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Determinants of paddy farmers' market information-seeking behavior in Soppeng District, Indonesia as implications for adaptive decision making toward sustainable agriculture

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Abstract. *Ardiansyah MFP, Salam M, Jamil MH, Rukka RM, Darma R, Akzar R. 2026. Determinants of paddy farmers' market information-seeking behavior in Soppeng District, Indonesia as implications for adaptive decision making toward sustainable agriculture. Asian J Agric 10 (1): g100152. https://doi.org/10.13057/asianjagric/g100152.* Access to accurate and timely agricultural market information is essential for improving farmers' decision-making, market participation, adoption of sustainable agricultural practices, biodiversity conservation, and their ability to respond to economic and environmental uncertainty, ultimately promoting sustainable agriculture. However, many farmers remain reluctant to seek such information actively. This study aimed to analyze the determinants of paddy farmers' market information-seeking behavior, explicitly distinguishing it from general agricultural information access that dominates existing studies. A cross-sectional survey was conducted with 190 paddy farmers in Soppeng District, South Sulawesi, Indonesia, selected using Cochrans' sampling method. The data were analyzed using descriptive statistics and binary logistic regression. Descriptive results show that farmer groups (30.43%) are the primary source of market information, followed by independent searching (20.11%), extension workers (19.02%), and fellow farmers (18.48%). Logistic regression results indicate that age ($\beta = -0.080$; $p < 0.05$) and farming experience ($\beta = -0.045$; $p < 0.10$) negatively influence information-seeking behavior, while education ($\beta = 0.325$; $p < 0.01$), crop diversification ($\beta = 2.790$; $p < 0.01$), extension contact ($\beta = 0.148$; $p < 0.10$), market distance ($\beta = 0.515$; $p < 0.10$), and credit access ($\beta = 1.273$; $p < 0.05$) have positive effects. The model demonstrates good fit (Hosmer-Lemeshow $p = 0.881$) and strong explanatory power (Nagelkerke $R^2 = 0.665$). These findings suggest that market information seeking is a behavioral response shaped by farmers' capacity, institutional exposure, and incentives to manage price and income uncertainty, rather than by information availability alone, with implications for how farmers adapt their sustainable production, resource use, and marketing strategies under changing economic and environmental conditions for sustainable agriculture goals. This study provides empirical evidence that strengthening behavior-sensitive extension systems, local information intermediaries, and integrated market information services is critical to enhancing farmers' decision-making and supporting sustainable agricultural systems.

Keywords: Binary logistic regression, market information, farmers' behavior, rural agricultural systems, sustainable agriculture

INTRODUCTION

Agricultural market information plays a pivotal role in improving the efficiency and competitiveness of agribusiness food systems (Sennuga et al. 2024; Shi et al. 2025) as timely and reliable information enables farmers to respond to market dynamics (Yaseen et al. 2023) alongside broader production, structural, and environmental challenges (Mittal and Mehar 2016; Rahman and Hye 2022), contributing to more sustainable agricultural systems (Deichmann et al. 2016; Abraham and Arunachalam 2021; Yaried and Bullo 2025). In developing countries, the improved information is widely recognized as a key instrument not only for enhancing farmers' productivity and welfare (Mwakalonge and Chingonikaya 2023; Bor et al. 2025) but also their bargaining positions within agri-food value chains (Phiri et al. 2018; Ndimbo et al. 2023) and contribute to broader agricultural development challenges (Wakoli et al. 2025). Beyond marketing performance, access to reliable market signals can also influence how farmers organize their farming systems, which shape the sustainability and resilience of smallholder agroecosystems (Adnan et al. 2018; Ullah 2026). However, disparities in the access, availability, and quality of information continue to constrain farmers' capacity and willingness to seek information (Shitaye et al. 2024; Ntsoane et al. 2025) despite the rapid expansion of digital technologies. Consequently, many farmers rely heavily on inherited experience, which often provides incomplete or outdated market signals and increases their vulnerability to price volatility and potential exploitation by intermediaries (Mushi et al. 2025).

In Indonesia, where smallholder agriculture dominates the rural economy, access to agricultural market

information has become critical as farmers face uncertainty across production, environmental, and market dimensions, requiring them to respond to both production risks and dynamic market conditions (Mariyono 2019; Nugroho 2021). However, rural areas continue to experience information asymmetry that limits farmers' ability to obtain timely and relevant market information (Liao and Chen 2017; Shitaye et al. 2024). This is exacerbated by the fact that the information availability does not automatically translate into active information-seeking behavior due to limited awareness and knowledge (Nugroho 2021; Shitaye et al. 2024). In this context, the effectiveness of institutional support and market-oriented approaches is closely linked to farmers' capacity to access, interpret, and utilize market information. These capabilities shape not only marketing decisions but also broader farm management practices, such as diversification and resource allocation, positioning market information as a key mechanism through which institutional support translates into adaptive responses within agricultural systems. This challenge is particularly evident in Soppeng District, one of the paddy production centers in South Sulawesi Province, where paddy production decreased by 6.62% from 259,791 tons in 2023 to 242,470 tons in 2024, indicating increasing pressure on agricultural performance (Badan Pusat Statistik (BPS)-Statistics Soppeng District 2025). Previous studies in Soppeng District, South Sulawesi, Indonesia, highlighted constraints such as marketing (Malebbi et al. 2023; Sahruni et al. 2023) and climate change (Winarno et al. 2021) that exposes smallholders to income vulnerability. Recent advances in information technology offer opportunities to strengthen farmers' market engagement and resilience; however, the extent to which farmers actively seek remains uneven, underscoring the need to understand better its behavioral dimensions in relation to farmers' adaptive decision-making processes.

Although a growing body of literature examines agricultural information access, utilization, and adoption, most studies primarily focus on post-information outcomes, such as the use of information systems (Mittal and Mehar 2016; Mdoda et al. 2024), participation in ICT-based services (Ogutu et al. 2014), or the impacts of information on productivity and profitability (Piabuo et al. 2020; Shitaye et al. 2025). These approaches emphasize how information is accessed or used, rather than how farmers make the initial decision to actively seek information. While some studies have explored information-seeking behavior, they generally examine general agricultural information or knowledge acquisition processes (Acheampong et al. 2017; Mahindarathne and Min 2018) rather than market-specific information relevant to selling decisions. Conversely, studies focusing on agricultural market information tend to analyze access and utilization rather than the behavioral decision to seek such information (Okello et al. 2014; Magesa et al. 2020). As a result, limited attention has been given to understanding market information seeking as a distinct behavioral process that precedes farmers' marketing decisions. This study addresses this gap by examining the determinants of farmers' active decision to seek market information prior to selling their output, extending binary choice models beyond access and utilization toward pre-decision behavioral analysis, and offering insights into how farmers respond to market signals and uncertainty in ways that may influence adaptive farm management.

Given the importance of having access to reliable and up-to-date information regarding the agricultural market, as discussed earlier, this study aimed to analyze the determinants of agricultural market information-seeking behavior among paddy farmers in the Soppeng District, by examining how socioeconomic characteristics, farm and livelihood attributes, institutional interactions, market accessibility, digital technology, and financial engagement influence farmers' decisions to seek market information actively. The research findings were expected to provide a framework for market information seeking as a pre-decisional behavioral process that underpins informed decision-making in sustainable agricultural systems. Furthermore, the findings would benefit policymakers, extension workers, and agribusiness actors in designing more targeted and behavior-sensitive agricultural information systems that support informed decision-making, thereby strengthening pathways toward sustainable agriculture.

This study hypothesizes that paddy farmers' decisions to seek market information are not solely driven by information availability but are significantly influenced by socioeconomic capacity, institutional exposure, and market-related incentives. Specifically, factors such as education, crop diversification, extension contact, market accessibility, and financial engagement are expected to positively influence information-seeking behavior, whereas age and farming experience may reduce the likelihood due to reliance on established practices. Accordingly, this study addresses the following research question: What are the key determinants shaping farmers' active decision to seek market information in a rural agricultural context?

MATERIALS AND METHODS

Study area

This study was conducted in Soppeng District, South Sulawesi Province, Indonesia (Figure 1). According to BPS-Statistics Soppeng District (2025), the district covers an area of approximately 1,500 km² is administratively divided into eight districts, and lies at an average altitude of approximately 25 meters above sea level. The population reached 241.3 thousand people, with a low growth rate of 0.16% in 2024. Agriculture constitutes the backbone of the local economy, with approximately 44% of the labor force engaged in the agricultural sector, reflecting a strong dependence on farm production and marketing activities. Paddy is the dominant commodity, covering 58,247.57 ha. Structurally compared with other rice-producing regions in the province with similar production levels, Soppeng District has a limited number of market facilities (20 units), suggesting constrained physical access to market interactions and price signals. Infrastructure conditions are mixed, with 50.58% of roads in good condition and 43.17%

severely damaged, which potentially increases transaction costs and limits mobility. Digital connectivity is also relatively limited, as indicated by only 120 Base Transceiver Station (BTS) towers available, potentially restricting access to real-time market information. At the same time, the presence of 71 farmer group associations reflects relatively strong social and institutional networks that facilitate information exchange among farmers. The Human Development Index (HDI) of 72.76 indicates a moderate level of human development, reflecting the population's overall capacity in terms of education, health, and living standards, which broadly shapes individual decision-making and behavioral patterns. These combined conditions create a heterogeneous information environment, making Soppeng a suitable behavioral-economic setting for examining farmers' market information-seeking behavior in rural agricultural systems.

Sampling and data collection

This study employed a cross-sectional survey design targeting paddy farmers in Soppeng District, conducted from January to March 2025. Due to the large, unknown, and dispersed nature of the farming population, the total number of paddy farmers could not be precisely determined. Under such conditions, where the population is effectively large or unknown, Cochran's sampling formula is widely recommended for determining an adequate sample size in survey-based studies (Ahmed 2024). The formula for Cochran's sample size calculation is as follows:

$$n = \frac{Z^2 \times p \times (1-p)}{e^2} \quad [1]$$

$$n = \frac{1.96^2 \times 0.5 \times (1-0.5)}{0.0712^2}$$

Where, n is the sample size, Z is the standard normal deviation corresponding to a 95% confidence level (1.96), p is the assumed population proportion (0.5), and e is the desired degree of precision (0.0712). This margin of error was adjusted to a 7.12% precision level to reflect practical constraints, such as the geographical dispersion of households across Soppeng District and logistical challenges in conducting face-to-face interviews. According to Geddafa et al. (2021) who use a similar value, this adjustment maintains an acceptable statistical reliability while ensuring the feasibility of high-quality data collection within the study's resource limits. Meanwhile Poudel et al. (2024) note that social science studies often adopt varying confidence levels depending on research context. In line with this, the margin of error applied in this study is consistent with values used in previous empirical studies in similar settings. Based on this specification, 190 paddy farmers were selected using a random sampling technique for participation in the survey.

Primary data were collected through structured, face-to-face interviews using a standardized questionnaire. Prior to the main survey, the questionnaire was pretested to avoid ambiguity and misunderstanding by adjusting the wording to align with local understanding and refining the sequence of questions to maintain a logical flow, thereby minimizing respondent confusion and inconsistent responses arising from similar or related questions presented in different orders. The questionnaire was subsequently revised and retested to ensure clarity and efficiency in data collection. This method was adopted to ensure consistency and data completeness, particularly given variations in farmers' literacy levels and record-keeping practices.

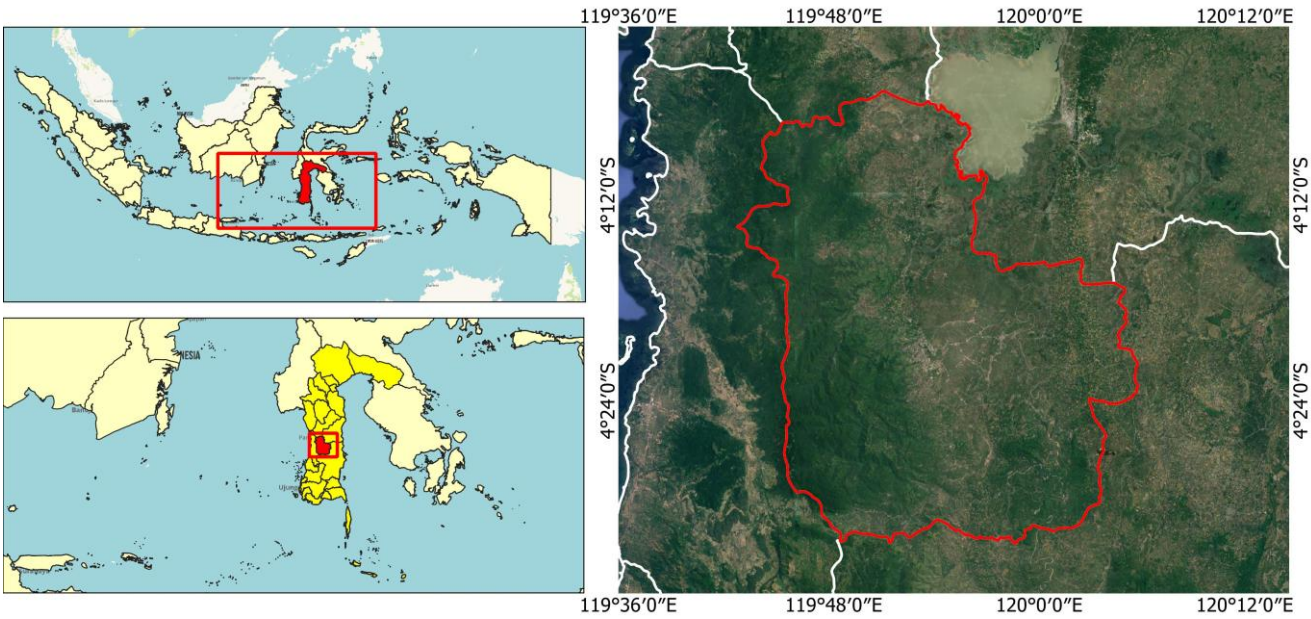

Figure 1. Location of study area

Data analysis

Descriptive statistics

Descriptive statistics were employed as the first step in quantitative data analysis and used to organize and summarize raw data into meaningful and interpretable information. In social science research, descriptive analysis plays a critical role in providing an initial empirical overview of respondent characteristics and observable patterns before more advanced inferential techniques are applied (Lynch 2013; Maravelakis 2019). The primary purpose of descriptive statistical procedures is to facilitate data description and summarization through numerical indicators and graphical representations that capture the key features of the distribution (Cooksey 2020).

In this study, descriptive statistics were employed to identify the main sources of agricultural market information accessed by paddy farmers. The proportion of farmers using each information source was calculated and presented in percentage form, allowing for a clear comparison of the relative prevalence of different information channels. Presenting data as percentages provides an effective means of summarizing categorical responses and highlighting dominant patterns within the sample (Cooksey 2020). The results were further visualized using bar charts to enhance interpretability and illustrate the distribution of information sources across respondents.

Binary logistic regression general equation and research model specification

The main objective of this study is to analyze the factors influencing farmers' seeking market information. The dependent variable in this research is therefore binary in nature, taking a value of 1 if a farmer actively seeks or accesses market information, and 0 otherwise. When the dependent variable is dichotomous, classical linear regression models are inappropriate because they may produce predicted probabilities outside the logical range of 0 and 1. For this reason, binary logistic regression is widely used as a standard econometric technique for modeling discrete choice (Harrell 2015; Ailobhio and Ikughur 2024) and has been widely applied in the agricultural field, including studies on agricultural production (Salam et al. 2024; Yuniarsih et al. 2024) and farmers' behavior (Agussabti et al. 2022; Tang et al. 2022). The general model of binary logistic regression is specified as follows:

$$ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon_i \quad [2]$$

Where, P_i is the probability of the i-th farmer seeking market information, β_0 is the intercept, β_k are the regression coefficients to be estimated, and X_{ki} represents the vector of independent variables. Based on Equation 2, we developed the model specification in this study, as presented in Equation 3:

$$ln\left(\frac{P_{SMI}}{1-P_{SMI}}\right) = \beta_0 + \beta_1 AGE + \beta_2 EDU + \beta_3 DEP + \beta_4 EXP + \beta_5 FSI + \beta_6 CDI + \beta_7 FG + \beta_8 EXT + \beta_9 LMD + \beta_{10} DIG + \beta_{11} NFI + \beta_{12} CRE + \varepsilon \quad [3]$$

In this specification, the dependent variable is defined as the farmer's decision to seek market information (SMI), where 1 if the answer is yes, and 0 if the answer is otherwise. The independent variables include age (AGE), education (EDU), dependent (DEP), experience (EXP), farm size (FSI), crop diversification (CDI), farmer group (FG), extension (EXT), local market distance (LMD), digital technology (DIG), non-farm income (NFI), and credit (CRE). The detail explanation of the independent variable is shown in Table 1.

Multicollinearity test

To ensure the independence of the independent variables, multicollinearity was assessed using the Variance Inflation Factor (VIF). The VIF was calculated for each predictor to detect multicollinearity by measuring how collinearity increases the estimated regression coefficient variance. A VIF value of 1 indicates the complete absence of correlation. For this study, a VIF value exceeding 10 was established as the critical threshold indicating serious multicollinearity that warrants corrective action, whereas values below 10 suggest that the model estimates are stable and reliable (Tang et al. 2022).

Goodness-of-fit test and coefficient determination

The Hosmer-Lemeshow goodness-of-fit test was employed to evaluate the adequacy of the model in reproducing observed outcomes based on predicted probabilities. The interpretation of this test relies on the p-value associated with the Chi-square statistic, where a non-significant result (p-value is greater than 0.05) is desirable, as it confirms that the model provides an adequate fit to the data, and a significant p-value (less than 0.05) would indicate a poor fit, suggesting that the model specification may need to be revisited (Ailobhio and Ikughur 2024).

The coefficient of determination was used to summarize the overall strength of the estimated model (Hu et al. 2006). In logistic regression, this is represented by pseudo R^2 measures, which serve a similar purpose to the R^2 in Ordinary Least Squares (OLS) regression, although the two are conceptually different (Smith and Mckenna 2013; Walker and Smith 2016). This study employed the Nagelkerke R-square, as it provides a normalized measure that is relatively close to the OLS R^2 value, making it more interpretable in practice (Smith and Mckenna 2013). In general, higher values of Nagelkerke R-square indicate a stronger model, and values closer to one suggest that the model better captures the variation in the observed outcome (Hu et al. 2006; Ailobhio and Ikughur 2024).

Likelihood ratio test and significance test

The overall significance of the logistic regression model was evaluated using the likelihood ratio test. The overall significance of the model was examined using the Likelihood Ratio (LR) test, which assesses whether the full model provides a statistically better fit than a null model with no independent variables. If the calculated p-value is less than the chosen significance level (typically 0.05), the null hypothesis is rejected. A significant result confirms that at least one of the independent variables contributes significantly to the prediction of the outcome, thereby validating the overall model (Salam et al. 2024).

Table 1. Variable definition, measurement unit, type of data, hypothesis sign, and expected significance results

Variable's name (Symbols)	Definitions	Measurement unit	Type of data	Expected results	References
Age (AGE)	Age in years at the time of data collection.	year	Continuous	Sig +/-	Mittal and Mehar (2016), Mahindarathne and Min (2019), Daniso (2022), Nikam et al. (2022)
Education (EDU)	Years of formal schooling completed	year	Continuous	Sig +	Mahindarathne and Min (2019), Nikam et al. (2022), Ntsoane et al. (2025)
Dependent (DEP)	Household members financially dependent	person	Continuous	Sig +	Ntsoane et al. (2025)
Experience (EXP)	Years engaged in paddy farming	year	Continuous	Sig +/-	Aonngernthayakorn and Pongquan (2017), Mahindarathne and Min (2019), Shitaye et al. (2024)
Farm size (FSI)	Total cultivated paddy land area	hectare	Continuous	Sig +	Brhane et al. (2017), Shitaye et al. (2024)
Crop diversification (CDI)	Cultivate other crops besides paddy	1=yes; 0=otherwise	Categorical	Sig +	Mahindarathne and Min (2019), Mihrete and Mihretu (2025)
Farmer group (FG)	Membership in a farmer group	1=yes; 0=otherwise	Categorical	Sig +	Okello et al. (2014), Nikam et al. (2022)
Extension (EXT)	The frequency of interaction with extension workers	times/year	Continuous	Sig +/-	Brhane et al. (2017), Maulu et al. (2021), Shitaye et al. (2024), Bor et al. (2025)
Local market distance (LMD)	Distance from the respondent's location to the nearest local market	kilometer	Continuous	Sig +	Okello et al. (2014), Brhane et al. (2017), Shitaye et al. (2024)
Digital technology (DIG)	The utilization of digital technology	1=yes; 0=otherwise	Categorical	Sig +	Okello et al. (2014), Brhane et al. (2017)
Non-farm income (NFI)	Have income outside farming activities	1=yes; 0=otherwise	Categorical	Sig +	Ntsoane et al. (2025)
Credit (CRE)	Experience in taking a credit or loan	1=yes; 0=otherwise	Categorical	Sig +	Daniso (2022), Bor et al. (2025)

Statistical significance was assessed at the 1%, 5%, and 10% levels. In interpreting the results, if the p-value associated with the Wald statistic is less than the significance level (e.g., $\alpha = 0.05$), the null hypothesis is rejected. This indicates that the specific variable has a statistically significant influence on the probability of farmers choosing the collector channel. Conversely, a p-value greater than 0.05 suggests that the variable does not have a significant partial effect in the context of the other variables included in the model (Agussabti et al. 2022).

Odds ratio

The odds ratio is defined as the ratio between the probability of an event occurring and the probability of it not occurring (Agussabti et al. 2022; Salam et al. 2024). As an effect size measure, the odds ratio indicates how changes in an independent variable influence the likelihood of the dependent event, where values greater than one reflect a positive association and values less than one indicate a negative association (Harrell 2015). In this study, the odds ratio is used to quantify the magnitude and direction of the effect of each independent variable on farmers' decisions to seek market information. The odds ratio is derived from the exponential function of the estimated regression coefficient (β), where a value below 1 indicating negative relationship and vice versa (Salam et al. 2024; Yuniarsih et al. 2024).

Hypothesis and variable selection

Table 1 presents the definitions, measurement units, data types, and expected signs of the variables included in the model, where the expected relationships are derived from theoretical considerations and prior empirical findings on farmers' information behavior. Variables such as education (EDU), dependent (DEP), farm size (FSI), crop diversification (CDI), farmer group (FG), local market distance (LMD), digital technology (DIG), non-farm income (NFI), and credit (CRE) are hypothesized to have positive effects on market information-seeking behavior, as they are associated with greater resource capacity, increased market exposure, and improved access to information channels, which collectively enhance farmers' incentives and ability to obtain market-related information. In contrast, age (AGE), experience (EXP), and extension (EXT) are expected to exhibit bidirectional effects. Previous studies have provided contrasting explanations, in which older and more experienced farmers may have greater accumulated knowledge and networks that support

information acquisition; however, they may also rely more on established practices and therefore show lower motivation to seek new information actively. Similarly, extension contact may either encourage information seeking by increasing awareness and exposure or reduce it by serving as a substitute source of information, thereby lowering the need for independent searches. These expected signs reflect the behavioral nature of information-seeking decisions.

RESULTS AND DISCUSSION

Sources of market information

Understanding where farmers obtain marketing information is essential for identifying how knowledge flows within rural agricultural systems and how decisions in both production and marketing activities are shaped (Linh et al. 2016). Based on the survey responses from paddy farmers in Soppeng District, Figure 2 presents the main actors who inform, encourage, or guide farmers in accessing market-related information. This classification focuses on interpersonal and institutional sources rather than technological platforms, emphasizing the social and organizational channels through which farmers obtain information related to prices, government policies, and broader economic conditions. This perspective aligns with studies that emphasize the role of social networks and institutional actors in structuring information exchange and decision-making among smallholder farmers (Izadi et al. 2024).

The descriptive results indicate that farmer groups and organizations are the most influential sources of market information, as reported by 30.43% of respondents. This finding underscores the central role of collective institutions in providing agricultural information (Kassem et al. 2022). Farmer groups serve as structured forums where members regularly exchange experiences, discuss prevailing market conditions, and collectively interpret information related to paddy prices, government support programs, and market opportunities. These organizations act as intermediaries between farmers and external stakeholders, such as extension services and local authorities, thereby strengthening information circulation within farming communities. In contrast to institutional sources, a notable proportion of farmers (20.11%) reported seeking market information independently, indicating an emerging pattern of self-initiated behavior. This includes accessing information through media, television, or digital platforms such as mobile phones and the internet. However, despite the increasing availability of digital information channels, farmer groups and similar organizations remain the primary source of information because they provide trusted, context-specific, and collectively validated knowledge that is directly relevant to local conditions. Unlike digital sources, which often require individual interpretation and technological capacity, farmer groups and similar organizations enable interactive communication, allowing farmers to verify, discuss, and adapt information through shared experiences. This indicates that market information systems in rural areas operate through a complementary pattern, in which emerging individual and digital-based information-seeking behaviors coexist with, rather than replace, established collective and institutional channels.

In addition to collective institutions, extension workers (19.02%) and fellow farmers (18.48%) represent other important sources of market information. The relatively similar proportions highlight the continued relevance of interpersonal communication, where formal advisory services and informal peer networks jointly shape farmers' awareness of market dynamics. Extension workers provide technical and institutional insights, whereas fellow farmers contribute experiential knowledge based on real-time market interactions. Together, these sources reinforce learning through both formal guidance and shared practical experience. In contrast, family members (6.52%) and buyers (5.43%) play only minor roles in providing market information. The limited reliance on buyers may reflect farmers' awareness of information asymmetry, where traders may strategically withhold or distort price information to their advantage, particularly in remote rural settings (Lokanathan et al. 2011; Courtois and Subervie 2015). Household members, meanwhile, are generally less involved in marketing-related decision-making processes.

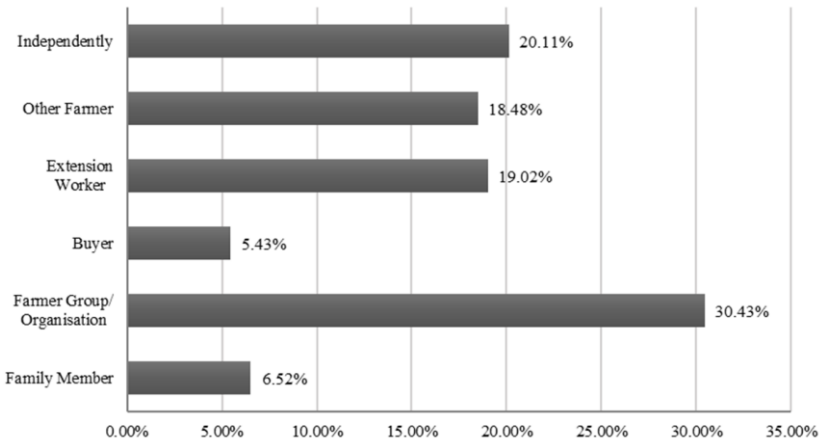

Figure 2. Source of market information received by farmers

Across all sources, the primary types of information sought by farmers include price information, government policy updates, and broader economic information, such as inflation and production cost trends. These forms of information are crucial for helping farmers determine appropriate marketing strategies and selling decisions (Courtois and Subervie 2015; Piabuo et al. 2020). Overall, the results suggest that while collective and interpersonal networks remain dominant, a significant share of farmers is becoming more proactive and autonomous in their efforts to obtain agricultural market information. Overall, the results suggest that while collective and interpersonal networks remain dominant, emerging individual-based behaviors are increasingly complementing traditional information channels within rural agricultural systems.

Binary logistic regression result

Prior to estimating the binary logistic regression model, a multicollinearity test was conducted to ensure the independence of the independent variables. Table 2 presents the VIF results, showing values ranging from 1.05 to 1.81, with a mean VIF of 1.25. These values indicate no evidence of multicollinearity among the regressors. These results suggest that the estimated coefficients are not affected by linear dependence among the independent variables. Having confirmed the absence of multicollinearity, the analysis proceeds to estimate the binary logistic regression model.

Table 3 presents the results of the binary logistic regression analysis. Model fit was assessed using the Hosmer-Lemeshow goodness-of-fit test, which produced a chi-square statistic of 3.72 with a p-value of 0.881. This non-significant result indicates that the predicted probabilities are consistent with the observed outcomes, confirming adequate model calibration. The independent power of the model, measured by the Nagelkerke pseudo R^2, was 0.665, indicating that approximately 66.5% of the variation in farmers' market information-seeking behavior was explained by the included covariates. In addition, the likelihood ratio test yielded a statistic of 131.19 with a p-value of 0.0001, confirming the joint statistical significance of the independent variables.

The regression results indicate that several independent variables have statistically significant associations with farmers' market information-seeking behavior at different confidence levels. Farmers' age shows a negative and statistically significant effect at the 5% level ($p < 0.05$), with an odds ratio of 0.923, implying that a one-year increase in age decreases the odds of seeking market information by approximately 7.7%, holding other variables constant. Similarly, farming experience shows a negative association and is significant at the 10% level ($p < 0.10$), with an odds ratio of 0.956, indicating that additional years of farming experience are associated with a 4.4% reduction in the odds of information seeking. In contrast, education demonstrates a positive and highly significant effect at the 1% level ($p < 0.01$), with an odds ratio of 1.384, suggesting that each additional year of schooling increases the odds of seeking market information by 38.4%, ceteris paribus. Crop diversification presents the strongest positive association ($p < 0.01$), with an odds ratio of 16.275, indicating that farmers who adopt crop diversification have substantially higher odds of engaging in market information-seeking behavior compared to those who do not. Credit access is also positively significant at the 5% level ($p < 0.05$), with an odds ratio of 3.571, implying that farmers with credit experience have more than three times higher odds of seeking market information than those without such experience. Extension contact shows a positive effect and is significant at the 10% level ($p < 0.10$), with an odds ratio of 1.160, indicating that more frequent interaction with extension services increases the odds of seeking market information by 16.0%. Local market distance is also positively associated with information-seeking behavior at the 10% significance level ($p < 0.10$), with an odds ratio of 1.673, suggesting that greater distance from local markets increases the odds of seeking market information by 67.3%. The remaining variables, including number of dependents, farm size, membership in farmer groups, digital technology use, and non-farm income, are not statistically significant (p-value > 0.10), indicating that these factors do not have a measurable partial effect on farmers' market information-seeking behavior within the estimated model.

Determinants of paddy farmers' behavior in seeking market information

Age influences market information seeking through behavioral patterns that shape how farmers interpret uncertainty and value new market knowledge. Decision-making among senior farmers in the study area is more strongly guided by accumulated experience and habitual practices, reducing their reliance on continuous information acquisition. In addition, older farmers often face greater challenges in adopting new information channels, particularly digital and Internet-based platforms, which further limits their engagement with external information sources. Similar results have been observed where older farmers exhibit lower responsiveness to changing market signals, as experiential knowledge substitutes for active information search (Mahindarathne and Min 2019; Daniso 2022). Mittal and Mehar (2016) said that senior farmers tend to rely on internalized knowledge systems, reinforcing the reduced perceived need to seek additional information.

Table 2. Multicollinearity test result

Variable	VIF	1/VIF
Age (AGE)	1.81	0.55
Education (EDU)	1.19	0.84
Dependent (DEP)	1.12	0.89
Experience (EXP)	1.75	0.57
Farm size (FSI)	1.15	0.87
Crop diversification (CDI)	1.26	0.80
Farmer group (FG)	1.07	0.94
Extension (EXT)	1.10	0.91
Local market distance (LMD)	1.15	0.87
Digital technology (DIG)	1.10	0.91
Non-farm income (NFI)	1.05	0.95
Credit (CRE)	1.21	0.83
Mean VIF	1.25	

Table 3. Binary logistic regression analysis result

Variable	Binary logistic regression result				
	Coefficient (β)	Standard Error	z	p-value	Odds Ratio
Age (AGE)	-0.080	0.032	-2.470	0.014**	0.923
Education (EDU)	0.325	0.079	4.110	0.000***	1.384
Dependent (DEP)	-0.331	0.215	-1.540	0.123	0.718
Experience (EXP)	-0.045	0.026	-1.760	0.079*	0.956
Farm size (FSI)	-0.294	0.238	-1.230	0.217	0.745
Crop diversification (CDI)	2.790	0.609	4.580	0.000***	16.275
Farmer group (FG)	-0.816	0.950	-0.860	0.391	0.442
Extension (EXT)	0.148	0.083	1.800	0.072*	1.160
Local market distance (LMD)	0.515	0.299	1.720	0.085*	1.673
Digital technology (DIG)	0.144	0.915	0.160	0.875	1.155
Non-farm income (NFI)	0.500	0.479	1.040	0.297	1.648
Credit (CRE)	1.273	0.525	2.430	0.015**	3.571
cons	-0.249	2.292	-0.110	0.914	0.780

Note: Number of obs = 190; Log likelihood = -66.09; Hosmer-Lemeshow chi2(8) = 3.72 (Prob > chi2 = 0.881); Pseudo R^2 = 0.498; Nagelkerke R^2 = 0.665; LR chi2 (12) = 131.19 (Prob >chi2 = 0.000l); ***, **, * means significant at P≤0.01, P≤0.05, P≤0.10, respectively

Education shapes farmers' cognitive capacity, confidence, and openness to external knowledge, which in turn influences how actively they seek agricultural marketing information. Farmers with longer education in the study area tend to have greater awareness and a clearer understanding of how information can improve marketing outcomes. It enhances analytical skills that enable farmers to interpret price movements, assess market risks, and evaluate alternative selling options more effectively. As a result, more educated farmers are better able to recognize information gaps and perceive market information as a valuable economic resource rather than merely a supplementary input. Previous studies consistently show that education strengthens farmers' capacity to process complex information and facilitates the adoption of modern information sources (Nikam et al. 2022; Ntsoane et al. 2025). Mahindarathne and Min (2019) further argue that education enhances farmers' learning orientation, encouraging continuous information acquisition rather than reliance on static knowledge.

Farming experience influences farmers' information-seeking behavior through long-term market embeddedness and the development of stable transactional relationships. In the study area, farmers with extensive experience in rice cultivation are more likely to engage in repeated interactions within established marketing channels, which reduces their reliance on explicit information sources. Through these ongoing exchanges, market signals such as price trends and demand conditions are often acquired indirectly and embedded within routine transactions rather than obtained through active searching. As a result, experienced farmers may not identify buyers or trading partners as primary information sources, even though these relationships continuously shape their market knowledge. Similar results have been observed in previous studies, which suggest that extensive experience may reduce farmers' motivation to seek additional information because confidence in existing practices replaces perceived informational needs (Mahindarathne and Min 2019). At the same time, the role of experience appears context-dependent, as other studies report positive effects where markets are more volatile or institutional engagement is stronger (Aonngernthayakorn and Pongquan 2017; Shitaye et al. 2024).

Crop diversification shapes farmers' market information-seeking behavior by increasing decision complexity and exposure to multiple market environments. In the study area, farmers who adopt this strategy must monitor different harvesting schedules, buyer requirements, and seasonal price movements across commodities, which encourages more proactive information seeking as a means of managing uncertainty and coordinating both production and marketing decisions. Diversification reflects a more commercial and adaptive farming orientation, in which farmers actively respond to market signals. Engaging in multiple commercial crops requires broader interaction with agribusiness actors, thereby expanding farmers' exposure to both formal and informal information networks. Previous studies have highlighted that mono-cropping systems require relatively limited market information, whereas diversified systems depend on continuous information flows to remain profitable (Mahindarathne and Min 2019). Moreover, diversification has been widely recognized as a risk management strategy, where farmers seek market information to reduce income volatility and stabilize returns across commodities (Kurdyś-Kujawska et al. 2021; Mihrete and Mihretu 2025).

Extension contact plays an enabling role in shaping farmers' market information-seeking behavior by strengthening their awareness, capacity, and confidence to access external information. Regular interactions with extension workers reinforce the perceived value of information in improving marketing decisions. In the study area, extension services are primarily focused on providing technical production advice rather than direct market or price information. However, frequent interactions with extension agents indirectly expose farmers to broader sources of information and encourage them to look beyond traditional interpersonal channels, including peer networks, institutional services, and digital media. This indirect

exposure enhances farmers' confidence in navigating multiple information sources and reduces dependence on established routines. Prior literature emphasizes that extension systems increasingly support market-oriented decision making by integrating price information, marketing guidance, and institutional linkages into advisory services (Brhane et al. 2017; Maulu et al. 2021). In this context, extension contact does not act as a direct provider of market information but serves as a catalyst that lowers information barriers and stimulates more proactive market information-seeking behavior among farmers.

Physical distance from local markets shapes farmers' incentives to seek market information by influencing their exposure to social interactions and informal information networks rather than direct buyer transactions. In Soppeng District, local markets do not function as primary selling points for paddy, but as important social spaces where farmers exchange information and interact with other market participants. Farmers located farther from these markets have fewer opportunities to engage in such interactions, increasing uncertainty regarding prevailing prices, marketing conditions, and policy-related information. As a result, farmers are more likely to compensate for limited face-to-face exposure by actively seeking information through alternative channels. This suggests that distance only acts as a barrier to information access but also induces compensatory behavior, where farmers proactively search for information to reduce uncertainty. This finding is consistent with previous studies showing that greater distance from markets increases farmers' reliance on alternative information channels, including ICT-based services (Okello et al. 2014; Brhane et al. 2017). Although Shitaye et al. (2024) noted that longer distances can sometimes reduce overall access to information, the present result indicates that such limitations instead stimulate more proactive information-seeking behavior among farmers.

Experience in accessing credit reflects a higher level of financial engagement and commercialization, which reshapes farmers' incentives to seek market information. In the study area, farmers involved in credit face increased financial responsibilities and a stronger commercial orientation, encouraging them to make more informed marketing decisions to ensure timely loan repayment. Engagement with credit providers also strengthens farmers' institutional linkages and expands their exposure to formal information networks, which in turn encourages them to actively seek information updates to minimize financial risks. Previous studies have found that access and utilization of credit significantly enhance farmers' engagement with multiple communication services and information sources (Daniso 2022; Bor et al. 2025). In addition, Mariyono (2019) emphasized that credit access plays a crucial role in promoting market participation and commercialization, as it enables farmers to engage more intensively in market-oriented farming activities, thereby increasing their demand for reliable market information.

Taken together, the results indicate that farmers' market information-seeking behavior is shaped by economic incentives and exposure to market-related uncertainty, highlighting that such behavior depends on how farmers perceive the relevance of information within their decision-making context. At the same time, the non-significant results observed for variables such as number of dependents (DEP), farm size (FSI), farmer group membership (FG), digital technology use (DIG), and non-farm income (NFI) suggest that their influence may be context-dependent and not uniformly expressed across all households. This may reflect measurement limitations, as well as limited variation across respondents, where certain characteristics (e.g., access and digital technology use) are widely shared among both information seekers and non-seekers, thereby reducing their ability to differentiate behavior.

Suggestions on policy implications

Based on these findings, several policy implications can be proposed. Strengthening farmers' capacity to seek and utilize market information requires more targeted and operational interventions, particularly by integrating market-oriented training into farmer education programs and redesigning extension services to include regular dissemination of price trends, market signals, and risk-related information. Extension approaches should be differentiated, with more intensive, trust-based, and non-digital strategies directed toward older and highly experienced farmers who are less inclined to seek information independently, while encouraging them to expand beyond established transaction-based knowledge. In addition, extension services should incorporate market-oriented guidance tailored to diversified farming systems, enabling farmers to manage multiple commodities through a better understanding of price dynamics, market timing, and cross-crop risks. Improving rural information systems should not rely solely on expanding digital or physical infrastructure but rather on strengthening the role of local institutions in managing information flows.

Farmer organizations can be strengthened to function as active information intermediaries by assigning dedicated roles to capable committee members responsible for accessing, interpreting, and translating external market information into locally relevant knowledge, thereby improving the consistency and reach of dissemination among farmers. At the same time, strengthening farmers' capacity to utilize digital platforms should be pursued progressively to ensure that rural communities are not left behind in the ongoing digital transition. From a value chain perspective, improving price transparency and strengthening information flows among agribusiness actors can reduce asymmetry and support more efficient market coordination. Aligning market information services with rural financial systems and local learning mechanisms can further enhance farmers' ability to make informed and adaptive decisions. Such integrated efforts not only improve marketing performance but also strengthen farmers' capacity to manage risk, allocate resources more efficiently, and contribute to sustainable agricultural development.

In conclusion, this study shows that paddy farmers' market information seeking is not a passive response to

information availability, but an intentional behavioral choice linked to how farmers perceive and manage market uncertainty. Farmers who are more vulnerable to price risks, commercialization pressures, and decision consequences are more likely to search actively for market information, whereas those who rely heavily on accumulated experience tend to substitute information seeking with habitual practices. This finding suggests that information behavior among farmers reflects underlying decisions related to risk management, market orientation, and adaptive capacity, rather than disparities in access to services or technology.

The binary logistic regression model shows strong explanatory power (Nagelkerke $R^2 = 0.665$) and good fit (Hosmer-Lemeshow $p = 0.881$), confirming the robustness of the results. Education ($\beta = 0.325$; OR = 1.384; $p < 0.01$), crop diversification ($\beta = 2.790$; OR = 16.275; $p < 0.01$), and credit access ($\beta = 1.273$; OR = 3.571; $p < 0.05$) emerge as the strongest positive determinants, with crop diversification exhibiting the largest effect size, indicating a substantially higher likelihood of market information-seeking behavior relative to other variables. In contrast, age ($\beta = -0.080$; OR = 0.923; $p < 0.05$) and farming experience ($\beta = -0.045$; OR = 0.956; $p < 0.10$) significantly reduce the likelihood of actively seeking market information. Extension contact ($\beta = 0.148$; OR = 1.160; $p < 0.10$) and distance to local markets ($\beta = 0.515$; OR = 1.673; $p < 0.10$) also positively influence behavior. Descriptive findings further indicate that farmer groups (30.43%) remain the dominant information source, although independent searching (20.11%) reflects an emerging behavioral shift. These results highlight that information seeking is driven more by risk management and commercialization pressures than by information availability alone, emphasizing the need for behavior-sensitive information systems and market-oriented extension strategies.

However, this study has limitations. It is based on a single cross-sectional dataset from one district, which may limit generalizability. In addition, the analysis captures only the decision to seek information (binary outcome) without measuring the intensity, frequency, or quality of information use. Future research should incorporate multi-region and longitudinal designs to capture dynamic behavioral changes and include more nuanced measures of information utilization, such as intensity and effectiveness. Integrating behavioral models with farm performance and income outcomes would further strengthen the understanding of how information-seeking behavior translates into sustainable agricultural development.

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