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AN ANALYSIS OF DETERMINANTS AND CONSTRAINTS AFFECTING THE ADOPTION OF AGRICULTURAL MARKET INTELLIGENCE AMONG THE FARMING COMMUNITY IN ASSAM INDIA

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ABSTRACT

The present study examines the determinants and constraints influencing the adoption of Agricultural Market Intelligence (MI) among 600 farmers across three Agro-climatic zones i.e. Central, Upper and Lower Brahmaputra Valley Zones of Assam by covering 10 districts randomly. Binary logistic regression was employed to identify the key factors affecting MI adoption among farmers, including a few variables e.g., age, education, landholding size, farming experience, financial access, market proximity and internet connectivity etc. The results of the study indicate that younger, better-educated farmers with larger landholdings, greater farming experience, improved financial access and stronger digital connectivity are more likely to adopt the MI services, while older farmers show lower adoption due to greater reliance on traditional practices. To identify the constraints of using Agricultural MI services, the Garrett Ranking technique was utilized. This analysis reveals several primary obstacles, including restricted market coverage, a lack of forward-looking price forecasts, and a persistent reliance on traditional information sources. Furthermore, the study highlights concern regarding data reliability and insufficient market linkages. By addressing these barriers through focused policy and institutional support, we can improve the adoption of market intelligence and foster sustainable agricultural growth in Assam.
***Keywords*:** Agricultural market intelligence, farmer empowerment, market proximity, technology adoption, price forecasting

Introduction

Market Intelligence (MI) has evolved as an integral pillar of modern agricultural systems, offering a systematic and knowledge-based managerial framework that facilitates strategic planning and evidence-based decision-making. MI is primarily derived from systematically collected market information, which is analysed over time to identify trends, assess market behaviour and forecast future developments. Through this systematic process, MI enables stakeholders to gain an in-depth understanding of trade dynamics, define strategic goals and uncover new opportunities in both domestic and global markets. According to Sharma and Burark (2015), Agricultural Market Intelligence (AMI) is vital for facilitating informed decisions among farmers, traders, firms and policymakers. It contributes to increasing producer income, strengthening regional trade and improving food security by ensuring timely and reliable access to market information. Hedin *et al.* (2014) conceptualise market intelligence as more than a mere collection of data, describing it as a strategic instrument that enables agricultural stakeholders to understand market dynamics better and formulate appropriate responses to rapidly evolving market conditions.

Since the establishment of Market Intelligence Units (MIUs) in 1954, following the recommendations of the Agricultural Prices Enquiry Committee, market intelligence has played a pivotal role in agricultural price policy formulation and market decision-making in India by systematically providing information on prices, arrivals, production forecasts and stock positions. This system was further strengthened with the launch of the Agricultural Marketing Information Network (AGMARKNET) in 2000 by the Directorate of Marketing and Inspection in collaboration with the National Informatics Centre (NIC), which enabled real-time nationwide dissemination of market data and regulatory information, thereby supporting price forecasting and informed marketing decisions (Shinde, 2018). Recognising the need for region-specific market intelligence, Assam Agricultural University established the Agricultural Market Intelligence Unit (AMIU) in 2021 under the World Bank funded Assam Agribusiness and Rural Transformation (APART) project to disseminate validated price and arrival data for price and arrival information for 22 major commodities across 57 wholesale markets in 16 districts of Assam through a dedicated digital platform and multiple outreach mechanisms. Despite these initiatives significantly improving information availability and reducing information asymmetry (Singh *et al.*, 2020 and Das *et al.*, 2021), agricultural marketing in Assam continues to be characterised by price volatility, fragmented markets and the predominance of traditional marketing channels, resulting in uneven utilisation of MI services across regions and socio-economic groups.

The utilisation of Market Intelligence (MI) services plays a critical role in improving agricultural marketing efficiency, farmers' income and resource allocation, yet its adoption remains uneven across regions and farmer groups. Empirical evidence suggests that MI utilisation is shaped by a range of interrelated socio-economic and infrastructural factors, including farmers' age, educational attainment, landholding size, financial capacity, access to digital infrastructure and proximity to markets, while several constraints such as limited market coverage, absence of forward-looking information, weak market linkages, technological limitations and inadequate awareness continue to impede effective use (Angles and Chinnadurai, 2018). Studies have demonstrated that MI significantly enhances farmers' livelihoods by increasing income, employment, asset creation, and marketing efficiency, while reducing transaction costs and post-harvest losses, thereby strengthening the competitiveness of smallholders (Swaminathan and Sivabalan, 2016). However, persistent challenges related to high marketing costs, excessive intermediation, limited crop coverage, untimely information dissemination, low technological access and inadequate institutional support remain substantial barriers, particularly for small and resource-poor farmers (Aggarwal and Singh, 2004).

Given the heterogeneity of Assam's agricultural landscape across the Central, Upper and Lower Brahmaputra Valley Zones, empirical evidence on regional variations in agricultural MI adoption and the relative importance of these constraints remains limited. Addressing this gap is essential for strengthening existing MI services and informing targeted policy interventions. Accordingly, the present study aims to identify the key determinants influencing farmers' utilisation of Market Intelligence services and to examine the major constraints encountered in their effective use, with the objective of supporting policy formulation and promoting sustainable agricultural growth and improved farmer livelihoods in Assam.

Materials and Methods

The present study focused on ten specific districts representing three of Assam's agro-climatic zones. These included the Central Brahmaputra Valley Zone (Nagaon and Morigaon), the Upper Brahmaputra Valley Zone (Golaghat, Jorhat and Sivasagar), and the Lower Brahmaputra Valley Zone (Kamrup Rural and Metro, Barpeta, Nalbari and Kokrajhar). Sample farmers from each district were selected from both users of market intelligence services offered by Assam Agricultural University and other sources, including the AGMARKNET portal and Krishi Vigyan Kendras (KVKs). Purposive random sampling was employed to select 600 farmers, with 300 MI users and 300 non-users. The data were collected through pre-tested questionnaires and personal interviews. Secondary information on market dynamics was gathered from AMIU Cell, AGMARKNET portal, Government offices and other published sources.

To investigate the factors influencing Market Intelligence (MI) utilization among farmers, binary logistic regression was performed, revealing seven highly influential determinants, namely age, education, landholding, farming experience, financial access, internet connectivity, and proximity to markets (Table 1).

Table 1 : Variable description and logistic regression model

Variable	Description
Age	Farmer's age (Continuous)
Education	Education level (Categorical: 1-Primary, 2-Secondary, 3-Graduate and Above)
Land holding	Size of cultivable land (ha) of the sample farmers (Continuous)
Size of the family	Number of family members involved in farming (Continuous)
Farming	Years of farming experience

experience	(Continuous)
Financial access	Access to financial facilities (Binary: 0- No, 1- Yes)
Proximity to market	Distance (km) covered from the farmer's household to the nearby market (Continuous)
Internet connectivity	Categorical Variable (1- Poor, 2- Intermediate, 3-Excellent)
MI usage	Outcome variable (Binary: 0- Non-user, 1- User)

To eliminate potential bias within the dataset, multicollinearity was assessed using IBM SPSS software. Multicollinearity occurs when strong linear relationships exist among independent variables, which can distort coefficient estimates, inflate standard errors, and undermine the model's predictive accuracy (Frank, 2001; Young, 2016). This was evaluated through the Variance Inflation Factor (VIF), a metric that quantifies the degree to which correlations between explanatory variables increase the variance of estimated regression coefficients (Shrestha, 2020). VIF is computed as follows:

$$VIF = \frac{1}{1-R^2} = \frac{1}{Tolerance}$$

Likewise, Binary logistic regression analysis was also conducted using SPSS software, employing the formula:

$$Logit(p_i) = \ln\left(\frac{p_i}{1-p_i}\right) = \beta_0 + \beta_1 x_{1,i} + \ldots\ldots\ldots\ldots + \beta_k x_{k,i}$$

Where,

p_i = Probability of using MI services

$X_1, X_2, X_3 \ldots\ldots X_n$ = Predictor variables

$\beta_0, \beta_1, \beta_2, \ldots, \beta_n$ = Coefficients estimated from the regression model.

Additionally, constraints encountered by the farmers in utilising agricultural MI services were ranked using Garrett's Ranking Technique using the formula:

$$Percent\ \ position = \frac{100(R_{ij} - 0.5)}{N_j}$$

Where R_{ij} represents the rank given to the ith attribute by the jth individual, and N_j is the number of attributes ranked by the jth individual. Using Garrett's table, the calculated percentage positions were converted into corresponding scores. For each factor, the scores assigned by all respondents were aggregated, and the mean score was computed. The resulting mean values for the attributes were then ranked in descending order, with the attribute obtaining the highest mean score considered the most important, followed sequentially by the others (Garrett and Woodworth, 1969)

Results and Discussion

Before conducting the binary logistic regression analysis to examine the determinants of market intelligence (MI) utilisation among farmers in Assam, comprehensive diagnostic tests were performed to assess the presence of multicollinearity (Table 2). Tolerance values nearing one and Variance Inflation Factor (VIF) values below 10 are typically regarded as acceptable levels of multicollinearity (Shrestha, 2020).

Table 2 : Collinearity statistics

Independent Variables	Collinearity statistics	
	Tolerance	**Variance influence factor**
Age	0.979	1.022
Education	0.980	1.020
Land Holding	0.987	1.013
Size of the family	0.950	1.053
Farming Experience	0.966	1.035
Financial Access	0.987	1.014
Proximity to Markets	0.954	1.048
Internet Connectivity	0.967	1.035

Source: Author's own computation based on field survey.

The obtained Tolerance values shown in Table 2 ranged from 0.946 to 0.987, while the corresponding VIF values ranged from 1.013 to 1.053. These findings collectively suggest that multicollinearity is not a significant concern in the model. The Tolerance values, reflecting the proportion of variance in an independent variable not explained by other predictors, all exceeded the conventional threshold of 0.90, signifying that each variable contributes unique information to the regression model. Likewise, the VIF values, which reflect the extent to which multicollinearity inflates the variance of coefficient estimates, remained well below the critical threshold of 10, confirming the absence of serious multicollinearity. These diagnostic measures ensure that the subsequent logistic regression coefficients remain reliable and interpretable. By confirming the absence of significant multicollinearity, the study guarantees that the factors influencing market intelligence adoption in Assam are independent, thereby enhancing the overall validity and credibility of the findings (Senaviratna, N. A. M. R. and Cooray, T. M. J. A. (2019).

Table 3 : Binary logistic regression analysis

Independent Variables	Coefficients	S.E.	p- value
Age	-0.380	0.140	0.007***
Education	0.330	0.150	0.028**
Land Holding	0.620	0.270	0.022**
Size of the Family	0.005	0.003	0.096^{NS}

Farming Experience	0.553	0.182	0.002***
Financial Access	0.180	0.090	0.046**
Proximity to the markets	-0.430	0.180	0.017**
Internet Connectivity	0.360	0.171	0.035**
Constant	0.354	0.341	0.298
Pseudo R^2	81.1		

Source: Author's own computation based on field survey
*** and ** Significant at 1 and 5 per cent level.
NS: Non-significant.

The results of the binary logistic regression analysis are shown in Table 3. First and foremost, Age emerges as a key determinant of MI adoption, showing statistical significance at the 1% level and indicating a balance between traditional practices and technological progress. Older farmers, who are more strongly embedded in traditional agricultural practices, tend to be less receptive to digital platforms, thereby limiting their utilisation of market intelligence. In contrast, younger farmers show a greater inclination towards technology-driven agricultural initiatives, indicating greater engagement with digital innovations (Meera *et al.*, 2004). Furthermore, higher levels of education significantly enhance farmers' ability to understand market dynamics and to utilise MI resources effectively. Additionally, the study highlighted the significance of financial accessibility in MI adoption. Farmers with greater financial resources demonstrated a higher propensity to utilise market intelligence services, highlighting the influence of economic capacity on adoption behaviour. Additionally, the availability of supportive infrastructure, particularly internet connectivity and mobile network coverage, emerged as a critical determinant of access to and utilisation of MI resources. The study further revealed that landholding size significantly influenced the adoption of MI services at the 5 per cent level, likely reflecting the higher levels of investment and risk associated with managing larger farm holdings, which incentivise the use of MI tools to improve production efficiency, manage market risks and maximise returns. Likewise, more experienced farmers demonstrated a stronger appreciation for the role of market intelligence in navigating market fluctuations. Angles and Chinnadurai (2018), in their study in Tamil Nadu, also employed the logistic regression to explore the factors that affect the adoption of market intelligence information among rural farmers. The analysis indicates that age, education, financial capacity, motivation and intention exerted significant influence on the utilisation of market intelligence information. In contrast, family size did not show a significant association with farmers' decisions to utilise market intelligence. Proximity to markets exerted a statistically significant adverse effect on the utilisation of market intelligence, indicating that farmers situated closer to markets were less likely to use MI services. It could be attributed to several factors, such as greater familiarity with local market dynamics, reduced reliance on formal information channels through direct engagement with local buyers, or limited perceived benefits of accessing MI resources compared to farmers in more remote areas. Furthermore, the study revealed a significant association between the utilisation of information and communication technology (ICT) tools and the adoption of market intelligence (MI) services. Farmers who reported using ICT tools exhibited a markedly higher propensity to utilise MI, with statistical significance at the 1% level. It underscores the pivotal role of ICT infrastructure in facilitating access to MI resources and enhancing farmers' engagement with market information. Examples of ICT tools that farmers in Assam may leverage include mobile applications providing real-time market prices, online platforms offering agricultural advisory services and SMS-based information dissemination systems. In their seminal study on agricultural Information Dissemination Using ICTs, Zhang *et al.* (2016) underscored the transformative influence of advanced ICTs on traditional agriculture. The adoption of these tools and technologies has led to substantial improvements in agricultural productivity and sustainability among farmers and farming communities, indicating a structural transformation within the agricultural sector. In India, a wide range of government and private-sector initiatives is similarly engaged in the regular dissemination of information to farmers. Notably, mobile phone coverage alone has led to significant market efficiencies, as evidenced by a 9% increase in profits for fishermen and a 4% decrease in consumer prices in Kerala. (Mwangi and Kariuki, 2015).

Several researchers have frequently employed Garrett's ranking technique to explore various aspects of inquiry. For example, Ao and Jamir (2020) applied this method to analyse the challenges faced by bamboo growers in Mokokchung District of Nagaland, India, with the objective of identifying the most influential factors. Similarly, Shwetha *et al*. (2022) employed the Garrett ranking technique to examine the constraints faced by cotton farmers in Nalgonda District, Telangana, during crop cultivation. In the present study, Garrett ranking method is employed to identify the constraints associated with using market intelligence (MI) services and determine the rank of the variables. The analysis of results from the Garrett ranking technique provides valuable insights into the factors influencing farmers' adoption of market intelligence services (Table 4).

Table 4 : Problems faced by MI users

Factors	Mean Score	Rank
Limited Market Coverage	57.43	1
No Future Prediction Offered	56.50	2
Higher Dependence on Traditional Channels	53.50	3
Data Credibility Concern	53.35	4
Limited Adoption of Market Insights	53.18	5
Unused for Crop Planning	52.23	6
Limited Market Linkage	47.98	7
Price Range Variation	46.61	8
Lack of Awareness and Knowledge	43.94	9
Limited Access to Technology	42.37	10
Poor Network Connectivity	37.89	11

Source: Author's Own Computation based on field survey.

The results shown in Table 4 revealed that "Limited Market Coverage" emerged as the most influential factor affecting farmers' utilisation of market intelligence services, ranking highest with a mean score of 57.43. It indicates that farmers perceived limited market representation as a critical barrier to accessing and leveraging market intelligence effectively. One possible reason is inadequate coverage of market information systems in certain regions, leading to disparities in access to crucial market data. The second-ranked factor, "No Future Prediction Offered," with a mean score of 56.5, underscores the importance of predictive capabilities in market intelligence services. Zhang *et al*. (2014) in their study also emphasizes the importance of accurate price prediction for agricultural products, noting that such forecasts are crucial for effective production planning and maintaining a balance between supply and demand. Farmers are less likely to utilise market intelligence services that do not provide insights into future market trends and price forecasts, as such information is crucial for informed decision-making related to crop planning, production, and marketing strategies. "Higher Dependence on Traditional Channels" ranked third, highlighting the prevalence of reliance on conventional methods of market information gathering and decision-making among the farmers. This factor, with a mean score of 53.5, suggests that entrenched practices and a lack of awareness about alternative sources of market intelligence could hinder the adoption of modern MI tools and technologies. "Data Credibility Concern" (mean score: 53.35) and "Limited Adoption of Market Insights" (mean score: 53.18) were also identified as significant barriers. Farmers may be hesitant to fully trust market intelligence data if they perceive credibility issues or if they have limited exposure and understanding of the benefits of utilising market insights in their farming practices. Moreover, factors such as "Unused for Crop Planning", "Limited Market Linkage" and "Price Range Variation" further contributed to the challenges farmers face in effectively utilising market intelligence. These findings underscore the multifaceted nature of barriers to MI adoption, ranging from technological limitations to systemic issues within agricultural markets. "Lack of Awareness and Knowledge" emerged as a significant constraint, underscoring the urgent need for targeted educational interventions to enhance farmers' understanding of market intelligence services; a similar issue of inadequate market knowledge regarding potential markets, arrival patterns, and price trends was reported by Sharma (2011) in his study on the behaviour of market arrivals and prices of tomato in selected markets of North India. In addition, "Limited Access to Technology" also surfaced as a major challenge, underscoring the necessity of improving digital infrastructure and technological outreach to enhance farmers' capacity to access and utilise market intelligence services effectively. Finally, "Poor Network Connectivity" was identified as a significant factor, reflecting the challenges posed by inadequate internet and telecommunications infrastructure in rural areas, which can impede farmers' ability to access real-time market information and digital MI platforms. The study conducted by Angles, S. and Chinnadurai, M. (2018) revealed similar findings. Farmers utilising market intelligence identified multiple constraints, including the unavailability of market-specific information, inadequate technological access especially mobile and internet connectivity limited accessibility at critical times, and insufficient and untimely coverage of market intelligence across crops. Conversely, non-users of market intelligence faced obstacles like inadequate training, lack of formal education, limited production and inconvenience in selling within the village.

Conclusions

The study identifies key socio-economic, infrastructural and market-related factors influencing the utilisation of Market Intelligence (MI) services among farmers across the Central, Upper and Lower Brahmaputra Valley Zones of Assam. Empirical results show that younger age, higher education, larger landholdings, greater farming experience, improved financial access and stronger internet connectivity significantly enhance MI adoption, highlighting the importance of human capital, economic capacity, and ICT infrastructure. In contrast, farmers located closer to markets exhibit lower reliance on formal MI services, reflecting continued dependence on informal information channels. Constraint analysis reveals that limited market coverage, lack of forward-looking price information, reliance on traditional marketing practices and concerns over data credibility constitute the most significant barriers to effective MI utilisation, further compounded by weak market linkages, technological limitations and inadequate awareness.

These findings suggest several policy priorities. Expanding MI coverage to rural and periodic markets through decentralised and digitally enabled data collection can improve inclusiveness and relevance. Integrating forward-looking components such as pre-sowing and pre-harvest price forecasts and demand projections is essential to enhance MI's value for crop planning and risk management. Strengthening rural ICT infrastructure, particularly mobile and internet connectivity, is critical for improving access and real-time information dissemination. In addition, MI platforms should be leveraged to strengthen market linkages by connecting farmers with cooperatives, organised buyers, agribusiness firms and government agencies. Targeted capacity-building initiatives, including training and awareness programmes, are necessary to build trust and promote wider adoption. Collectively, these measures can enhance MI effectiveness and support sustainable agricultural growth and resilience in Assam.

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