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INTEGRATED BEHAVIOURAL AND ECONOMETRIC ANALYSIS OF CONSUMER BEHAVIOUR TOWARDS GEOGRAPHICAL INDICATION (GI) RICE VARIETIES IN KERALA, INDIA

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ABSTRACT
Geographical Indications (GIs) are increasingly positioned as instruments for rural development, biodiversity conservation, and safeguarding traditional agricultural knowledge, yet consumer-facing research on GI food products remains disproportionately thin relative to producer and institution-centred scholarship. Kerala is the only Indian state with six registered GI rice varieties, several cultivated under low-input, organic systems integrated with traditional aquaculture, but participatory marketing and consumer engagement have lagged behind institutional recognition. This study examines consumer attribute preferences, willingness to pay (WTP), and decision-making behaviour toward GI rice varieties in Kerala using an integrated analytical framework combining Maximum Difference Scaling (MaxDiff), contingent valuation with binary and ordered logistic regression, and Partial Least Squares Structural Equation Modelling (PLS-SEM) grounded in the Engel-Kollat-Blackwell (EKB) consumer decision-making model. Survey data were collected from 240 consumers across six GI rice-producing districts using purposive and snowball sampling. Results show that intrinsic quality attributes (taste, nutritional value, cooking quality) outweigh extrinsic, certification-based cues in shaping consumer preference. Behavioural constructs, particularly evaluation of alternatives, explain willingness to pay more strongly than socio-demographic characteristics, with information search and income showing a notable reversal in effect between the decision to pay a premium and the premium's magnitude. Consumer decision-making follows the sequential EKB path from need recognition through post-purchase satisfaction. These findings indicate that strengthening product-specific awareness, information credibility, and intrinsic-quality communication, rather than certification recognition alone, is central to expanding sustainable premium demand for GI rice varieties.

KEYWORDS: GI rice, MaxDiff analysis; Contingent valuation; PLS-SEM; Engel-Kollat-Blackwell model; Price premium

INTRODUCTION
Geographical Indications (GIs) link a product's quality, reputation, or cultural identity to a defined geographical origin, and are increasingly positioned as tools for rural development, biodiversity conservation, and safeguarding traditional agricultural knowledge (Nirosha and Mansingh, 2024). India's GI ecosystem has grown quickly: the country crossed 600 registered GIs by 2024, with agricultural products forming the second-largest category after handicrafts (Teuber, 2010). Kerala is the only Indian state with six registered GI rice varieties: Pokkali, Navara, Kaipad, Palakkadan Matta, Wayanadan Jeerakasala, and Wayanadan Gandhakasala; several cultivated under low-input or organic systems integrated with traditional aquaculture (Jena and Grote, 2012). Post-registration evidence shows GI status has raised farm-gate prices for these varieties, yet consumer-facing marketing has lagged behind institutional recognition (Radhika, 2021).
This asymmetry mirrors a pattern seen across GI food markets generally: awareness of GI labels routinely outpaces actual purchase and repeat consumption (Tregear et al., 2007; Verbeke and Roosen, 2009; Tan et al., 2024). Consumers may associate GI labelling with authenticity in principle, but purchase decisions are shaped more directly by perceived

value, price sensitivity, and prior familiarity than by certification cues alone (Grunert, 2005; Bernabéu et al., 2012). Compounding this, the proliferation of certification marks and origin claims on food packaging can generate information overload; heightening confusion rather than confidence, particularly where quality attributes cannot be verified before purchase (Jacoby et al., 1974; Eppler and Mengis, 2004; Ying et al., 2025).

Existing research on Kerala's rice GIs has concentrated on producer welfare, certification governance, and market institutions (Das, 2010; Jena and Grote, 2012; Radhika, 2021), while comparatively little work examines how consumers prioritise attributes or arrive at purchase decisions. Consumer choice itself weighs both intrinsic cues: taste, nutritional composition, cooking performance against extrinsic cues such as certification and branding (Van Ittersum et al., 2003), and GI labelling tends to shift behaviour only when reinforced by genuine experiential quality (Belletti and Marescotti, 2011). Willingness to pay (WTP) studies across GI and origin-labelled foods consistently report positive premiums, though premium size varies with familiarity and trust (Bowen and Zapata, 2009; Belletti et al., 2017), and behavioural factors tend to explain premium acceptance better than socio-demographic variables alone (Swait and Adamowicz, 2001).

The Engel-Kollat-Blackwell (EKB) model offers a useful lens for this: consumer behaviour as a sequential process of need recognition, information search, evaluation of alternatives, purchase decision, and post-purchase satisfaction (Engel et al., 1995). Recent applications continue to validate this sequence across food contexts (Narsis, 2023; Were, 2023), yet few studies integrate attribute preference, WTP estimation, and EKB-based decision processes within one framework for any GI food product, and none for Indian GI rice specifically (Baishakhy et al., 2026). Given that GI rice's long-term viability as a livelihood and heritage-conservation strategy depends on consumer acceptance rather than certification alone, closing this gap carries both empirical and policy relevance.

This study therefore examines consumer perceptions, attribute preferences, purchase behaviour, and willingness to pay for GI rice varieties in Kerala, using an integrated framework combining Maximum Difference Scaling (MaxDiff), contingent valuation, binary and ordered logistic regression, and Partial Least Squares Structural Equation Modelling (PLS-SEM) grounded in the EKB model. Three hypotheses guide the analysis:

H_1, that intrinsic quality attributes are prioritised more highly than extrinsic, certification-based attributes in consumer evaluation of GI rice;

H_2, that willingness to pay a premium is influenced more strongly by behavioural constructs than by socio-demographic characteristics; and

H_3, that consumer decision-making for GI rice follows the sequential EKB path from need recognition through post-purchase satisfaction.

MATERIAL AND METHODS

Study area and sampling design

The study was conducted across six major GI rice-producing districts of Kerala: Ernakulam, Thrissur, Palakkad, Malappuram, Wayanad, and Kannur. A total of 240 consumers (40 per district) were selected using purposive and snowball sampling to ensure inclusion of regular rice purchasers with varying familiarity with GI rice. Data were collected through a structured questionnaire administered both online and through personal interviews.

Survey instrument

The questionnaire captured socio-demographic characteristics, consumption behaviour, attribute preferences, WTP, and behavioural constructs corresponding to the five EKB stages (Engel et al., 1995). Attribute importance was assessed using MaxDiff (Louviere et al., 2015), addressing H1; WTP was elicited through payment-card contingent valuation (Mitchell and Carson, 1989; Bateman et al., 2002), informing H2; EKB-stage behavioural constructs were measured using multi-item Likert scales to test H3. The instrument was reviewed by subject experts and pilot-tested before the final survey.

MaxDiff analysis

Consumer preferences for GI rice attributes were assessed using MaxDiff analysis. Choice sets were generated through a Balanced Incomplete Block Design (BIBD) to ensure balanced attribute presentation and reduce respondent burden (Cochran and Cox, 1957). Relative importance scores were derived by converting best–worst counts into normalised scores using min–max scaling.

Willingness-to-pay estimation

WTP premiums were estimated using midpoint values of selected payment-card intervals. Determinants of WTP were analysed using binary logistic regression (first hurdle: whether the consumer is willing to pay any premium) and ordered logistic regression (second hurdle: premium magnitude among willing payers), following Hosmer et al. (2013).

Mean WTP=∑(f_i×m_i) / N
where:
fi= frequency of respondents in category i
mi = midpoint of category i
N= total number of respondents

For binary logistic regression (First Hurdle of CVM: whether you are willing to pay for GI rice or not?):
$$\log (P(WTP= 1)/1- P(WTP=1))= \beta_0 + \Sigma k\ \ \beta_1 X_k$$

For ordered logistic regression (Second Hurdle of CVM: if you are willing to pay for GI rice, how much more you pay?):
$$WTP\ Band_i= \beta_0 + \Sigma k\ \beta_1 X_k$$
The observed premium categories are determined as:
$$WTP\ Band_i \begin{cases} 1 & \text{if WTP Bandi} \le \mu 1 \\ & \text{if } \mu 1 < \text{WTP Bandi} \le \mu 2 \\ & \text{if } \mu 2 < \text{WTP Bandi} \le \mu 3 \\ & \text{if } \mu 3 < \text{WTP Bandi} \le \mu 4 \\ & \text{if } \mu 4 < \text{WTP Bandi} \le \mu 5 \\ & \text{if WTP Bandi} > \mu 5 \end{cases}$$
where:
Category 1 = Up to 20% premium; Category 2 = 20–30% premium; Category 3 = 30–40% premium; Category 4 = 40–50% premium; Category 5 = 50–60% premium; Category 6 = Above 60% premium; X_k represents socio-demographic characteristics, GI awareness, product recognition and behavioural scores derived from the EKB framework.
Model adequacy was assessed using pseudo-R^2, McFadden R^2, deviance, and AIC.

PLS-SEM analysis
Consumer decision-making was examined using PLS-SEM, suited to predictive modelling and behavioural research with modest samples and non-normal data (Hair et al., 2021). Reliability and convergent validity were evaluated using factor loadings, Composite Reliability (CR), Cronbach's alpha, and Average Variance Extracted (AVE), following Nunnally (1978), Fornell and Larcker (1981), and Chin (1998).

Measurement model assessment: Internal consistency was examined using CR (≥ 0.70), with Cronbach's alpha above 0.50 considered acceptable for exploratory behavioural research (Nunnally, 1978). Convergent validity was established through AVE (≥ 0.50).

Structural model assessment: Path coefficients across the five EKB stages were estimated using bootstrapped resampling (Chin, 1998).
The reflective measurement model was specified as:
$$x_{ij} = \lambda_{ij}\ \eta_j + \varepsilon_{ij}$$
where,
xij = observed score of indicator i associated with latent construct j
λij = factor loading of indicator i on latent construct j
ηj = latent construct score for construct j
εij = measurement error associated with indicator i

The structural model for the EKB stages was expressed as:
$$IS= \beta_1\ NR + \varepsilon_1\ ,\quad EA= \beta_2\ IS + \varepsilon_2,\quad PD= \beta_3\ EA + \varepsilon_3,\quad PS= \beta_4\ PD + \varepsilon_4$$
Where,

NR; Need Recognition, IS; Information Search, EA; Evaluation of Alternatives, PD; Purchase Decision and PS; Post-Purchase Satisfaction. ε_1, ε_2, ε_3 and ε_4 are residual terms capturing unexplained variation in each endogenous construct.

Latent construct scores were estimated using the composite model:

$$\eta_j=\sum w_{ij}\ x_{ij}$$
where,
η_j = composite score of latent construct j

w_{ij} = outer weight assigned to indicator i for construct j
x_{ij} = observed value of indicator i associated with construct j
Model explanatory power was assessed through R^2, while global model adequacy was evaluated using the Goodness-of-Fit (GoF) index (Tenenhaus et al., 2005). All analyses were performed using R version 4.4.1.

RESULTS

Consumer profile and awareness patterns

The respondent profile (Table 1) broadly mirrored Kerala's demographic composition. Familiarity varied considerably across GI rice varieties (Fig. 1): Palakkadan Matta recorded the highest recognition (88.33%), followed by Navara and Wayanadan Jeerakashala (58.75% each), while Kaipad showed the lowest (22.92%), likely reflecting its smaller cultivated area and market presence. Supermarkets were the dominant purchase channel (Fig. 2), and media was the leading information source.

Table 1: Sample description of GI rice consumers

Variables	**Value**	**Sample average**	**State average**
Age (year) (%)	18 to 25	16.67	***15.79
	26-35	28.33	***15.15
	36-45	21.25	***14.94
	46-55	19.17	***12.80
	Above 55	14.58	***17.88
Gender (%)	Male	35.42	*47.98
	Female	64.58	*52.02
Number of family members	Mean	4.50	**4.2
	Standard deviation	0.70	
Educational level (%)	Primary education	0.83	No data
	SSLC/ 10^{th}	5.00	
	Higher secondary	9.58	
	Under graduation	41.25	
	Post-graduation and above	43.33	
Occupation (%)	Agriculture	6.67	No data
	Business	3.75	
	Government service	18.75	
	Private service	30.42	
	Homemaker	15.83	
	Retired Employee	5.00	
	Student	19.58	
Household Income (%)	Rs. 10,000 to 25,000	19.17	No data
	Rs. 25,001 to 50,000	27.50	
	Rs. 50,001 to 1,00,000	40.42	
	Above Rs. 1,00,000	12.92	
District of Residence (%)	Thrissur	16.66	*9.34
	Palakkad	16.66	*8.41
	Malappuram	16.66	*12.31
	Wayanad	16.66	*2.44
	Kannur	16.66	*7.55
	Ernakulam	16.66	*9.82

Note:
*DES, Government of Kerala (Ecostat Dataset 58), **Census of India (Catalog No. 7141), *** Kerala population, Statistics Times (2025)

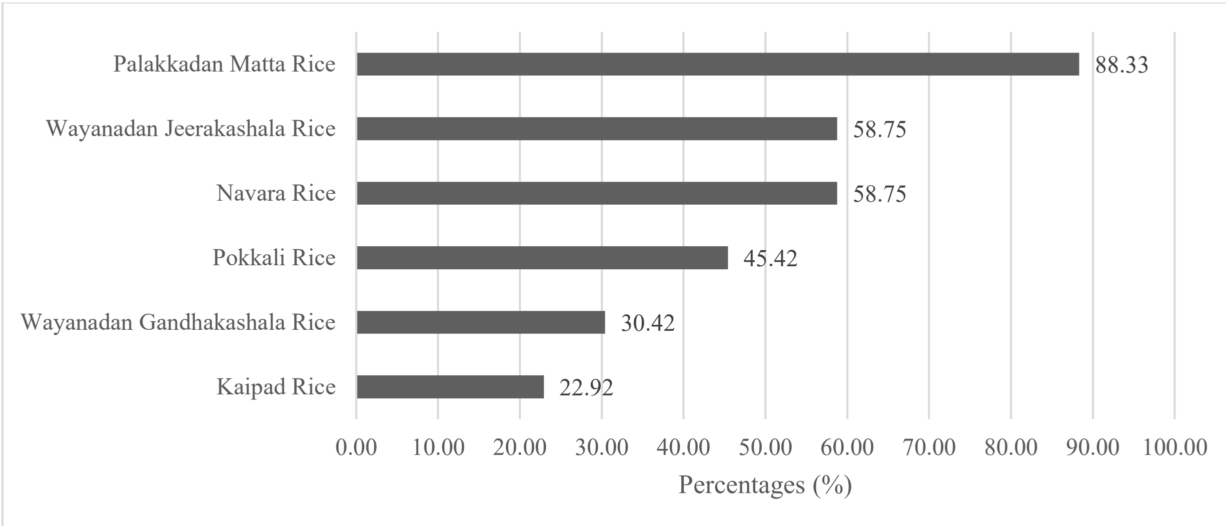

Fig. 1: Consumer awareness of specific GI rice varieties

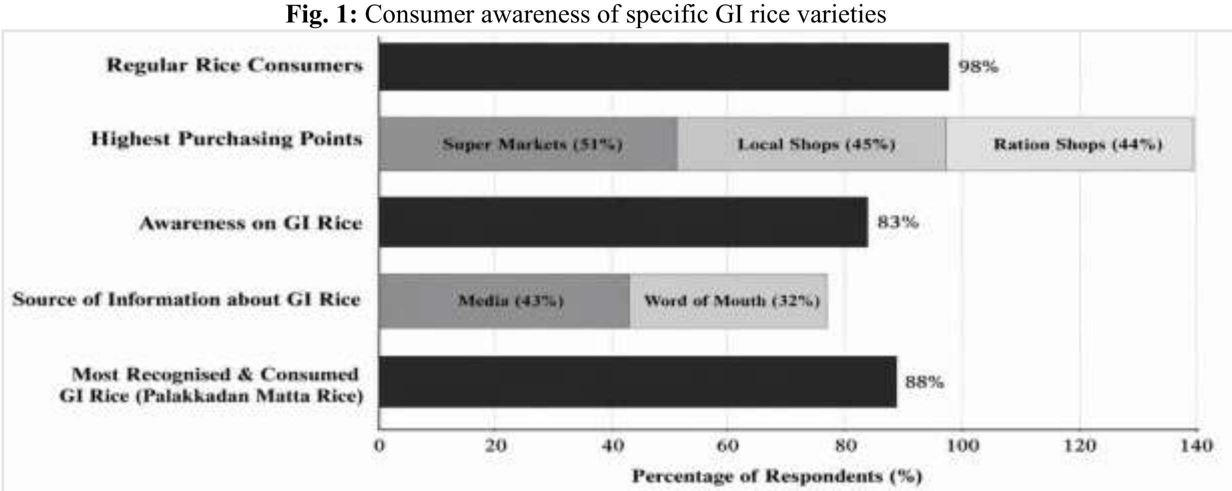

Fig. 2: Awareness and purchase behavior towards GI rice

Attribute importance: MaxDiff analysis

MaxDiff results (Table 2) showed taste ranking highest, followed by nutritional value, cooking quality, and availability, while GI certification, branding, and origin scored lowest; supporting H_1. This is consistent with evidence that credence attributes, which cannot be verified at the point of sale, are trusted less than directly assessable sensory cues (Yeh et al., 2020; Schrobback et al., 2023). This has particular relevance for Kerala's wetland-cultivated varieties (Pokkali, Kaipad), grown under low-input, saline-tolerant systems tied to documented wetland biodiversity value (Halder and Ghosh, 2024): consumer engagement should communicate these ecological and organic-cultivation credentials alongside sensory quality rather than relying on the certification mark alone.

Table 2: MaxDiff ranking of attributes influencing consumer preference for GI rice

Attributes	Total Appearances	Times Chosen Most	Times Chosen Least	Raw Score	Scaled Score	Rank
Taste	708	584	124	460	100	1
Nutritional Value	531	483	48	435	96.98	2
Cooking Quality	392	342	50	292	79.73	3
Availability	181	126	55	71	53.08	4
Price	432	229	203	26	47.65	5
Packaging	188	33	155	-122	29.79	6
GI Certification	705	228	477	-249	14.48	7
Aroma	456	99	357	-258	13.39	8
Brand Name	378	46	332	-286	10.01	9

Origin of Rice	829	230	599	-369	0	10

Willingness to pay for GI rice and its determinants

First hurdle: The WTP analysis showed substantial consumer acceptance of premium-priced GI rice; 80.83% of respondents were willing to pay a premium (Table 3). The binary logistic model (Table 4, Table 5) was significant overall (LR $\chi^2 = 46.75$, $p < 0.01$; McFadden $R^2 = 0.210$). Education and income both showed significant negative effects, while recognition and evaluation of alternatives were strong positive predictors (evaluation: odds ratio 6.475), and information search showed a significant negative effect.

Table 3: Distribution of consumers across premium payment bands for GI rice (n= 240)

Premium Band	Frequency	Share (per cent)	Payment Card Midpoint	WTP (Rs.)	Effective GI Rice Premium Price
Up-20 per cent	61	25.42	0.10	10	110
20-30 per cent	61	25.42	0.25	25	125
30-40 per cent	38	15.83	0.35	35	135
40-50 per cent	24	10.00	0.45	45	145
50-60 per cent	4	1.67	0.55	55	155
More Than 60 per cent	6	2.50	0.65	65	165
No Premium	46	19.17	-	-	100

Table 4: Determinants of consumers' willingness to pay for GI rice: Binary logistic regression results (first hurdle)

Variable	Coefficient (β)	Std. Error	Odds Ratio [Exp(β)]	p-value
Intercept	-2.766	1.923	0.063	0.150
Age	0.293	0.181	1.341	0.105
Education	-0.786**	0.324	0.456	0.015
Monthly Income	-0.522**	0.218	0.594	0.017
Awareness of GI Rice	0.490	0.517	1.632	0.343
Recognition of GI Rice	0.275**	0.131	1.317	0.035
Need Recognition Score	-0.213	0.335	0.808	0.526
Information Search Score	-0.684**	0.327	0.505	0.036
Evaluation Score	1.868***	0.565	6.475	0.001
Purchase Score	0.218	0.405	1.244	0.591
Post-Purchase Satisfaction Score	0.574*	0.347	1.775	0.098

Table 5. Model Statistics of binary logistic regression

Statistic	Value
Number of Observations	240
Log-Likelihood	-87.918
LR χ^2 (10)	46.753***
McFadden R^2	0.210
AIC	197.84

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Second hurdle: Among willing payers, age and income showed significant positive effects on premium magnitude (Table 6, Table 7), and information search reversed direction entirely (odds ratio 2.422); the opposite of its first-hurdle effect.

Two results merit reconciliation, together substantiating H_2: behavioural constructs: evaluation, information search, post-purchase satisfaction carry more explanatory weight across the WTP process than socio-demographic characteristics alone. Information search reduced the odds of paying any premium but increased premium magnitude among willing payers; consistent with information overload initially raising uncertainty before resolving into stronger conviction (Ying et al., 2025). Income showed the same reversal, a stage-dependent effect also reported for organic food WTP (Kim and Kim, 2024): higher-income consumers act as selective gatekeepers at entry but commit more once persuaded of value.

Table 6. Determinants of consumers' willingness to pay for GI rice: Ordered logistic regression results (second hurdle)

Variable	Coefficient (β)	Std. Error	p-value	Odds Ratio
Age	0.255**	0.116	0.028	1.290
Education	0.060	0.181	0.742	1.061
Monthly Income	0.327**	0.166	0.049	1.386
Awareness of GI Rice	0.184	0.454	0.685	1.202
Recognition of GI Rice	-0.032	0.085	0.705	0.968
Need Recognition Score	0.107	0.274	0.696	1.113
Information Search Score	0.885***	0.239	0.000	2.422
Evaluation Score	-0.317	0.416	0.446	0.728
Satisfaction Score	0.324	0.323	0.317	1.382
Post-Purchase Satisfaction Score	0.747**	0.298	0.012	2.110

Table 7. Model Statistics of ordered logistic regression

Model Statistics	Value
Number of Observations	196
Log-Likelihood (Null Model)	-285.823
Log-Likelihood (Full Model)	-252.708
Likelihood Ratio χ^2 (10)	66.230***
McFadden Pseudo R^2	0.116
Residual Deviance	505.416
AIC	535.416

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$

Motivators and demotivators for GI rice adoption

Quality assurance, health benefits, and taste were the leading motivators for GI rice adoption, while limited availability, high price, and low certification visibility emerged as the principal barriers (Fig. 3). Consumers thus appear to recognise the quality advantages of GI rice while facing real constraints around access and affordability; a pattern echoed in other GI food markets, where perceived quality drives adoption even as price and market access cap regular consumption (Belletti et al., 2017).

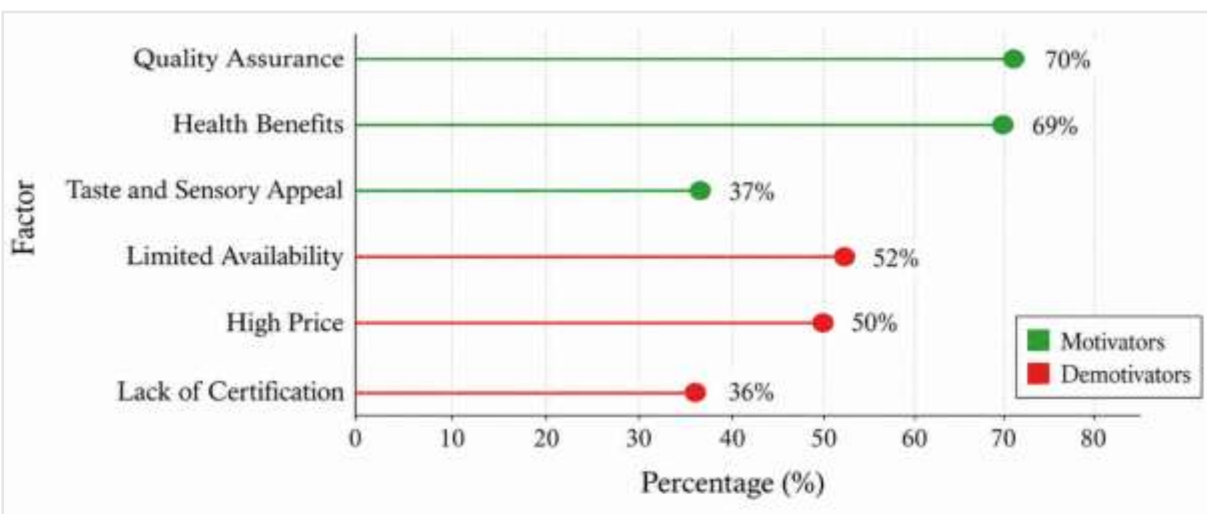

Fig 3: Motivators and demotivators influencing consumers' preference for GI rice

Consumer decision-making process: PLS-SEM results

The refined measurement model, after removing weak indicators, showed acceptable reliability and convergent validity (Tables 8 and 9). Composite Reliability ranged from 0.727 to 0.870, indicating adequate internal consistency, while Average Variance Extracted (AVE) ranged from 0.401 to 0.675, indicating acceptable convergent validity

(Dijkstra and Henseler, 2015). Cronbach's alpha values, spanning 0.451–0.776, reflect the exploratory nature of the behavioural constructs used.

Table 8: Refined measurement model (Outer model)

Indicator	Loading	Communality	Redundancy
Need Sub Construct 1 (I often look for healthier alternatives to regular rice)	0.862	0.743	0.000
Need Sub Construct 2 (I prefer rice that has cultural or regional identity (e.g., traditional varieties))	0.736	0.541	0.000
Information Sub Construct 1 (I actively seek information about the origin or quality of the rice I purchase)	0.704	0.495	0.047
Information Sub Construct 2 (I actively search for food products that have certifications or tags (e.g., GI, Organic)	0.859	0.738	0.070
Information Sub Construct 3 (I have searched online or asked others about GI-tagged rice)	0.703	0.494	0.047
Evaluation Sub Construct 1 (I compare different types of rice before making a purchase decision)	0.699	0.489	0.105
Evaluation Sub Construct 2 (I am willing to pay more for rice with better assured quality or certifications)	0.763	0.581	0.124
Evaluation Sub Construct 3 (I consider certification from credible and authentic sources (e.g. GI-tag, Govt recognized brands...))	0.638	0.407	0.087
Evaluation Sub Construct 4 (Taste, aroma and cooking quality matter more to me than price.)	0.472	0.223	0.042
Purchase Sub Construct 1 (I make rice purchase decisions jointly with my family)	0.821	0.673	0.057
Purchase Sub Construct 2 (My choice of rice is influenced by recommendations from others (e.g. friends, relatives, shop keepers...))	0.823	0.678	0.057
Post Purchase Sub Construct 1 (I feel satisfied after buying a traditional GI-tagged rice variety)	0.936	0.877	0.020
Post Purchase Sub Construct 2 (I am continuing to repurchase GI-tagged rice after a positive experience)	0.881	0.777	0.018
Post Purchase Sub Construct 3 (I share my experience about GI rice with others (e.g., family, friends).)	0.488	0.238	0.005

Table 9: Reliability and convergent validity of measurement model

Construct	No. of indicators	Cronbach's Alpha (α)	Composite Reliability (CR / DG.rho)	Average Variance Extracted (AVE)
Need Recognition	2	0.451	0.785	0.642
Information Search	3	0.631	0.803	0.576
Evaluation of Alternatives	4	0.501	0.727	0.401
Purchase Decision	2	0.520	0.806	0.675
Post-Purchase Satisfaction	3	0.776	0.870	0.630

The structural model results confirmed H3, supporting the sequential logic of the EKB consumer decision-making framework (Table 10, Fig. 4). Need recognition significantly predicted information search ($\beta = 0.308$, $p < 0.001$), which in turn shaped evaluation of alternatives ($\beta = 0.462$, $p < 0.001$). Evaluation positively influenced purchase decisions ($\beta = 0.290$, $p < 0.001$), and purchase decisions significantly predicted post-purchase satisfaction ($\beta = 0.150$, p = 0.020). Every hypothesised path was statistically significant, confirming a structured progression from initial need recognition through to post-purchase evaluation.

Table 10: Path coefficients of structural model (inner model) in the EKB framework

Path	Estimate	Std. Error	t-value	p-value	R-square value
Stage 1 → Stage 2	0.308***	0.062	4.993	<0.001	0.094
Stage 2 → Stage 3	0.462***	0.057	8.046	<0.001	0.213
Stage 3 → Stage 4	0.290***	0.062	4.670	<0.001	0.084
Stage 4 → Stage 5	0.150*	0.064	2.343	0.020	0.022

Note: *** $p < 0.001$ (99.9 per cent confidence level), * $p < 0.05$ (95 per cent confidence level)

Explanatory power was modest overall, with R^2 ranging from 0.022 to 0.213 across endogenous constructs; evaluation of alternatives showed the highest explanatory power ($R^2 = 0.213$), underlining its central role in shaping GI rice purchase decisions. Together, these findings suggest that consumer behaviour toward GI rice follows a cognitively structured, sequential decision process rather than an impulsive one; directly reinforcing the EKB-based logic of H_3.

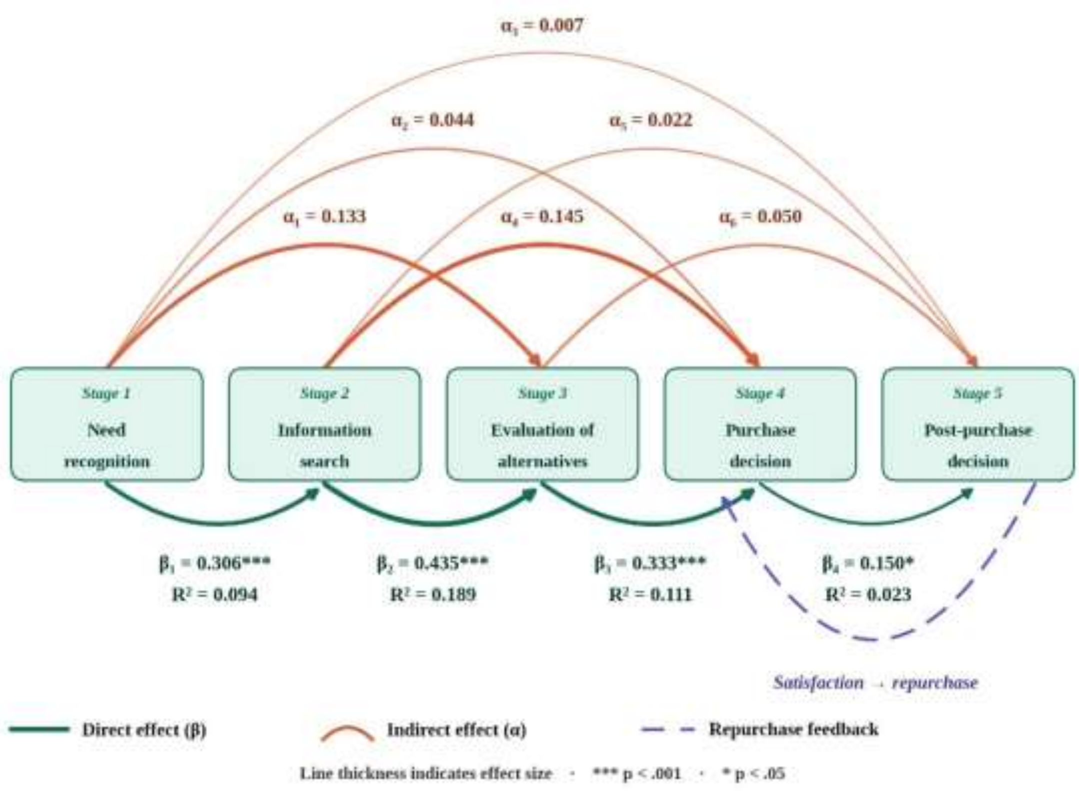

Fig. 4: EKB Consumer behavior model for GI rice

Table 11: Direct, indirect and total effects of refined model

Path	Direct Effect	Indirect Effect	Total Effect
Need → Information Search	**0.306**	0.000	0.306
Need → Evaluation	0.000	**0.133**	0.133
Need → Purchase	0.000	**0.044**	0.044
Need → Post-purchase	0.000	**0.007**	0.007
Information Search → Evaluation	**0.435**	0.000	0.435
Information Search → Purchase	0.000	**0.145**	0.145
Information Search → Post-purchase	0.000	**0.022**	0.022

Evaluation → Purchase	**0.333**	0.000	0.333
Evaluation → Post-purchase	0.000	**0.050**	0.050
Purchase → Post-purchase	**0.150**	0.000	0.150

The direct, indirect, and total effects (Table 11 and Fig.4) show how influence propagates through the EKB chain. Need recognition's effect on downstream constructs weakens sharply as it passes through intervening stages from 0.306 on information search to just 0.007 on post-purchase satisfaction; consistent with a fully mediated sequential process. Information search's influence on purchase decision (total effect 0.145) operates almost entirely through evaluation of alternatives, which itself exerts the strongest direct effect on purchase decision (0.333) of any inner-model path, confirming its pivotal role in translating information and need into actual buying behaviour.

DISCUSSION AND CONCLUSION

This study examined consumer attribute preferences, willingness to pay, and decision-making behaviour toward GI-tagged rice in Kerala, testing three hypotheses through MaxDiff analysis, contingent valuation with binary and ordered logistic regression, and PLS-SEM within the EKB framework. The results extend the predominantly producer-focused literature on Indian GI foods (Das, 2010; Jena and Grote, 2012; Radhika, 2021) to the consumer side, with direct implications for positioning GI certification within sustainable and organic food systems.

H_1 (intrinsic attributes prioritised over extrinsic/certification cues) was supported: intrinsic attributes (taste, nutritional value, cooking quality) outweighed extrinsic cues (certification, branding, origin), consistent with evidence that credence attributes, which cannot be verified at the point of sale are trusted less than directly assessable sensory cues (Yeh et al., 2020; Schrobback et al., 2023). This is notable for Kerala's wetland-cultivated varieties (Pokkali, Kaipad), grown under low-input, saline-tolerant systems tied to traditional aquaculture and documented wetland biodiversity value (Halder and Ghosh, 2024): consumer engagement strategies should communicate these ecological and organic-cultivation credentials alongside sensory quality rather than relying on the certification mark alone.

H_2 (WTP driven more by behavioural constructs than socio-demographics) was also supported: behavioural constructs outperformed socio-demographic variables in explaining premium acceptance. Two results merit brief reconciliation. Information search reduced the odds of paying any premium (first hurdle) but increased premium magnitude among willing payers (second hurdle) — consistent with information overload initially raising uncertainty before resolving into stronger conviction (Ying et al., 2025). Income showed the same reversal, a stage-dependent effect also reported for organic food WTP (Kim and Kim, 2024): higher-income consumers act as selective gatekeepers at entry but commit more once persuaded of value. Both patterns point to evaluation of alternatives as the mediating mechanism converting uncertainty into valuation, consistent with its central role in the SEM model (Section 4.4).

H_3 (sequential EKB decision path) was fully supported: all four EKB paths were significant, confirming that GI rice purchase follows a structured, sequential process rather than impulsive buying — aligning with recent EKB validations in other food contexts (Narsis, 2023). Evaluation of alternatives was the pivotal stage across both the logit and SEM models, indicating that conviction about product quality and authenticity, not certification recognition, is the primary gateway to premium acceptance and repurchase.

These findings carry a clear sustainability rationale. GI codes of practice often impose input, soil, and water-management requirements that align certification with environmentally sound cultivation (Zhang and Liu et al., 2025), while GI premiums directly support smallholder incomes for traditional, low-input rice systems (Radhika, 2021). The consumer evidence here, majority premium acceptance, driven by quality perception rather than certification awareness; indicates the market conditions for this producer–consumer sustainability link exist in Kerala but remain under-realised, given the persistent awareness–purchase gap documented across GI markets generally (Tan et al., 2024).

Consumer acceptance of GI rice in Kerala is governed less by certification recognition than by direct product experience, evaluative confidence, and information quality. For producer groups, certifying bodies, and policymakers aiming to convert GI registration into durable demand for sustainably and organically cultivated traditional rice, the priority levers are product-specific awareness building, credible and consistent information channels, and marketing that foregrounds intrinsic quality alongside origin and ecological credentials rather than certification status in isolation.

Theoretical and Practical Implications

This study's integration of MaxDiff, contingent valuation, logistic regression, and PLS-SEM within a single EKB-based framework remains rare for GI agri-food products and largely absent for Indian GI rice (Baishakhy et al., 2026), reinforcing the theoretical distinction between search and credence attributes (H1; Yeh et al., 2020; Schrobback et al., 2023), supporting behavioural over purely economic models of premium acceptance (H2), and extending EKB validation (Narsis, 2023) to the GI rice category (H3). Practically, these findings point to standardising grain quality and branding around taste and health benefits rather than certification alone; bundled, value-based pricing with continued MSP-linked procurement support for less visible varieties such as Kaipad and Navara; deeper FPO integration and dedicated supermarket shelving; and QR-based traceability (Modica, 2026) alongside indigenous crop knowledge in school curricula to build long-term recognition of heritage varieties tied to wetland biodiversity conservation (Halder and Ghosh, 2024).

Limitations and Future Research

The findings are subject to certain constraints. Non-probability (purposive and snowball) sampling, confined to six Kerala districts and a comparatively modest sample, limits generalisability to the broader consumer population and other GI products. WTP estimates, being stated rather than revealed preferences, may also be subject to hypothetical bias. Future research should apply probability-based sampling across a wider geographic and product scope, use longitudinal or incentive-compatible valuation designs, and examine digital traceability and organic-cultivation attributes as explicit drivers of demand.

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Conflicts of interest

The authors declare that they do not have any conflicts of interest.

Data availability

Data supporting the findings of this study are available from the corresponding author upon reasonable request.

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