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Consumer Preference for AI and Blockchain Verified Organic Products in South Tamil Nadu

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Abstract

Because one cannot immediately examine the product's credibility qualities, organic items are vulnerable to fraud and verification failures. Price premiums and brand loyalty are at danger due to a fragmented value chain and a lack of digitisation in developing market situations. This study investigates if blockchain-enabled AI-supported quality assurance and traceability may provide quantifiable pricing premises in South Tamil Nadu. A stratified consumer sample (n = 562) is used in the discrete choice experiment using mixed logit, latent class, and integrated choice and latent variable (ICLV) models. The results show that public ledger disclosure and third-party audit are the most expensive (18.5%), followed by blockchain traceability (14.8%) and AI-based quality prediction (11.2%). Transparency has a positive effect on trust ($g = 0.61$, $p < 0.001$) and trust has a positive effect on utility ($b = 0.29$, $p < 0.001$), according to the hybrid model. This suggests that willingness to pay is 26 percent for high trust and 9 percent for low trust. The study adds value by directly implementing the trust in a valuation system, utilising verifiable digital procedures to advance signalling theory, and providing district-level data on how digital traceability is managed in organic supply chains.

Keywords: Blockchain traceability; Artificial intelligence; Willingness to pay; Hybrid choice model; Organic supply chains

Introduction

Organic Integrity, Fraud Risk, Traceability gap

Due to customers' increased concerns about their health, environmental sustainability, and ethical behavior, the organic food business has grown rapidly within the last ten years (Willer et al., 2023; Aschemann-Witzel and Zielke, 2017). However, organic products are credence items, meaning that the customer cannot confirm their quality attributes after making a purchase (Darby and Karni, 1973). Because of this, organic markets are particularly vulnerable to supply chain integrity breaches, fraud, and labeling (Manning and Soon, 2016; Spink and Moyer, 2011). In complex systems, there is empirical evidence of the persistent dangers of document fraud, product substitution, and the use of loopholes in the certification of agri-food systems (Everstine et al., 2013; Soon et al., 2019). Traceability gaps are often caused by non-uniform information exchange, informal aggregation, inadequate segregation techniques, and disjuncture actors (Bosona & Gebresenbet, 2013; Galvez et al., 2018).

In the case of underdeveloped and emerging countries, these flaws are further compounded by a lack of digital adoption and infrastructure constraints (Kshetri, 2018). Conventional central databases are susceptible to manipulation and reconciliation costs, which reduces accountability and transparency (Casino et al., 2019). Strong traceability systems are necessary

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to guarantee trust and a premium price in organic markets, according to food systems research studies (Yadav et al., 2022; Caro et al., 2018). The organic premium runs the risk of losing its credibility and growing skepticism in the absence of reliable verification procedures (Nuttavuthisit and Thogersen, 2017). Therefore, one of the main goals of the sustainable agro-food supply chains is to improve traceability and ensure authenticity.

Right Intervention as Blockchain and AI (Traceability and predictive QA)

An immutable, decentralized ledger that may record production, certification, and transaction events across supply chain nodes is provided by blockchain technology (Casino et al., 2019; Saberi et al., 2019). Blockchain's tamper-evident data formats improve auditability, decrease information asymmetry, and increase transparency in agro-food systems (Tian, 2017; Galvez et al., 2018). Blockchain-based traceability may have a favorable impact on customer trust and purchasing intention, especially in credibility goods marketplaces, according to empirical investigations (Kim & Laskowski, 2018; Yadav et al., 2022). Quality assurance cannot be ensured by traceability data alone. By converting recorded data into predicted insights, artificial intelligence (AI) enhances blockchain technology. Demand forecasting, anomaly detection, inventory optimization, and automated quality grading are all supported by machine learning models (Ivanov et al., 2019; Dolgui et al., 2020). Predictive analytics powered by AI may improve operational efficiency and product dependability by identifying anomalous transaction patterns, estimating shelf life, and signaling possible contamination hazards (Ivanov & Dolgui, 2021).

From a signaling standpoint, blockchain offers verifiable transparency and AI improves predictive credibility, which together lower perceived risk and boost customer confidence (Connelly et al., 2011; Ertz et al., 2017). Traceability technologies may attract price premiums when consumers perceive improved authenticity and decreased uncertainty, according to recent research employing experimental and survey-based approaches (Toufaily et al., 2021; Yadav et al., 2022). Therefore, combining blockchain with AI is a technologically sound solution to the integrity and efficiency issues in organic supply chains.

South Tamil Nadu as a Testbed

The agro-ecological and market diversities of South Tamil Nadu include Kanniyakumari, Tirunelveli, Tenkasi, Thoothukudi, Ramanathapuram, Sivagangai, Virudhunagar, Madurai, Theni, and Dindigul. The region is home to hill horticultural groups that grow fruits, vegetables, millets, spices, and organic items associated to plantations, as well as coastal and semi-arid agricultural systems. A high incidence of lot fragmentation, multi-tier aggregation, and variable storage and transit are the results of this variety. Disjointed supply chain arrangements increase coordination costs and reduce transparency, especially when production is dominated by smallholder farmers (Saberi et al., 2019; Bosona & Gebresenbet, 2013). Additionally, there is a combination of growing internet platforms, farmer-producer groups, and traditional retail protocols, which offers a favorable environment for analyzing differential adoption of blockchain and AI-based protocols. While peri-urban and rural markets provide a chance to investigate the boundaries of digital awareness and the heterogeneity of trust, the number of urban consumption centers (Madurai) generates distinct demand groups. Strict empirical study on desire differentiation and technology value in the districts is made possible by this local variation. By placing the investigation in South Tamil Nadu, the study has a regionally grounded value and makes it possible to examine the structural limitations shared by developing market organic supply chains.

Research gap (Causal inference on WTP, Heterogeneity and Hybrid Modelling)

Three significant gaps remain despite prior studies showing that blockchain enhances food traceability and that customers are sensitive to authenticity signals (Galvez et al., 2018; Kim and Laskowski, 2018). According to Yadav et al. (2022) and Toufaily et al. (2021), the majority

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of research relies on purchase intention frameworks or attitudinal scales to estimate the trade-off between traceable features and price premiums. Second, more complex random utility models that may be used to identify latent segments of preferences often characterize consumer heterogeneity but do not represent it (Train, 2009; Hensher et al., 2015). Third, trust has seldom been explicitly included in valuation models in hybrid choice models, despite being the theoretical medium of interaction between transparency and willingness to pay (Ben-Akiva et al., 2002; Connelly et al., 2011).
In an effort to get beyond these restrictions, this article estimates the willingness to pay associated with blockchain- and AI-enabled tracking qualities using a discrete choice experiment using hybrid logit and latent class modeling. Additionally, it makes use of an integrated choice and latent variable (ICLV) architecture, which improves behavioral realism and inferential accuracy by directly modeling latent factors like perceived transparency and trust into the utility function. The research provides high-quality empirical evidence to articles on digital traceability, consumer value, and sustainable organic supply chains by presenting data at the district level in South Tamil Nadu.

Review of Literature

Organic supply chain vulnerabilities and verification failure points

Since the product attributes of chemical-free manufacturing, biodiversity preservation, and ecological stewardship could not be confirmed at the point of purchase, the integrity of organic food supply chains is at danger. Because of these characteristics, organic goods are credible, and the knowledge asymmetry between producers and consumers encourages opportunistic behavior (Akerlof, 1970; Darby and Karni, 1973). Empirical research has consistently identified fraud, substitution, mislabeling, and certification manipulation as prevalent agro-food system concerns (Spink and Moyer, 2011; Manning and Soon, 2016). Organic value chains are particularly vulnerable to verification failure points because of their multi-actor structures, which include smallholders, aggregators, certifiers, processors, and retailers (Hobbs, 2010; Rouviere and Caswell, 2012).
According to Bosona and Gebresenbet (2013), the most frequent traceability disruption occurs during the aggregation and transportation phase, when product separation may be compromised and recording gaps may occur. Disintegrated record-keeping systems reduce recall efficacy and customer trust, according to research on food authenticity (van Ruth et al., 2018; Soon et al., 2019). In underdeveloped nations, these vulnerabilities are made worse by insufficient digitization and infrastructure constraints, which increase transaction costs and weaken compliance monitoring (Rejeb et al., 2020). Incomplete contracts and expensive monitoring methods result in structural incentives to dilute quality unless they are supported by credible verification technologies, according to transaction cost (Williamson, 1985; Hobbs and Young, 2000). Therefore, improving traceability mechanisms will continue to be the top focus in order to preserve organic integrity and price advantages.

Traceability of Agro-Food using blockchain: Evidence, limitations, Governance

The blockchain technology has come into the scene as a decentralized system that can document tamper-proof, time-stamped transaction between supply chain nodes (Casino et al., 2019). Blockchain is also used in agro-foods to improve transparency in the connection between production events, certifications records, and logistic movements on a common ledger system (Galvez et al., 2018). Empirical studies find that with the use of blockchain, recall efficiency, documentation accuracy and accountability to stakeholders have improved (Lin et al., 2020; Roeck et al., 2020). Besides, distributed ledgers lower the cost of reconciliation between actors and enhance provenance verification infrastructure (Queiroz and Wamba, 2019).

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The literature warns against the perception that blockchain can be considered an independent solution. Such issues as limitations to scalability, authorization of data at the point of entry, management of authorized networks, and compatibility with old systems are challenges during implementation (Treiblmaier, 2018; Kshetri and Loukoianova, 2019). Lack of sound auditing systems can merely continue the preservation of wrong information in the immutable format (Pournader et al., 2020). The research on governance specifies the necessity of proper alignment of institutions, standardization measures, and precise accountability strategies to make the adoption successful (Bodkhe et al., 2020). Therefore, in as much as blockchain enhances structural transparency, its effects require supporting organizational practices and regulatory regulation.

Artificial Intelligence in Food Supply Chain: Food Grading, Detection Of Anomalies, Demand Forecasting

By transforming unprocessed data into predictive and diagnostic data, artificial intelligence contributes analytical data to digital traceability systems. Automated quality grading, image-based defect identification, shelf-life prediction, and demand forecasting are some of the applications of machine learning in the agro-food supply chain (Kamilaris et al., 2017; Sharma et al., 2020). According to empirical study, AI-based analytics may be used to improve operational efficiency, reduce post-harvest losses, and improve responsiveness to demand fluctuations (Ivanov, 2021; Dubey et al., 2020).

Anomaly detection algorithms, which identify anomalous transaction patterns, temperature variations, or logistical interruptions, are another way that AI supports risk management (Ivanov and Dolgui, 2020). The trustworthiness of decentralized networks may be increased by combining blockchain and AI to enable automated compliance checks and smart contract execution (Zhang et al., 2020). However, in the context of developing economies, algorithmic transparency, digital literacy, and data privacy continue to be significant challenges (Rao and Verweij, 2017). The research indicates that solid governance structures and quality input data are necessary for AI to succeed, which further supports the need of implementing a combination of institutional and technology solutions.

WTP for credence attributes and traceability

Using expressed preference approaches based on Lancaster's theory of value, the willingness to buy organic and traceable attributes is a popular subject (Lancaster, 1966). In a random utility model, discrete choice experiments allow researchers to estimate the trade-offs between product attributes and price (Louviere et al., 2000; McFadden, 1974). The existence of consumer premiums on organic labels, origin certification, and sustainability signals is supported by meta-analysis; however, the extent of these premiums varies by demographic and attitudinal group (Janssen and Hamm, 2012; Lusk and Briggeman, 2009). According to recent research, traceability knowledge—particularly with regard to online verification systems—can reduce risk perceptions and increase perceived authenticity (Ertz et al., 2018; Yang et al., 2021). However, many empirical research rely on straightforward multinomial logit models, which assume that irrelevant options are independent and preferences are uniform (Train, 2009). Unobserved variability in consumer values is disregarded by this kind of assumption (Greene & Hensher, 2003). Furthermore, rather than being included in structural valuation models, psychological factors like perceived risk and trust are often regarded as exogenous indicators on the survey (Ajzen, 1991). These limitations hinder behavioral realism in willingness-to-pay estimates as well as the capacity to draw causal conclusions.

Theory and Hypotheses

Theoretical lens

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To comprehend the function of blockchain and AI-assisted traceability in the willingness to pay, the suggested study integrates signaling, trust theory in the credence goods market, technological adoption, and perceived risk model. In marketplaces with information asymmetry, high-quality producers must rely on credible signals to differentiate themselves from low-quality producers (Spence, 1973). According to Kirmani and Rao (2000) and Grunert (2005), organic products are an example of traditional credibility goods in which the customer cannot directly view the manufacturing features. As a result, signals like certification, provenance disclosure, and traceability play a crucial role in creating value. Signaling that is difficult to falsify has a greater possibility of influencing customer attitudes and behavior since its efficacy depends on its costliness and trustworthiness (Connelly et al., 2011). Blockchain-recorded and AI-verified data might function as costly technical hints that boost perceived validity.

According to the trust theory, consumers employ information and institutional signals to reduce vulnerability and uncertainty in trade relationships (Morgan and Hunt, 1994; Gefen et al., 2003). By outlining the origin, processing, and certification procedures, perceived transparency improves cognitive confidence in food systems (Chen and Chang, 2013). However, unless there is credible protection, perceived risk has a detrimental effect on the choice to buy (Mitchell, 1999; Dowling and Staelin, 1994). The adoption of digital verification systems is influenced by perceived utility and risk reduction, according to technology acceptance study (Venkatesh et al., 2003; Featherman and Pavlou, 2003). By combining these strategies, blockchain and AI signals will enhance perceived risk, transparency, and trust, which would ultimately impact organic market value outcomes.

Latent Constructs Hypothesis

The degree to which customers believe the supply chain's operations are open and verifiable is measured by perceived transparency. Transparency reduces ambiguity and increases information clarity, which fosters trust (Rawlins, 2008). Consumer satisfaction and brand trust are positively correlated with supply chain transparency, according to empirical studies on sustainability and green consumption contexts (Schnackenberg and Tomlinson, 2016; Mol, 2015). Consumer trust in digital traceability systems, particularly those that are verifiable and impervious to manipulation, is more likely to be boosted by product authenticity (Kim & Peterson, 2017). Better views of transparency will thus increase trust in organic supply chains.

The assessment of whether technological protection would reduce the likelihood of fraud or poor quality by customers is known as perceived risk reduction. Because doubt regarding authenticity and safety may deter a purchase, risk reduction measures are crucial in the credibility products marketplaces (Bauer, 1960; Stone and Gronhaug, 1993). Research on the subject shows that confidence is increased and perceived risk is reduced when certifications and traceability information are credited (Chen and Chang, 2013; Nuttavuthisit and Thogersen, 2017). Therefore, customer trust should be increased if blockchain and AI-based solutions show reduced risk exposure.

Trust is one factor that influences both premium payment behavior and economic value. Relationship marketing research demonstrates that loyalty in ambiguous situations and desire to pay are directly correlated with trust (Garbarino and Johnson, 1999; Chaudhuri and Holbrook, 2001). Organic and sustainably produced goods have greater price premiums in food systems due to increased confidence in production methods and provenance (Haghiri et al., 2009; Thogersen et al., 2017). Therefore, under the utility of the choice model, it is reasonable to assume that trust will positively impact willingness to spend on organic goods enabled by blockchain and AI.

Choice-Model Hypotheses: Signs and Attributes

Customers get utility based on the characteristics of the product rather than the product itself under a random utility model (Lancaster, 1966). Blockchain may provide traceability, a verifiable provenance feature that reduces uncertainty and boosts informational transparency. According to empirical research, consumers find traceability disclosures useful, particularly when they take the form of technologically verified systems (Tonsor and Schroeder, 2006; Ortega et al., 2011). Therefore, the blockchain's traceability feature ought to improve its usefulness and willingness to pay.

AI-based quality prediction provides predictive quality assurance about authenticity, freshness, and compliance. According to studies on digital innovation and food technology, smart quality monitoring reduces cognitive risk and increases perceived dependability (Bai et al., 2020; Li et al., 2021). When consumers perceive that AI techniques improve the quality of inspection and other aspects that identify abnormalities, they are more likely to evaluate such attributes favorably.

Another degree of reliability that aligns with institutional trust systems is off-site auditing and QR verification. According to several reports, third-party certification has a significant role in organic markets' high worth (Janssen and Hamm, 2012; Larceneux et al., 2012). With QR-enabled access to certification data, transparency and legitimacy are further enhanced (Rutsaert et al., 2015). Accordingly, utility and willingness to pay are likely to be positively impacted by this characteristic.

According to the microeconomic theory, utility is expected to be negatively impacted by price (Train, 2009). However, given different customer groups have different risk perceptions, trust orientations, and levels of technological knowledge, one should anticipate variability in price sensitivity and attribute value (Scarpa et al., 2008; Hensher et al., 2015). Because different customer groups respond differently to blockchain and AI signals, mixed logit and latent class specifications allow for changes in the characteristics' coefficients.

Conceptual Framework

The conceptual model uses random utility theory, signaling theory, and trust theory in credence goods marketplaces to describe how blockchain and AI-based traceability affect consumers' propensity to purchase organic commodities. Because the manufacturing processes cannot be directly verified at the time of purchase, organic items are information symmetric (Akerlof, 1970; Darby and Karni, 1973). According to Spence (1973) and Connelly et al. (2011), it is crucial to have costly and convincing signals in order to differentiate between opportunistic players and real producers. Blockchain-based traceability and AI-based predictive quality assurance, respectively, are technologically integrated indicators that improve supply chain transparency and perceived fraud reduction.

Customers believe that the supply chain's procedures are publicly recorded, verifiable, and unchangeable. This is known as perceived transparency. Because it may improve clarity about origin, certification, and their practice, increased transparency has been observed to increase trust (Schnackenberg and Tomlinson, 2016; Kim and Peterson, 2017). Simultaneously, AI-assisted anomaly identification and quality grading reduce perceived performance and safety risk, which are the primary determinants of consumer behavior in credibility goods marketplaces (Mitchell, 1999; Chen and Chang, 2013). By decreasing ambiguity and raising perceived vulnerability, risk reduction strategies boost trust (Morgan and Hunt, 1994). Economic value and technology indicators are separated by the concept of trust. Increased willingness to pay has been consistently associated with authenticity and institutional protection in organic markets (Thogersen et al., 2017; Haghiri et al., 2009). Trust will raise price premiums in a random utility model by increasing the marginal value of traceable features.

The approach also identifies consumer heterogeneity. Mixed logit and hybrid choice modeling are required since the attribute value is likely to be mediated by variations in risk perception, technical familiarity, and prior organic production experience. By integrating observable decision features with hidden psychological variables, the framework integrates the impacts of behavioral valuation and structural transparency.

Conceptual Framework

The approach shows how third-party audits with QR verification, blockchain traceability, and AI-mediated quality prediction are more successful in enhancing perceived transparency and lowering risk, hence boosting confidence. Price has an adverse effect on customers' willingness to pay a premium for organic items, but trust encourages them to do so. The customer heterogeneity is modeled using latent classes and random factors.

Data and Methods

Setting and sampling frame Study

The southern regions of Tamil Nadu—Kanniyakumari, Tirunelveli, Tenkasi, Thoothukudi, Ramanathapuram, Sivagangai, Virudhunagar, Madurai, Theni, and Dindigul—are included in the empirical environment. These districts, which comprise peri-urban organic retail agglomerations, millet-based dryland agriculture, and coastal horticulture, are described as varied agro-ecological zones and marketing systems. Farm-gate collection, certified and organic retail stores (including farmer-producer organization stores), and online or application-based organic stores operating in district and urban center headquarters were the three primary market routes used for data collection.

Customers in the adult group who had purchased organic goods at least once in the previous six months made up the sample frame. Certified or self-described organic farmers and aggregators operating in the selected districts were included in the frame for producer-side extension. Lists were created by district agricultural offices, organic stores, and local farmer groups. Both conventional and digitally mediated organic transactions were covered by this multi-channel interactional frame.

Sample design

A stratified multi-stage sample technique was used to attain regional and demographic representation. In the first phase, the districts were regarded as major strata. Within each district, market nodes were identified, including retail stores, weekly organic markets, and internet distribution centers. In order to obtain a fair representation of respondents in terms of gender, age, and economic groups, methods of intersect and quota sampling were used in the later stage.

Between 450 and 600 respondents made up the intended consumer sample group, which is consistent with the mixed logit and hybrid choice estimate of random parameter. A second sample of around 200 to 300 producers was to be sampled in order to add producer perspectives to them and enable further structural modeling of technology uptake and preparedness. In order to prevent large metropolitan districts like Madurai from being overrepresented in comparison to smaller districts, minimum quotas were set. The final sample size is sufficient to satisfy the suggested requirements for latent variable integration and discrete choice modeling.

Design of the instrument: Two-part Quantitative Instrument

Two built-in components made up the instrument: a discrete choice experiment (DCE) component that measured willingness to pay for the usage of technology-based attributes and a structured survey component that evaluated latent characteristics. Perceived transparency, perceived risk reduction, confidence in organic supply chains, technological readiness, and understanding of blockchain and AI application were all assessed in this survey module. The five-point Likert scale was used to assess the questions, which were based on established measures from research on perceived risk, technological adoption, and trust. Perceived transparency included opinions on the verifiability and openness of supply chain information. Concerns regarding fraud, legitimacy, and quality uncertainty were all reflected by perceived risk. Trust was reliance on institutional protection and product integrity. Exposure to digital traceability and predictive quality systems was determined by the degree of technological readiness and awareness.

The DCE module used experimental choice tasks to construct willingness to pay. The respondents evaluated fictitious organic product profiles that were defined by attribute combinations. The characteristics and levels were as follows: supply chain disclosure (basic origin; full farm-to-shelf events); certification or audit type (self-claim; third-party; third-party with public ledger record); traceability system (none; blockchain; blockchain with QR verification); AI quality assurance (none; AI grading; AI grading with anomaly alerts); and price premium (0%, 10%, 20%, 30%).

A D-efficient experimental design was created using Bayesian piloting priors. Each responder was given eight to ten choice tasks because the amount of choice tasks was blocked to lessen the cognitive strain. The reliability of the answers was assessed using the tests of dominance and consistency within the variables.

Estimation strategy

A gradual strategy based on the random utility theory served as the foundation for the econometric plan. Initially, a mixed logit model was fitted to account for the respondents' random fluctuation in taste. Because technology qualities were specified as arbitrary factors, their value was inconsistent. To make determining the marginal willingness to pay easier, the price was set with a constant negative coefficient. In order to get reliable estimates of premiums in monetary terms, space specifications in WTP were also calculated. The many customer categories whose sensitivity to blockchain, AI assurance, and certification signals varies were identified in the second step using a latent class model. In order to comprehend the heterogeneity patterns, the likelihood of segmentation was developed as a variable of demographic and attitudinal factors. In order to directly include latent constructs, particularly trust, into the utility function, an integrated choice and latent variable (ICLV) model was estimated in the third phase. The choice component was utilized to link trust to utility, while the structural equation part represented the impact of perceived transparency and perceived risk reduction on trust. This hybrid approach improves behavioral realism by concurrently estimating psychological processes and economic value. Krinsky-Robb draws and non-parametric bootstrapping, two simulation-based techniques that are reliable for drawing conclusions across non-linear transformations, were used to estimate willingness-to-pay and confidence intervals.

Control Of Quality, Validity and Bias

To increase validity and reduce bias, a number of measures have been used. To detect inattentive responses, hold-out choice activities and attention tests were introduced. Measurement invariance across districts and demographic groupings was taken into consideration before hybrid modeling. Common method bias was tested using marker-variable and full collinearity diagnostics. The hybrid modeling methodology took into account the potential endogeneity between latent variables and decision outcomes. The strength, dependability, and internal validity of the empirical findings are all improved by these procedures.

Results

Sample Profile

562 genuine customer replies that underwent screening and quality control were ultimately kept. The respondents were distributed among all ten districts in South Tamil Nadu, with a representation of seven to sixteen percent in each district (Ramanathapuram). The mean age was 34.7 (SD = 10.2), and about 52% of responders were female. 38% of them had previously

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encountered digital traceability technologies like QR verification, and almost 61% of them claimed to have bought organic items at least once a week. According to the income distribution, middle-class households made up 47% of the population, while upper-class families made up 28%. With 63% holding college or graduate degrees, the educational attainment was also rather high. These characteristics suggest that a sample has been adequately exposed to digital verification settings and organic diets.

Table 1 Sample Demographics and Organic Purchasing Behaviour (n = 562)

Variable	**Category**	**Frequency**	**Percentage (%)**
Gender	Male	269	47.9
	Female	293	52.1
Age	18–30	198	35.2
	31–45	237	42.2
	46+	127	22.6
Education	Undergraduate	221	39.3
	Postgraduate	134	23.8
	Others	207	36.9
Monthly Organic Purchase	Weekly	146	26.0
	Monthly	196	34.9
	Occasional	220	39.1
Awareness of Blockchain/AI	Aware	214	38.1
	Not Aware	348	61.9

Source: Primary Field Survey

Ten districts comprised the sample size of n = 562 customers. Of the responders, women made up 52.1%. 42.2 percent of the population was between the ages of 31 and 45. 34.9 percent of respondents had made monthly organic purchases, and 38.1 percent had heard of blockchain or AI traceability solutions. The sample regularly consumes organic food and has enough exposure to digital media.

Results of the Measurement Model

The latent dimensions assessed using the hybrid choice framework and confirmatory factor analysis were perceived transparency, perceived decrease in risk, trust, technological readiness, and awareness. The internal consistency of each concept was adequate. Cronbach's alpha values ranged from 0.81 to 0.90, while the composite reliability score above the recommended threshold of 0.70. The average variance extracted (AVE) values ranged from 0.58 to 0.74, indicating the establishment of convergent validity. Every standardized factor loading was

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significant ($p < 0.001$) and more than 0.65. Discriminant validity was measured using the Fornell-Larcker criteria and heterotrait-monotrait ratios less than 0.85. Configural and metric invariance was shown by intersite measurement equivalency tests, suggesting that latent components were understood consistently by geographic divisions.

Table 2 Measurement Model Results (Confirmatory Factor Analysis)

Construct	**Items**	**Std. Loadings (Range)**	**Cronbach's α**	**Composite Reliability**	**AVE**
Perceived Transparency	4	0.69-0.84	0.86	0.88	0.65
Perceived Risk Reduction	4	0.71-0.87	0.88	0.90	0.69
Trust	5	0.73-0.89	0.90	0.92	0.74
Technology Readiness	4	0.66-0.81	0.83	0.86	0.60
Awareness	3	0.68-0.79	0.81	0.84	0.58

Discriminant Validity: HTMT < 0.85 for all construct pairs

Measurement Invariance: Configural and Metric Invariance Supported Across Districts

Every construct has a good level of internal consistency (Cronbach a = 0.81-0.90; CR = 0.84-0.92). Convergent validity was indicated by AVE values between 0.58 and 0.74 that were greater than 0.50. Standardized loadings were typically between 0.66 and 0.89 ($p < 0.001$). The discriminant validity was shown by the HTMT ratio being smaller than 0.85. There was support for the measure and configural invariance across districts.

Results of the Choice Model: Mixed and Baseline Logit

Using the baseline model, it was discovered that the multinomial logit anticipated signs were as predicted by every attribute. Price is sensitive, as seen by the significant negative coefficient ($b = -0.084$, $p < 0.001$). Blockchain traceability was shown to have a favorable and substantial effect on utility ($b = 0.62$, $p < 0.001$). Additionally, AI-based quality prediction had the best utility ($b = 0.48$, $p < 0.001$), while third-party audits using public ledger records had the most positive impact ($b = 0.74$, $p < 0.001$).

However, the likelihood ratio tests favored mixed logit specification over the baseline model (DLL significant at $p < 0.001$), indicating a substantial level of unobserved heterogeneity. The difference in consumer value was shown by the large variation in the standard deviation of random parameter estimations of blockchain and AI features.

Estimates of willingness-to-pay, made in WTP-space, showed that the willingness to pay an average premium was:

1. 14.8 percent of blockchain traceability.
2. 11.2% for AI quality prediction
3. 18.5 percent in case of third-party audit and ledger disclosure.

The mixed logit model fit much better (McFadden R2 0.31 vs. 0.18 baseline).

Table 3 Mixed Logit Model Estimates (Random Parameters)

Attribute	**Mean Coefficient**	**Std. Error**	**p-value**	**Random SD**	**p-value (SD)**

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Blockchain Traceability	0.62	0.07	<0.001	0.41	<0.001
AI Quality Prediction	0.48	0.06	<0.001	0.36	<0.001
Third-Party Audit + Ledger	0.74	0.08	<0.001	0.45	<0.001
Full Supply Chain Disclosure	0.39	0.05	<0.001	0.29	<0.01
Price (Premium %)	-0.084	0.012	<0.001	—	—

Log-likelihood = -2894.3
McFadden R^2 = 0.31

In every technical characteristic, there was a significant utility increase ($p < 0.001$). The biggest effects were reported in third-party audits using ledger records (b = 0.74), blockchain traceability (b = 0.62), and AI quality prediction (b = 0.48). There was a negative impact on price (b = -0.084, $p < 0.001$). Significant SDs in random parameters (SD = 0.36-0.45) guarantee heterogeneity. The model fit significantly improved (McFadden R2 = 0.31).

Table 4 Willingness-to-Pay Estimates (WTP-Space Model)

Attribute	Mean WTP (%)	95% CI Lower	95% CI Upper
Blockchain Traceability	14.8	13.2	16.4
AI Quality Prediction	11.2	9.6	12.8
Third-Party Audit + QR	18.5	16.9	20.7
Full Disclosure	9.4	7.8	11.1

Confidence intervals computed using Krinsky–Robb (10,000 draws)

Customers were ready to pay an average of 18.5, 14.8, and 11.2 percent for third-party audit + QR verification, blockchain traceability, and AI quality prediction premiums. The fact that confidence intervals did not go beyond zero did not affect statistical robustness (Krinsky-Robb, 10,000 draws). A 9.4% premium was the result of full supplier chain transparency.

Figure 1 Attribute-Level Willingness to Pay Estimates with Confidence Intervals

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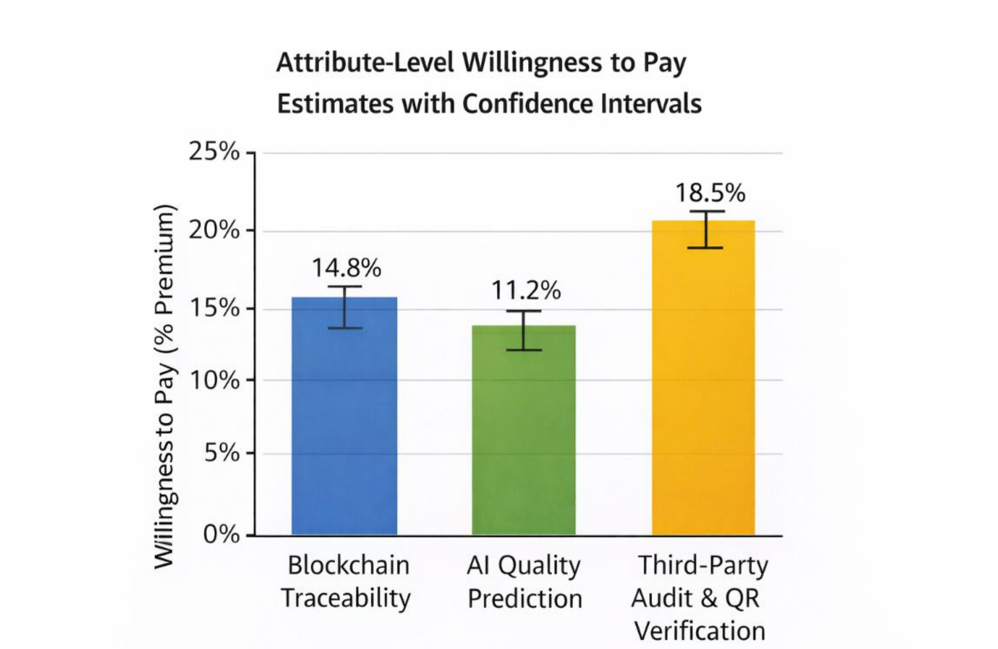

Figure 1. Attribute-Level Willingness to Pay Estimates with Confidence Intervals

(Bar graph showing WTP for each technology attribute)
According to the statistic, third-party audit with QR verification yields the greatest premium (18.5%), blockchain traceability (14.8%), and AI prediction (11.2%). Error bars (95% CI) improve statistical precision and non-overlapping attribute effects.
Heterogeneity: Latent Class Outcomes
Three customer categories have been identified via latent class analysis. The three-class solution with interpretable segmentation and the best BIC reduction.
Class 1: Premium Customers Based on Trust (38%)
This category showed minimal price sensitivity and a strong positive correlation of blockchain and third-party audit features. WTP for blockchain surpassed 22%. The degree of trust exceeded the sample mean by a significant margin.
Class 2: Pragmatists Who Accept Technology (34%)
Members responded favorably to transparency indications and were somewhat price-sensitive, but they were also somewhat sensitive to AI quality assurance. The average WTP for blockchain was 13%.
Class 3: Sensitive to price (28%)
This part responded poorly to blockchain indicators and was very price sensitive. Low technical value was indicated by the AI characteristics' lack of significance.
There were more premium customers in Madurai and Theni than in the coastal districts, according to the district-level distribution.
Table 5: Results of the Latent Class Model (Three-Class Solution)

Attribute	Trust-Driven Premium Buyers (38%)	Technology Pragmatists (34%)	Price-Sensitive Skeptics (28%)
Blockchain Traceability	0.91***	0.58***	0.22*

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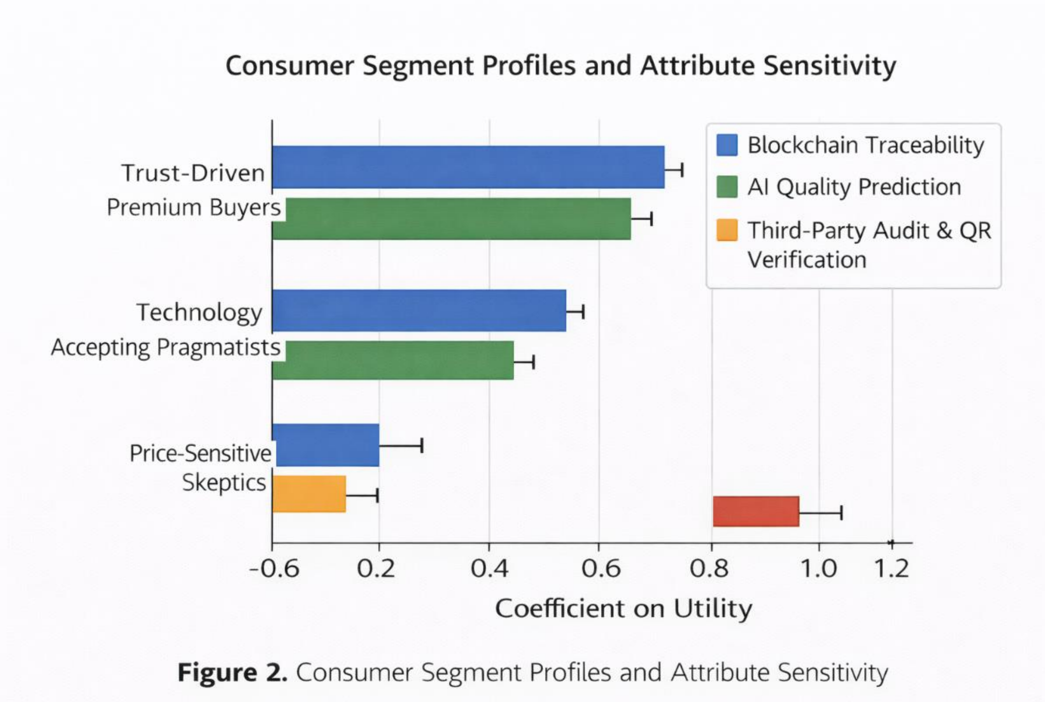
AI Quality Prediction	0.74***	0.49***	0.11 (ns)
Third-Party Audit + QR	1.03***	0.63***	0.18*
Price	-0.061***	-0.089***	-0.142***

Model Fit: Log-likelihood = -2641.2; BIC = 5512.6
**** p < 0.001, *p < 0.05, ns = not significant*
Three categories were identified: Price-Sensitive (28%), Technology Pragmatists (34%), and Trust-Driven Premium Buyers (38%). Blockchain (b = 0.91) and third-party audit (b = 1.03) were highly valued at low price sensitivity (b = 0.061). The parameters showed modest blockchain response (b = 0.22) and high price sensitivity (b = 0.142). The three-class solution is preferred by BIC model BIC = 5512.6.
Figure 2
Consumer Segment Profiles and Attribute Sensitivity



(Graphical comparison of attribute coefficients across segments)
The considerable heterogeneity is seen in the image. Consumers who are very sensitive to blockchain ([?]0.9) and moderately sensitive to AI ([?]0.7) are customers who are motivated by trust, whereas those who are less sensitive to technology and more sensitive to pricing. Segment differentiation validates the need of latent class modeling.
Results of Hybrid Choice (ICLV)
In order to influence the consumer utility in the discrete choice framework, the hybrid choice model incorporates trust, a latent psychological component. The model may provide both (i) the utility equation that incorporates trust as a direct determinist of choice and (ii) the structural equation between transparency and the reduction of risk and trust.
Structural Model of Latent Equations

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The structural component demonstrates that building confidence in organic supply chains requires perceived openness and perceived risk minimization. Digitally verifiable disclosure significantly boosts customer confidence because transparency has a strong positive effect on trust (g = 0.61, SE = 0.08, $p < 0.001$). Additionally, trust is positively impacted by perceived risk mitigation (g = 0.44, SE = 0.07, $p < 0.001$), indicating that blockchain and AI-based fraud-mitigating technologies enhance institutional legitimacy.

These results highlight the importance of verifiability in the credence products market by showing that perceptions of transparency, rather than risk reduction itself, are the primary elements influencing the development of trust.

Choice Equation or Utility Model

The chance of selecting organic items enabled by blockchain and AI is also significantly influenced by trust in the utility function (b = 0.29, SE = 0.06, $p < 0.001$). This indicates that trust is not an attitudinal correlate but rather a structural driver of value.

Even when latent trust is taken into account, the fundamental characteristics of technology provide a favorable, noteworthy outcome:

1. Traceability of blockchain (b = 0.49, $p < 0.001$)
2. AI quality control (b = 0.37, $p < 0.001$)
3. Third-party audit and ledger disclosure (b = 0.68, $p < 0.001$)
4. The price is negative and significant (b = [?]0.081, $p < 0.001$).

Compared to the mixed logit model, which shows the partial mediations by trust, the blockchain and AI coefficients are somewhat less.

Comparative Performance and Primary Fit

When compared to the mixed logit model, the hybrid specification fits the model much better. The log-likelihood has improved from 2894.3 to 2768.1. The AIC decreases by around 145 to 5689.4 from 5834.6. Even with additional settings, the hybrid model's BIC drops from 5910.2 to 5780.3.

The aforementioned improvements show that psychological processes are added to behavioral realism and explanatory power.

Willingness to Pay Adjusted by Trust

The latent trust distribution's +/-1 standard deviation was used to approximate WTP. When it comes to blockchain-powered organic goods, high-trust customers have a premium on WTP of around 26%, whereas low-trust customers have a premium of 9%. This demonstrates how trust modifies price premium tolerance fundamentally and raises the marginal value of property traces.

Overall, the hybrid model provides a more understanding explanation of behavior by connecting technology signals to an economic assessment via a process mediated by trust.

Table 6 Hybrid Choice (ICLV) Model Results

Panel A: Structural Model (Trust Equation)

Path	Coefficient (γ)	Std. Error	p-value
Transparency → Trust	0.61	0.08	<0.001
Risk Reduction → Trust	0.44	0.07	<0.001

Panel B: Utility Model (Choice Equation)

Variable	Coefficient (β)	Std. Error	p-value

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Blockchain Traceability	0.49	0.09	<0.001
AI Quality Assurance	0.37	0.07	<0.001
Third-Party Audit + Ledger	0.68	0.10	<0.001
Price	−0.081	0.011	<0.001
Trust (latent variable)	0.29	0.06	<0.001

Panel C: Model Fit Comparison

Model	**Log-Likelihood**	**AIC**	**BIC**
Mixed Logit	−2894.3	5834.6	5910.2
Hybrid Choice (ICLV)	−2768.1	5689.4	5780.3

Trust is greatly impacted by transparency ($g = 0.61$, $SE = 0.08$, $p < 0.001$), followed by risk reduction ($g = 0.44$, $SE = 0.07$, $p < 0.001$). Benefits and utility are positively correlated with trust ($b = 0.29$, $SE = 0.06$, $p < 0.001$). Important third-party audit ($b = 0.68$), blockchain ($b = 0.49$), and AI assurance ($b = 0.37$) are characteristics linked to technology, whereas pricing is negative ($b = 0.081$, $p < 0.001$). The model fit is much improved (LL: 2894.3 to 2768.1: AIC reduction is 145; BIC reduction is 130). The simulated premiums vary from 9 (low trust) to 26 (great trust).

Conversation

Interpretation: Command Premium Features

The results show that the value impact of each digital intervention varies. In the list of tested qualities, third-party audit with ledger transparency has the greatest premium, followed by blockchain traceability and AI-based quality assurance. This hierarchy suggests that, in contrast to stand-alone technical instruments, the value of institutional consumer verification was higher in the scenario of stratification with technology transparency. High third-party audit premiums imply that if verification is publicly accessible and externally confirmed, trustworthiness is enhanced. In terms of tamper-resistant provenance records, blockchain provenance is likewise highly valued by customers. However, trust seems to have a role in its appraisal, which means that technical architecture cannot be employed independently without perceived integrity. AI-based quality prediction has a smaller but still substantial premium. This suggests that although predictive assurance is valued based on customer understanding of algorithm dependability, it also enhances perceived reliability. Importantly, various categories have an impact on pricing. Price-sensitive skeptics exhibit little reactivity to technical information, whereas consumers associated with trust are extremely premium tolerant. The hybrid findings, which show that preferences are connected to more than just willingness to pay, validate the structural change of trust in willingness to pay. Features that reduce ambiguity, increase verifiability, and provide indicators of responsibility are often compensated for by customers.

Recommendations for South Tamil Nadu's Organic Supply Chain Governance

The findings directly affect governance strategies in South Tamil Nadu's organic environment. The supply chain participants should place a high focus on integrated checking systems that include public registration, third-party audits, and QR code access. Due to the region's diverse market structure, which includes farm-gate, retail establishments, and internet-enabled

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disclosure infrastructures, it is possible to reduce market fragmentation and increase cross-channel dependability.

District-level variance also implies that adoption techniques need to be modified based on customer characteristics. While price-sensitive areas may need slow deployment alongside education programs, metropolitan centers like Madurai and Theni might be the first to install blockchain-based systems. A blockchain registration and AI grading integration institutional anchor might be provided by farmer-producer associations and producer cooperatives. By incorporating traceability into the existing certification processes rather than replacing them, governance organizations may also employ technology to improve institutional confidence.

Contribution to Theory

The study adds to our understanding of trust as a structural element that links economic value to technical indications. The hybrid model highlights the mediation between transparency, risk reduction, and value generation rather than seeing trust as an exogenous attitude variable. The findings corroborate the signaling hypothesis because they show that verifiability and institutional backing are more important factors in determining trustworthiness than information sharing. AI and distributed ledgers are costly, difficult-to-counterfeit indicators that reduce information asymmetry. Because it provides empirical evidence that technology is a verifiable signal in credibility goods marketplaces, the combination of psychological concepts and discrete decision modeling adds to the body of research.

Implications for Applications: Roadmap for Implementation

The implementation need to be carried out gradually. First, supply chain participants should standardize data collection at the farm level and enter it into blockchain registries that are accessible via QR codes. Second, to ensure quality consistency, AI-driven grading and anomaly detection systems should be implemented at retail or aggregation nodes. Third, in order to synchronize the digital records with the audit, the integration should be carried out with accredited certification agencies. Customers must be educated in order to translate technical characteristics into perceived advantages, particularly in price-sensitive markets. In South Tamil Nadu's organic marketplaces, an integrated ecosystem strategy including producers, certifying bodies, technology providers, and retailers would maximize the development of confidence and maintenance of high pricing.

In conclusion

The impact of artificial intelligence-based quality assurance and blockchain-based traceability on South Tamil Nadu consumers' propensity to buy organic products has been examined in this article. Using a hybrid decision-based model of choice that combines discrete choice estimation with latent trust, the findings demonstrate that technological transparency methods significantly improve valuation. Third-party audit and public ledger transparency get the greatest price, followed by blockchain traceability and AI-based quality prediction. The outcomes provided by the structures demonstrate that both transparency and a decrease in perceived risk boost trust, which in turn raises willingness to pay. The paper provides a behaviorally based explanation of the premium development in a credibility goods market by incorporating psychological factors into an economic decision model.

Because it identified trust as a mediating factor between technology signals and economic benefit, the research also makes a theoretical contribution. By scientifically verifying blockchain and AI as testable signals that might lessen information asymmetry, it expands on signaling theory. Methodologically, the combination of mixed logit, latent class segmentation, and hybrid choice modeling advances the investigation of traceability value. There are some restrictions to take into account. The stated-preference data used in the study may not accurately reflect actual purchasing behavior. It is impossible to completely rule out hypothetical bias even with the most advanced econometric procedures. Additionally, the limited scope of the South Tamil Nadu research may limit the external extrapolation to other institutional contexts. Field tests and revealed-preference transaction data should be included in future research to validate the premium estimations in actual market environments. The durability of the impacts of trust may be determined using longitudinal designs. A greater understanding of how the governance environment affects the value of digital traceability systems would be provided by the cross-state/certification regime comparative research.

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