



# Understanding Farmers' Multi-channel Communication Preference in West Bengal Using Association Rule Mining

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## ABSTRACT

The present study was conducted during October, 2025 at Bandh Nabagram village, Sriniketan block, Birbhum district, West Bengal, India to investigate communication behaviours of fifty farmers using Association Rule Mining (ARM). ARM is a data mining technique to identify probabilistic relationships among channels such as Krishak Bandhu, social media, Television, Radio, Agricultural Officers/KVK, and Local Input Dealers. Field-level agricultural communication was inherently complex, as farmers rely on multiple channels whose usage patterns and interdependencies vary across individuals. Each farmer's channel usage was encoded as a transaction, allowing ARM to generate association rules, with strength and relevance quantified through support, confidence, lift, leverage, and conviction. The analysis revealed sixty-two combinations of communication channel usage among respondent farmers. Support values ranged from 0.46 to 0.54, indicating frequent co-usage of certain channels. Confidence values spanned 0.46 to 1, highlighting deterministic and complementary pairings. Lift (1–2.17) and leverage (0–0.248) identified synergistic combinations exceeding random expectations, while conviction (1–∞) highlighted highly reliable predictive relationships. Notably, combinations such as Radio with Agricultural Officers/KVK and social media with Krishak Bandhu demonstrated perfect predictability, emphasizing their importance in extension design. The findings underscored farmers' multi-channel information-seeking behaviour and indicated that integrated digital and interpersonal strategies optimized knowledge dissemination. Policymakers and extension agencies prioritized impactful channel combinations, enhanced adoption of innovative practices, and designed context-specific interventions in rural West Bengal. Future research was suggested to examine temporal dynamics, larger populations, and emerging digital tools.

**KEYWORDS:** Association rule mining, communication, channels, probabilistic relationships

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**Data Availability Statement:** Legal restrictions are imposed on the public sharing of raw data. However, author have full right to transfer or share the data in raw form upon request subject to either meeting the conditions of the original consents and the original research study. Further, access of data needs to meet whether the user complies with the ethical and legal obligations as data controllers to allow for secondary use of the data outside of the original study.

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## 1. INTRODUCTION

Field-level agricultural communication operates within a highly complex and pluralistic environment in which multiple information channels coexist and farmers' preferences vary widely across socio-economic and contextual settings (Madhushekar et al., 2024; Mtega, 2021). Farmers seldom depend on a single source of information; instead, they navigate a mosaic of formal, informal, interpersonal, mass media and digital channels to access agricultural knowledge (Mtega, 2021; Bhaskara and Bawa, 2021; Colussi et al., 2024). Consequently, understanding communication behaviour requires more than identifying channels in isolation. It necessitates examining how channels co-occur, interact and reinforce one another within farmers' information networks, including farmer-to-farmer exchanges and social media mediated interactions (Begho and Ogisi, 2025; Colussi et al., 2024). Ignoring these interdependencies risks extension strategies remaining fragmented and misaligned with farmers' actual information-seeking practices (Mtega, 2021; Wang et al., 2023).

Effective dissemination of agricultural information is critical for enhancing farmers' knowledge, strengthening decision-making and accelerating the adoption of improved technologies and practices (Goeb et al., 2025; Giulivi et al., 2022; Wang et al., 2023; Khatri et al., 2024; Pandey and Rai, 2024). While traditional extension systems relied primarily on interpersonal channels such as extension personnel, lead farmers and input dealers (Suleiman et al., 2021; Abukari et al., 2021; Begho and Ogisi, 2025; Wang et al., 2023), contemporary rural communication landscapes now integrate radio, television, mobile phones, interactive voice response, smartphone applications, videos, SMS and web-based platforms (Verma et al., 2024; Khatri et al., 2024). Evidence consistently showed that these channels operate in complementary and interdependent ways, shaping how information is accessed, trusted and acted upon (Mtega, 2021; Goeb et al., 2025; Giulivi et al., 2022; Begho and Ogisi, 2025). Understanding these interactions is therefore essential for designing efficient, context-specific extension strategies that integrate interpersonal, community-based and ICT-enabled approaches (Giulivi et al., 2022; Begho and Ogisi, 2025; Wang et al., 2023; Khatri et al., 2024).

Despite this complexity, much of the existing literature continues to emphasize frequency-based identification of communication channels using descriptive statistics (Mtega, 2021; Abukari et al., 2021; Antwi-Agyei and Stringer, 2021). Such approaches inadequately capture probabilistic relationships, complementarities and cross-channel influences (Isaac et al., 2025; Colussi et al., 2024). Emerging evidence on interdependencies between community-based,

interpersonal and mass media channels underscores the need for network- and pattern-oriented analyses, particularly in rapidly evolving institutional and digital contexts and during crises such as pest outbreaks or climate shocks (Abukari et al., 2021; Goeb et al., 2025).

To address this gap, the present study employed Association Rule Mining (ARM), a data mining technique used to uncover meaningful relationships within complex agricultural datasets (Fister et al., 2022; Bhatia and Gupta, 2021; Tasnim et al., 2025). ARM identifies relationships between antecedent channel use and consequent channel adoption, quantified through metrics such as support, confidence, lift, leverage and conviction (Fister et al., 2022; Fister et al., 2025; Agago et al., 2025; Bhatia and Gupta, 2021; Tasnim et al., 2025; Isaac et al., 2025; Colussi et al., 2024). Applied to data from fifty farmers in Bandh Nabagram village, West Bengal, the analysis focused on state-run advisory services, social media, mass media, public extension and local input dealers, reflecting widely observed multi-channel use patterns (Mtega, 2021; Antwi-Agyei and Stringer, 2021). The findings offer actionable insights into high-yield channel combinations and information pathways, contributing to more effective, network-aware agricultural extension strategies in increasingly interconnected rural environments (Wang et al., 2023; Khatri et al., 2024; Bhaskara and Bawa, 2021). The objective of the research to find communication behaviours of fifty farmers using Association Rule Mining demonstrating probabilistic relationships among different channels.

## 2. MATERIALS AND METHODS

The present study was conducted during October, 2025 at Bandh Nabagram village, Sriniketan block, Birbhum district, West (Kigatiira and Mberia, 2018). Each farmer's usage of communication channels, including Television (TV), Radio, social media, Krishak Bandhu, Agricultural Officers/Krishi Vigyan Kendra (KVK) SMS, and Local Input Dealers, was recorded using a structured interview schedule (Lamprey and Donkoh, 2024). Responses were encoded allowing each farmer's communication behaviour to be represented as a transaction  $T_i$ , which is a subset of the universal set of communication channels  $I$ . The full dataset, consisting of all fifty farmers, was represented as the set of transactions  $T = \{T_1, T_2, \dots, T_{50}\}$ .

The study employed Association Rule Mining (ARM), a robust data mining technique grounded in set theory, probability, and combinatorial analysis, to identify meaningful relationships among communication channels (Malamsha and Nyambo, 2023). ARM generated rules of the form  $A \Rightarrow B$ , where  $A$  represented the antecedent set,  $B$  represented the consequent set, and  $A \cap B = \emptyset$ . The strength and relevance of the rules were quantified using

standard metrics. Support measured the proportion of transactions containing both antecedent and consequent, confidence quantified the conditional probability of the consequent given the antecedent, lift measured the strength of association beyond random chance, leverage captured deviation from independence, and conviction measured the degree of implication between antecedent and consequent (Belkadi and Drias, 2023).

To comprehensively explore patterns of information co-usage, the study considered both single-channel antecedents and combinatorial antecedents of up to three channels ( $|A| \leq 3$ ), generating complex multivariate association rules (Suleiman and Ikani, 2021). Minimum thresholds for support and confidence were set empirically to filter out statistically weak rules, producing a robust set of association rules (Malamsha and Nyambo, 2023). The Apriori algorithm was used to identify frequent item sets, a foundational algorithm widely used in agricultural and social science data analytics (Ginting et al., 2019).

The analysis was implemented in Python 3.11, using pandas for data handling, mlxtend.frequent\_patterns for frequent itemset generation via the Apriori algorithm, mlxtend.frequent\_patterns.association\_rules for computation of confidence, lift, leverage, and conviction, and matplotlib and seaborn for visualization of co-occurrence patterns and rule strengths (Han et al., 2011). This mathematically rigorous approach enabled a comprehensive understanding of information flow among farmers, highlighting interdependencies among communication channels and providing actionable insights for agricultural extension design, policy-making, and targeted knowledge dissemination in rural West Bengal (Iqbal et al., 2023).

### 3. RESULTS AND DISCUSSION

The association rule mining results provided a comprehensive understanding of how farmers adopted and combined different communication channels. The analysis revealed sixty-two combinations of adopted communication channels showcased in table 1.

Table 1: Association rules of farmers' communication channel usage

| Sl. No. | Antecedents                  | Consequents        | Support | Confidence | Lift     | Leverage | Conviction |
|---------|------------------------------|--------------------|---------|------------|----------|----------|------------|
| 1.      | Krishak bandhu               | Social media       | 0.54    | 0.54       | 1        | 0        | 1          |
| 2.      | Social media                 | Krishak bandhu     | 0.54    | 1          | 1        | 0        | $\infty$   |
| 3.      | TV                           | Social media       | 0.5     | 1          | 1.851852 | 0.23     | $\infty$   |
| 4.      | Social media                 | TV                 | 0.5     | 0.925926   | 1.851852 | 0.23     | 6.75       |
| 5.      | Radio                        | Krishak bandhu     | 0.46    | 1          | 1        | 0        | $\infty$   |
| 6.      | Krishak bandhu               | Radio              | 0.46    | 0.46       | 1        | 0        | 1          |
| 7.      | Ag. officers/ KVK            | Radio              | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 8.      | Radio                        | Ag. officers/ KVK  | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 9.      | Local input dealer           | Radio              | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 10.     | Radio                        | Local input dealer | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 11.     | Ag. officers/ KVK            | Krishak bandhu     | 0.46    | 1          | 1        | 0        | $\infty$   |
| 12.     | Krishak bandhu               | Ag. officers/KVK   | 0.46    | 0.46       | 1        | 0        | 1          |
| 13.     | TV                           | Krishak bandhu     | 0.5     | 1          | 1        | 0        | $\infty$   |
| 14.     | Krishak bandhu               | TV                 | 0.5     | 0.5        | 1        | 0        | 1          |
| 15.     | Local input dealer           | Krishak bandhu     | 0.46    | 1          | 1        | 0        | $\infty$   |
| 16.     | Krishak bandhu               | Local input dealer | 0.46    | 0.46       | 1        | 0        | 1          |
| 17.     | Local input dealer           | Ag. officers/ KVK  | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 18.     | Ag. officers/ KVK            | Local input dealer | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 19.     | TV, Krishak bandhu           | Social media       | 0.5     | 1          | 1.851852 | 0.23     | $\infty$   |
| 20.     | TV, Social media             | Krishak bandhu     | 0.5     | 1          | 1        | 0        | $\infty$   |
| 21.     | Krishak bandhu, Social media | TV                 | 0.5     | 0.925926   | 1.851852 | 0.23     | 6.75       |

| Sl. No. | Antecedents                           | Consequents                           | Support | Confidence | Lift     | Leverage | Conviction |
|---------|---------------------------------------|---------------------------------------|---------|------------|----------|----------|------------|
| 22.     | TV                                    | Krishak bandhu, Social media          | 0.5     | 1          | 1.851852 | 0.23     | $\infty$   |
| 23.     | Krishak bandhu                        | TV, Social media                      | 0.5     | 0.5        | 1        | 0        | 1          |
| 24.     | Social media                          | TV, Krishak bandhu                    | 0.5     | 0.925926   | 1.851852 | 0.23     | 6.75       |
| 25.     | Ag. officers/ KVK, Radio              | Krishak Bandhu                        | 0.46    | 1          | 1        | 0        | $\infty$   |
| 26.     | Ag. officers/ KVK, Krishak bandhu     | Radio                                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 27.     | Radio, Krishak bandhu                 | Ag. officers/KVK                      | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 28.     | Ag. officers/ KVK                     | Radio, Krishak bandhu                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 29.     | Radio                                 | Ag. Officers/KVK, Krishak bandhu      | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 30.     | Krishak bandhu                        | Ag. officers/KVK, Radio               | 0.46    | 0.46       | 1        | 0        | 1          |
| 31.     | Local input dealer, Radio             | Krishak bandhu                        | 0.46    | 1          | 1        | 0        | $\infty$   |
| 32.     | Local input dealer, Krishak bandhu    | Radio                                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 33.     | Radio, Krishak bandhu                 | Local input dealer                    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 34.     | Local input dealer                    | Radio, Krishak bandhu                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 35.     | Radio                                 | Local input dealer, Krishak bandhu    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 36.     | Krishak bandhu                        | Local input dealer, Radio             | 0.46    | 0.46       | 1        | 0        | 1          |
| 37.     | Local input dealer, Ag. officers/ KVK | Radio                                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 38.     | Local input dealer, Radio             | Ag. officers/ KVK                     | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 39.     | Ag. officers/ KVK, Radio              | Local Input Dealer                    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 40.     | Local input dealer                    | Ag. officers/KVK, Radio               | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 41.     | Ag. officers/ KVK                     | Local input dealer, Radio             | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 42.     | Radio                                 | Local input dealer, Ag. officers/ KVK | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 43.     | Local input dealer, Ag. officers/ KVK | Krishak bandhu                        | 0.46    | 1          | 1        | 0        | $\infty$   |
| 44.     | Local input dealer, Krishak bandhu    | Ag. officers/ KVK                     | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 45.     | Ag. officers/ KVK, Krishak bandhu     | Local input dealer                    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 46.     | Local input dealer                    | Ag. officers/ KVK, Krishak bandhu     | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 47.     | Ag. officers/ KVK                     | Local input dealer, Krishak bandhu    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 48.     | Krishak bandhu                        | Local input dealer, Ag. officers/ KVK | 0.46    | 0.46       | 1        | 0        | 1          |

Table 1: Continue...

| Sl. No. | Antecedents                                           | Consequents                                           | Support | Confidence | Lift     | Leverage | Conviction |
|---------|-------------------------------------------------------|-------------------------------------------------------|---------|------------|----------|----------|------------|
| 49.     | Local input dealer, Ag. officers/ KVK, Radio          | Krishak bandhu                                        | 0.46    | 1          | 1        | 0        | $\infty$   |
| 50.     | Local input dealer, Ag. officers/ KVK, Krishak Bandhu | Radio                                                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 51.     | Local input dealer, Radio, Krishak bandhu             | Ag. Officers/ KVK                                     | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 52.     | Ag. officers/ KVK, Radio, Krishak Bandhu              | Local input dealer                                    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 53.     | Local input dealer, Ag. Officers/ KVK                 | Radio, Krishak bandhu                                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 54.     | Local input dealer, Radio                             | Ag. officers/ KVK, Krishak bandhu                     | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 55.     | Local input dealer, Krishak bandhu                    | Ag. officers/ KVK, Radio                              | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 56.     | Ag. officers/ KVK, Radio                              | Local input dealer, Krishak bandhu                    | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 57.     | Ag. officers/KVK, Krishak bandhu                      | Local input dealer, Radio                             | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 58.     | Radio, Krishak bandhu                                 | Local input dealer, Ag. Officers/ KVK                 | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 59.     | Local input dealer                                    | Ag. officers/ KVK, Radio, Krishak bandhu              | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 60.     | Ag. officers/ KVK                                     | Local input dealer, Radio, Krishak bandhu             | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 61.     | Radio                                                 | Local input dealer, Ag. officers/ KVK, Krishak bandhu | 0.46    | 1          | 2.173913 | 0.2484   | $\infty$   |
| 62.     | Krishak bandhu                                        | Local input dealer, Ag. officers/ KVK, Radio          | 0.46    | 0.46       | 1        | 0        | 1          |

The Support metric measured how frequently a combination of communication channels occurred among farmers. In the study, support metric values ranged from 0.46 to 0.54, indicating that nearly half of the surveyed farmers used certain channels together. For instance, Krishak Bandhu along with social media had a support of 0.54, while TV along with social media had 0.50, suggesting that these pairs were widely adopted. Similarly, combinations like Radio along with Agricultural Officers/KVK and Local Input Dealer along with Radio had support of 0.46, reflecting moderate but meaningful co-usage (Figure 1). Higher-order combinations, such as TV, Krishak Bandhu, and social media, also had support of 0.50, highlighting that farmers frequently used multiple channels simultaneously (Akbas et al., 2022). These values emphasized the prominence of face-to-face, social media, and broadcast channels in

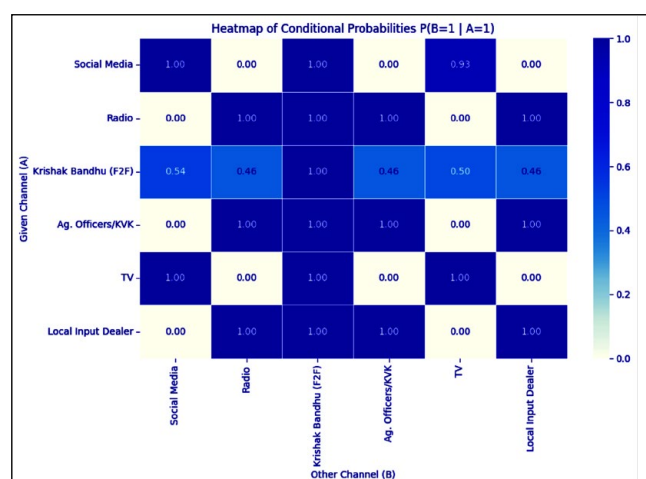


Figure 1: Likelihood of co-usage between agricultural communication channels

agricultural communication networks, consistent with previous applications of association rule mining (ARM) that identified frequently co-occurring variables in behavioural datasets (Istrat and Lalic, 2017).

Confidence reflected the likelihood that a consequent channel was used given the antecedent channel, representing predictability. In the study, confidence ranged from 0.46 to 1 (Figure 2). Deterministic rules included social media along with Krishak Bandhu, Radio along with Agricultural Officers/KVK, and Local Input Dealer along with Radio, all with confidence= 1, indicating that every farmer using the antecedent also used the consequent. Partial predictability was observed for rules like Krishak Bandhu along with social media (confidence=0.54) and Krishak Bandhu along with TV (confidence=0.50), suggesting that these channels were sometimes used independently (Azevedo and Jorge 2007). Confidence analysis highlighted which channels acted as complementary sources of information and which were consistently paired, providing actionable insight for designing multi-channel dissemination strategies, in line with similar findings on the use of confidence as a behavioural indicator in ARM (Zehtabchi et al., 2023).

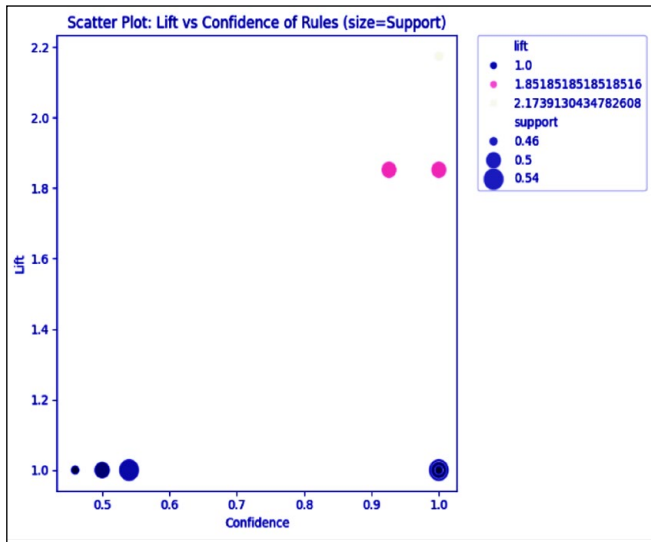


Figure 2: Scatter plot of lift vs confidence of association rules

Lift measured how much more often channels occurred together than expected by chance, with values greater than 1 indicating positive association. Lift values ranged from 1 to 2.17 (McNicholas et al., 2008). For example, Radio along with Agricultural officers/KVK and Local Input Dealer along with Radio had lift of 2.17, indicating a strong positive association, as these channels co-occurred more than twice the expected frequency (figure 1). TV along with social media had lift of 1.85, also showing a strong link, while Krishak Bandhu along with social media had lift of 1, meaning its co-occurrence matched what was expected

from individual usage rates. Lift values thus distinguished channel combinations that were synergistic from those that were simply popular, helping identify the most effective pairings for information delivery, a principle emphasized in enhanced evaluation methodologies for ARM (Bao and Mao, 2021; Ganghishetti and Vadlamani, 2014).

Leverage represented the difference between the observed co-occurrence and what would be expected if channels were independent. Leverage values ranged from 0 to 0.248. Rules with high leverage included Radio along with Agricultural Officers/KVK and Local Input Dealer along with Radio (leverage=0.248), showing a substantial positive deviation from independence, indicating meaningful combined usage. Conversely, rules like Krishak Bandhu with social media had leverage of 0, suggesting their co-occurrence was entirely explained by individual usage frequencies (Azevedo and Jorge 2007). Moderate leverage values, such as TV along with social media (0.23), highlighted combinations that were slightly more informative than expected by chance, helping prioritize channel pairings with the most incremental impact on farmer outreach, reflecting ARM's utility in detecting statistically meaningful co-occurrence patterns (Figure 3) (Akbas et al., 2022).

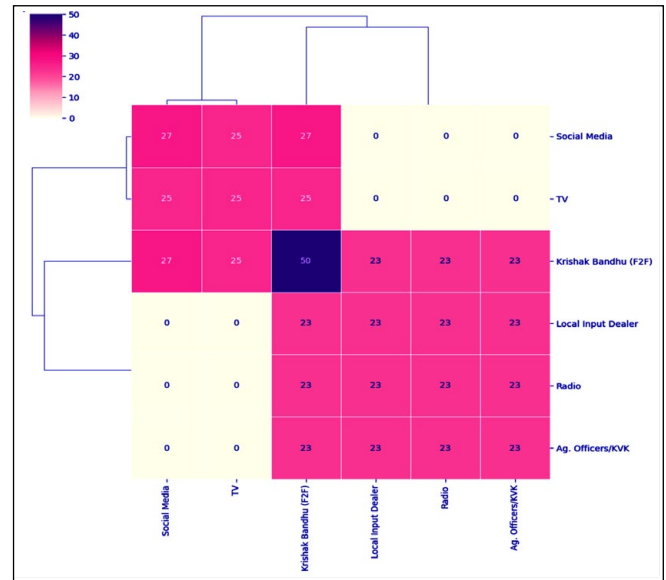


Figure 3: Clustered heatmap of channel cooccurrence

Conviction evaluated the degree of implication from antecedent to consequent, indicating predictive reliability. Conviction values ranged from 1 to infinity ( $\infty$ ). Rules like social media along with Krishak Bandhu and Radio along with Local Input Dealer had conviction of infinity, showing perfect predictability, as the consequent always occurred when the antecedent was present. Rules such as social media along with TV and Krishak Bandhu, social media along with TV had conviction of 6.75, indicating strong, though

not perfect, predictive power. In contrast, Krishak Bandhu along with social media had conviction of 1, reflecting a neutral relationship despite moderate co-usage. Conviction thus highlighted which channel pairs or combinations were highly reliable for predicting farmers' communication behaviour, supporting targeted extension interventions, in alignment with prior studies using conviction to assess directional predictability (Bao and Mao, 2021).

#### 4. CONCLUSION

Farmers in Bandh Nabagram village relied on digital, mass media, and interpersonal channels for agricultural information, showing distinct co-usage and interdependence. Association Rule Mining revealed frequent, predictive combinations like Krishak Bandhu with social media and Radio with Agricultural Officers/KVK. Metrics such as support, confidence, lift, leverage, and conviction underscored reliable and complementary pairings. Findings emphasized synergistic communication behaviours, suggesting integrated multi-channel extension strategies to maximize outreach, enhance adoption, and optimize resources, with future scope for broader, evolving analyses.

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#### 6. REFERENCES

Abukari, A.B.T., Bawa, K., Awuni, J.A., 2021. Adoption determinants of agricultural extension communication channels in emergency and non-emergency situations in Ghana. *Cogent Food & Agriculture* 7(1), 1872193. <https://doi.org/10.1080/23311932.2021.1872193>.

Agago, G.M., Cherenet, Y.M., Aweke, C.S., Endris, G.S., 2025. Seasonal information needs of vegetable farmers via indigenous and ICT communication channels in Haramaya and Kombolcha Woredas, East Hararghe, Ethiopia. *Journal of Agribusiness in Developing and Emerging Economies*, 1–23. DOI: 10.1108/jadee-11-2024-0399.

Akbas, K.E., Kivrak, M., Arslan, A.K., Yakınbas, T., Korkmaz, H., Onalan, E., Colak, C., 2022. Assessment of association rule mining using interest measures on the gene data. *Medical Records* 4(3), 286–292. DOI: 10.37990/medr.1088631.

Antwi-Agyei, P., Stringer, L.C., 2021. Improving the effectiveness of agricultural extension services in supporting farmers to adapt to climate change: Insights from northeastern Ghana. *Climate Risk Management* 32, 100304. <https://doi.org/10.1016/j.crm.2021.100304>.

Azevedo, P.J., Jorge, A.M., 2007. Comparing rule measures for predictive association rules. In: *European Conference on Machine Learning*, Berlin, Heidelberg, 510–517. Springer Berlin Heidelberg. DOI: 10.1007/978-3-540-74958-5\_47.

Bao, G., Mao, J., 2021. An improved evaluation methodology for mining association rules. *Axioms* 10(3), 200. <https://doi.org/10.3390/axioms11010017>.

Begho, T., Ogisi, O.D., 2025. A systematic review of the role of networks in information dissemination and resource pooling among farmers in Sub-Saharan Africa: Impact on farm improvements, empowerment and behaviour change. *Journal of International Development* 37(5), 1070–1081. DOI: 10.1002/jid.4004.

Belkadi, W.H., Drias, Y., Drias, H., Dali, M., Hamdous, S., Kamel, N., Aksa, D., 2024. A SCORPAN-based data warehouse for digital soil mapping and association rule mining in support of sustainable agriculture and climate change analysis in the Maghreb region. *Expert Systems* 41(7), e13464. DOI: 10.1111/exsy.13464.

Bhaskara, S., Bawa, K., 2021. Societal digital platforms for sustainability: agriculture. *Sustainability* 13, 5048. <https://doi.org/10.3390/su13095048>.

Bhatia, J., Gupta, A., 2021. Association rule mining by discretization of agricultural data using extended partitioning algorithm. In: *2021 6<sup>th</sup> International Conference for Convergence in Technology (I2CT)*, 1–6. DOI: 10.1109/i2ct51068.2021.9417954.

Colussi, J., Sonka, S., Schnitkey, G., Morgan, E., Padula, A., 2024. A Comparative study of the influence of communication on the adoption of digital agriculture in the United States and Brazil. *Agriculture* 14(7). <https://doi.org/10.3390/agriculture14071027>.

Fister Jr, I., Salcedo-Sanz, S., Alexandre-Cortizo, E., Novak, D., Fister, I., Podgorelec, V., Gorenjak, M., 2025. Toward explainable time-series numerical association rule mining: a case study in smart-agriculture. *Mathematics* 13(13), 2122. DOI: 10.3390/math13132122.

Fister, I., Fister, D., Fister, I., Podgorelec, V., Salcedo-Sanz, S., 2022. Time series numerical association rule mining variants in smart agriculture. *Journal of Ambient Intelligence and Humanized Computing* 14, 16853–16866. <https://doi.org/10.1007/s12652-023-04694-7>.

Ganghishetti, P., Vadlamani, R., 2014. Association rule mining via evolutionary multi-objective optimization. In: *Murty, M.N., He, X., Chillarige, R.R., Weng, P. (Eds.), Multi-disciplinary trends in artificial intelligence. MIWAI 2014. Lecture Notes in Computer Science*, vol 8875. Springer, Cham, 35–46. DOI: 10.1007/978-3-319-13365-2\_4.

Ginting, P.L., Dengen, N., Taruk, M., 2019. Comparison

- of priori and fp-growth algorithms in determining association rules. In: 2019 International Conference on Electrical, Electronics and Information Engineering (ICEEIE), 320–323. DOI: 10.1109/ICEEIE47180.2019.8981438.
- Giulivi, N., Harou, A., Gautam, S., Guereña, D., 2022. Getting the message out: Information and communication technologies and agricultural extension. *American Journal of Agricultural Economics* 105(3), 1011–1045. <https://doi.org/10.1111/ajae.12348>.
- Goeb, J., Maredia, M., Herrington, C., Zu, A., 2025. Information delivery in times of crisis: evaluating digitally-supported agricultural extension in Myanmar. *Agricultural Economics* 56(6), 1225–1240. <https://doi.org/10.1111/agec.70058>.
- Han, J., Kamber, M., Pei, J., 2012. *Data mining: Concepts and techniques* (3<sup>rd</sup> Edn.). Morgan Kaufmann. Available from: <https://shop.elsevier.com/books/data-mining-concepts-and-techniques/han/978-0-12-381479-1>.
- Iqbal, A., Salam, A., Farooq, Q.S., 2023. Relationship between the use of social media and interpersonal channels by farmers. *Global Sociological Review* VIII(I), 198–210. [https://doi.org/10.31703/gsr.2023\(VIII-I\).19](https://doi.org/10.31703/gsr.2023(VIII-I).19).
- Isaac, O., Oyewusi, A., Kayode, O., 2025. Assessment of communication channels in cocoa farming: Utilization, impact and constraints, in Ekiti West local government area. *World Journal of Advanced Research and Reviews* 26(03), 1058–1072. <https://doi.org/10.30574/wjarr.2025.26.3.2243>.
- Istrat, V., Lalic, N., 2017. Association rules as a decision making model in the textile industry. *Fibres & Textiles in Eastern Europe* 25, 8–14. DOI:10.5604/01.3001.0010.2302.
- Khatri, A., Lallawmkimi, M.C., Rana, P., Panigrahi, C.K., Minj, A., Koushal, S., Ali, M.U., 2024. Integration of ICT in agricultural extension services: A review. *Journal of Experimental Agriculture International* 46(12), 394–410. DOI: 10.9734/jeai/2024/v46i123146.
- Kigatiira, K.K., Mberia, H.K., Wangula, K., 2018. The effect of communication channels used between extension officers and farmers on the adoption of Irish Potato farming. *International Journal of Academic Research in Business and Social Sciences* 8(4), 377–391. DOI: 10.6007/ijarbss/v8-i4/4020.
- Lampitey, C.Y., Donkoh, S.A., Azumah, S.B., Zakaria, A., Sulemana, N., Zakaria, H., 2024. Channels and methods of communicating agricultural innovations to rice farmers in the Northern Region of Ghana. *Ghana Journal of Science, Technology and Development* 9(2), 61–76. DOI: 10.47881/353.967x.
- Madhushekar, B.R., Rani, V.S., Padmaveni, C., Reddy, M.M., Kumar, B.A., 2024. Effectiveness of agricultural information disseminated through mobile apps and social media. *International Journal of Bio-resource and Stress Management* 15(1), 01–08. <https://doi.org/10.23910/1.2024.4990>.
- Malamsha, G.C., Nyambo, D.G., 2023. Multi-level association rule mining for the discovery of strong underrepresented patterns: the case study of small dairy farms in Tanzania. *Engineering, Technology & Applied Science Research* 13(2), 10377–10383. DOI: 10.48084/etasr.5683.
- McNicholas, P.D., Murphy, T.B., O'Regan, M., 2008. Standardising the lift of an association rule. *Computational Statistics & Data Analysis* 52(10), 4712–4721. DOI: 10.1016/j.csda.2008.03.013.
- Mtega, W.P., 2021. Communication channels for exchanging agricultural information among Tanzanian farmers: A meta-analysis. *IFLA Journal* 47(4), 570–579. <https://doi.org/10.1177/03400352211023837>.
- Pandey, A., Rai, D.P., 2024. Women in animal husbandry: examining socioeconomic, communication, psychological characteristics and constraints to decision-making. *International Journal of Bio-resource and Stress Management* 15(1), 01–06. <https://doi.org/10.23910/1.2024.5017a>.
- Suleiman, R.A., Ikani, E.I., Mamma, S., Ariyo, O.C., Oladele, O.N., Adelani, O.D., 2021. Assessment of extension communication channels among agroforestry farmers in Ekiti state, Nigeria. *Russian Journal of Agricultural and Socio-Economic Sciences* 117(9), 102–116. DOI: 10.18551/rjoas.2021-09.12.
- Tasnim, F., Habib, I., Symon, N., Arefin, M., Reza, A., 2025. Integrating machine learning with association rule mining for enhanced crop disease classification. 2025 International Conference on Quantum Photonics, Artificial Intelligence, and Networking (QPAIN), 1–6. <https://doi.org/10.1109/qpain66474.2025.11171940>.
- Verma, A., Bharti, A., Rawat, R., Singh, A., Singh, P., Tripathi, S., 2024. Emerging role of information communication technologies in agriculture extension. *International Journal of Agriculture Extension and Social Development* 7(2), 299. DOI: 10.33545/26180723.2024.v7.i2a.299.
- Wang, X., Drabik, D., Zhang, J., 2023. How channels of knowledge acquisition affect farmers' adoption of green agricultural technologies: evidence from Hubei province, China. *International Journal of Agricultural Sustainability* 21(1), 2270254. <https://doi.org/10.1080/14735903.2023.2270254>.
- Zehtabchi, S., Daneshpour, N., Safkhani, M., 2023. A new method for privacy preserving association rule mining using homomorphic encryption with a secure communication protocol. *Wireless Networks* 29(3), 1197–1212. <https://doi.org/10.1007/s11276-022-03185-5>.