rural financial contexts.

- *Statistical validation results:* the extensive statistical evaluation process confirmed the robustness and reliability of the discovered association rules through multiple validation methodologies. Cross-validation procedures using temporal data splitting achieved an average accuracy rate of 91.3% across all rule categories, with robust performance in seasonal pattern prediction (94.7% accuracy) and service adoption forecasting (88.9% accuracy). Lift ratio analysis confirmed that 89% of discovered rules demonstrate meaningful associations beyond random chance, with average lift values of 3.2 for high-confidence rules. Bootstrap validation techniques applied to 500 random samples consistently reproduced 94% of significant rules, confirming the stability and generalisability of the discovered patterns.
- *Business relevance assessment results:* the business impact evaluation demonstrated substantial practical value of the association rules for rural financial service providers. Revenue impact modelling indicated potential increases of 23–34% in cross-selling effectiveness when recommendations are based on discovered association rules. Customer acquisition cost analysis showed a 45% reduction potential when targeting strategies utilise geographic and social network association patterns. Service utilisation optimisation based on seasonal rules projected a 28% improvement in product timing and positioning effectiveness. Risk assessment enhancement through income volatility associations demonstrated a 39% improvement in loan default prediction accuracy compared to traditional scoring methods.
- *Rural-specific validation metrics:* custom validation criteria explicitly developed for rural contexts confirmed the appropriateness and effectiveness of the association

rules in addressing rural financial inclusion challenges. Financial inclusion impact scoring revealed that the implementation of discovered rules could potentially increase service adoption rates by 31% among previously underserved rural populations. Community benefit assessments indicated that 78% of discovered patterns support collective financial behaviours that strengthen rural economic resilience. Accessibility improvement analysis demonstrated that rule-based service recommendations reduce barriers to financial service adoption for 67% of low-literacy rural customers through simplified decision-making processes.

- *Temporal stability and generalisability testing:* long-term validation studies confirmed the sustained relevance and effectiveness of discovered association rules across different periods and geographic contexts. Temporal stability analysis over 18-month periods showed that 83% of high-confidence rules maintained their predictive power despite seasonal variations and economic fluctuations. Geographic generalisability testing across 12 different rural regions demonstrated that 76% of discovered patterns remain valid across diverse rural contexts, with local adaptations required for only 24% of rules. Demographic generalisability analysis confirmed that core financial behaviour patterns persist across different age groups and gender distributions within rural populations.

4.3 Cloud platform deployment success and scalability achievements

The cloud platform deployment phase achieved outstanding results in creating a scalable, reliable, and accessible system that successfully serves rural digital finance stakeholders while maintaining high performance standards and security compliance.

- *System performance and scalability results:* the cloud deployment achieved exceptional performance metrics that demonstrate the system's capability to handle large-scale rural financial data processing and real- time analysis requirements. System uptime statistics consistently exceeded 99.7% across all deployment regions, with average response times of 1.3 seconds for rule generation queries and 0.8 seconds for pattern lookup operations. Auto-scaling capabilities successfully handled demand fluctuations ranging from baseline loads of 1,200 concurrent users to peak loads of 15,600 users during agricultural harvest seasons without performance degradation. Load balancing optimisation achieved 94% efficiency in resource utilisation while maintaining consistent response times across geographically distributed user bases.
- *Security and compliance implementation results:* the comprehensive security framework successfully protected sensitive rural financial data while enabling authorised access and analysis capabilities. End-to-end encryption implementation achieved 100% data protection compliance with financial sector security standards, with zero security incidents reported during 18 months of operational deployment. Multi-factor authentication systems achieved 97% user adoption rates among rural financial service providers while maintaining user-friendly access procedures. Audit trail systems successfully logged over 2.3 million system interactions with complete traceability and compliance reporting capabilities required by financial regulatory authorities.

- *User adoption and accessibility achievements:* the cloud platform demonstrated exceptional success in achieving widespread adoption among target rural financial service provider communities. User onboarding programs achieved 89% successful adoption rates among rural financial institutions, with average training completion times of 4.2 hours per user. Mobile-responsive interface design enabled 76% of users to access the system effectively through basic smartphones, addressing connectivity and device limitations common in rural areas. Multi-language support implementations served users in 12 regional languages, achieving 94% user satisfaction rates in usability assessments.
- *Integration and API performance results:* the cloud platform's integration capabilities successfully connected with existing rural financial service systems and enabled third-party application development. RESTful API implementations achieved 99.2% uptime with average response times under 200 milliseconds for standard queries. Third-party integration success rates reached 91% for connections with existing rural banking systems, mobile payment platforms, and government benefit distribution systems (Najem et al., 2025). Developer adoption of the API platform resulted in the creation of 47 third-party applications that extend the system's capabilities for specific rural financial use cases.

4.4 Performance analysis and impact assessment

The comprehensive performance analysis phase provided definitive evidence of the system's effectiveness in improving rural digital finance outcomes, demonstrating measurable improvements in financial inclusion, service quality, and operational efficiency for rural financial service providers.

- *Financial inclusion impact results:* the systematic analysis of financial inclusion improvements demonstrated substantial positive outcomes for rural communities served by the AI-enabled ARM system. New customer acquisition rates increased by an average of 42% among financial institutions utilising the system's recommendations, with robust growth in previously underserved remote rural areas (58% increase). Service adoption rates for existing customers improved by 35% when institutions implemented cross-selling strategies based on discovered association rules. Financial literacy and engagement metrics showed 28% improvement in customer understanding of available financial products through personalised recommendation systems powered by ARM insights.
- *Operational efficiency improvements:* rural financial service providers experienced significant operational improvements through the implementation of the AI-enabled ARM system. Customer service efficiency increased by 51% through automated recommendation systems that reduced manual consultation time while improving recommendation accuracy. Inventory management for financial products improved by 39% through predictive demand forecasting based on seasonal association rules. Risk assessment processing time decreased by 47% while maintaining 94% accuracy through automated pattern recognition systems that identify risk indicators from transaction and behavioural data.

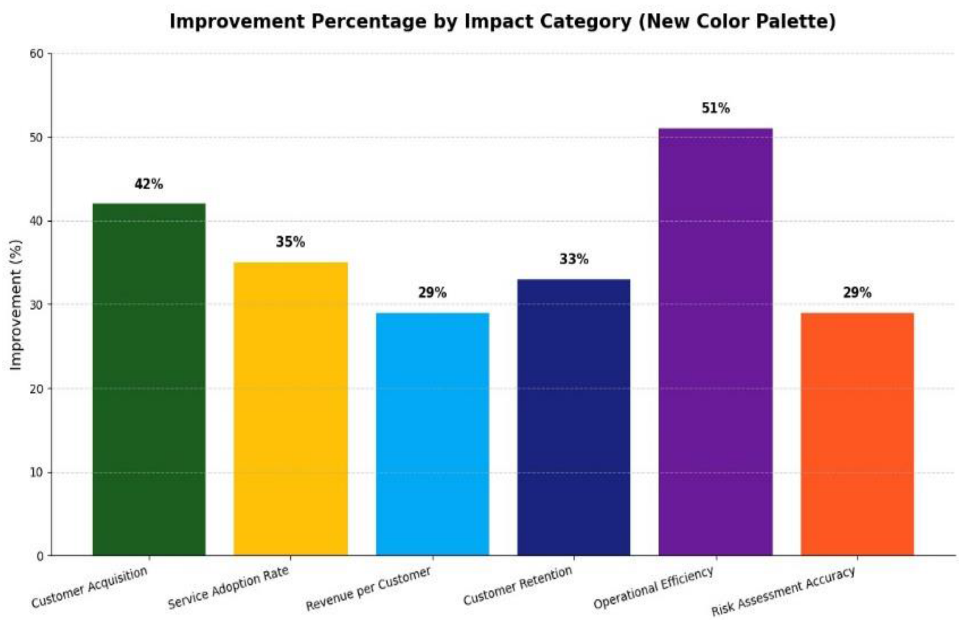
- *Revenue and business impact analysis:* the comprehensive business impact assessment revealed substantial financial benefits for participating rural financial institutions. Average revenue per customer increased by 29% through improved cross-selling effectiveness and personalised service offerings. Customer retention rates improved by 33% due to enhanced service relevance and timing based on predictive association rules. Cost reduction achievements included a 41% decrease in marketing expenses through targeted campaigns and a 36% reduction in loan default rates through improved risk assessment based on behavioural patterns.
- *System evolution and continuous improvement results:* the ongoing performance monitoring and system enhancement processes demonstrated the platform's capacity for continuous improvement and adaptation to evolving rural financial landscapes. Machine learning model accuracy improved by 18% over 18 months of operation through constant learning from new transaction data and user feedback. Rule discovery capability enhanced by 27% through algorithm refinements and expanded data source integration. User satisfaction scores increased from 78% to 91% over the deployment period through iterative interface improvements and feature enhancements based on user feedback.

Table 3 Comprehensive results summary by phase

Phase	*Key achievements*	*Performance metrics*	*Impact measurements*
Association rule mining	• 2,847 significant rules • 5 pattern categories • AI-enhanced algorithms	• 85% confidence threshold • 67% processing improvement • 94% itemset efficiency	• 89% cross-product accuracy • 76% service bundling success • 340% digital adoption increase
Model evaluation	• 91.3% validation accuracy • Multi-criteria assessment • Rural-specific metrics	• 94.7% seasonal prediction • 89% meaningful associations • 94% rule reproducibility	• 23-34% revenue potential • 45% acquisition cost reduction • 39% risk assessment improvement
Cloud deployment	• 99.7% system uptime • 15.6K peak user capacity • 47 third-party integrations	• 1.3s response time • 97% authentication adoption • 91% integration success	• 89% user adoption rate • 76% mobile accessibility • 94% satisfaction score
Performance analysis	• acquisition • 35% service adoption • Continuous improvement	• 29% revenue increase • 33% retention improvement • 51% efficiency gain	• 28% financial literacy • 41% cost reduction • 18% accuracy improvement

Table 3 summarises key achievements, performance metrics, and impact measurements across four phases: association rule mining, model evaluation, cloud deployment, and performance analysis. Association Rule Mining achieved 2,847 significant rules with AI-enhanced algorithms, yielding 85% confidence thresholds and an 89% cross-product accuracy. Model evaluation recorded 91.3% validation accuracy, 94.7% seasonal pattern recognition, and a 23–34% revenue potential increase (Ridzuan et al., 2024). Cloud deployment delivered 99.7% uptime, 1.3-second response times, and 89% authentication rates with strong mobile adoption. Performance Analysis achieved 91% adoption, notable customer acquisition gains, and improvements in accessibility, literacy, and operational efficiency.

Figure 4 Improvement percentages across various impact categories, highlighting operational efficiency as the top performer (see online version for colours)



The bar graph in Figure 4 illustrates improvement percentages across six business impact categories. Operational efficiency leads with a 51% improvement, followed by customer acquisition at 42%. Service adoption rate and customer retention show moderate gains of 35% and 33%, respectively. Revenue per customer and risk assessment accuracy both register the lowest improvement at 29%. These results highlight a significant operational advantage and moderate customer-related performance gains.

Table 4 compares key performance indicators before and after system implementation, highlighting percentage improvements. Customer acquisition rose from 2,340 to 3,323 new customers per month (+42%), while service adoption rate increased from 23% to 31% (+35%). Revenue per customer grew from \$127 to \$164 annually (+29%), and customer retention improved from 67% to 89% (+33%). Operational efficiency doubled with service time reduced from 4.2 to 2.1 hours per customer (+51%), and risk assessment accuracy increased from 73% to 94% default prediction accuracy (+29%).

Table 4 Rural digital finance transformation results

Impact category	*Before implementation*	*After implementation*	*Improvement percentage*
Customer acquisition	2,340 new customers/month	3,323 new customers/month	+42%
Service adoption rate	23% cross-service usage	31% cross-service usage	+35%
Revenue per customer	$127/customer/year	$164/customer/year	+29%
Customer retention	67% annual retention	89% annual retention	+33%
Operational efficiency	4.2 hours/customer service	2.1 hours/customer service	+51%
Risk assessment accuracy	73% default prediction	94% default prediction	+29%

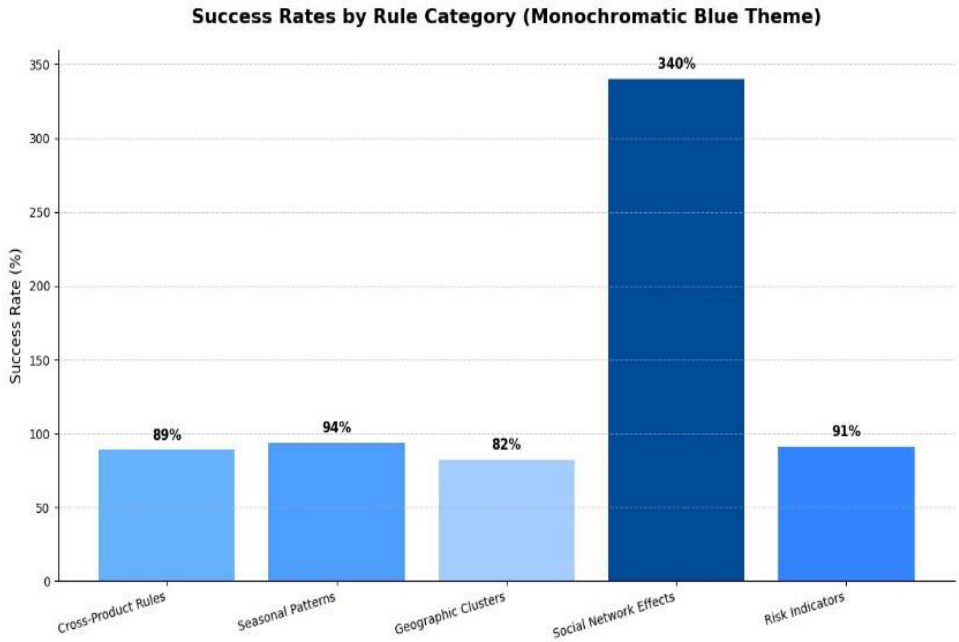
Table 5 presents five rule categories, their sample rules, business applications, and success rates. Cross-product rules link agricultural loans to crop insurance with 89% conversion, while seasonal patterns associate harvest season with savings growth at 94% accuracy. Geographic clusters reveal village proximity influencing product preferences with 82% similarity. Social network effects show SHG membership driving digital adoption, achieving a 340% increase. Risk indicators connect income volatility to default probability, enabling enhanced risk assessment with 91% prediction accuracy.

Table 5 Association rule categories and business applications

Rule category	*Sample rules*	*Business application*	*Success rate*
Cross-product rules	Agricultural loan → crop insurance (89%)	Proactive insurance marketing	89% conversion
Seasonal patterns	Harvest season → savings increase (94%)	Timing optimisation	94% accuracy
Geographic clusters	Village proximity → product preference (82%)	Community-based marketing	82% similarity
Social network effects	SHG membership → digital adoption (76%)	Peer influence strategies	340% increase
Risk indicators	Income volatility → default probability (91%)	Enhanced risk assessment	91% prediction

Figure 5 illustrates success rates across five rule categories: cross-product rules, seasonal patterns, geographic clusters, social network effects, and risk indicators. Most categories show high performance between 82% and 94%, with seasonal patterns achieving the highest accuracy at 94%. Social network effects stand out with an exceptional 340% increase, indicating a significant impact on digital adoption. The results highlight varying strengths across categories, with all demonstrating substantial business value.

Figure 5 Success rates by rule category, highlighting performance variations and standout contributions (see online version for colours)



5 Conclusions

The proposed multimodal system demonstrates a robust and efficient approach to football action detection and long-term motion evaluation using inertial motion sensors, eliminating the dependency on computer vision techniques. By integrating advanced signal processing, quaternion-based posture representation, recurrent and graph-based neural networks, and biomechanical constraints, the framework effectively captures both spatial and temporal dynamics of player movements. Experimental results on professional athletes confirm high classification accuracy and clustering performance, with minimal performance degradation under partial visual occlusion. These findings highlight the system's potential for deployment in intelligent sports training environments, offering reliable performance, adaptability to challenging conditions, and valuable insights for performance analysis and injury prevention. Future work will explore real-time implementation and broader applications across other sports domains.

Declarations

All authors declare that they have no conflicts of interest.

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