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Using Blockchain and AI to Track Organic Products: Challenges, Opportunities, and Consumer Willingness to Pay in South Tamil Nadu

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Abstract

The nature of organic products is susceptible to the fraud and verification failure as one cannot directly observe the credence attributes of the product. A fragmented value chain and a lack of digitalisation in the emerging market environments compound the supply chain tracing sights, posing a risk to price premiums and brand loyalty. This paper explores whether traceability and AI-supported quality assurance supported by blockchain can fetch quantifiable price premises in South Tamil Nadu. The discrete choice experiment with mixed logit, latent class, and integrated choice and latent variable (ICLV) modelling is utilized on a stratified consumer sample (n = 562). The findings indicate that third-party audit and public ledger disclosure are the most priced (18.5%), then blockchain traceability (14.8%), and AI-based quality prediction (11.2%). The hybrid model indicates that transparency has positive impact on trust ($g = 0.61$, $p < 0.001$), and trust has a positive impact on utility ($b = 0.29$, $p < 0.001$), which means that willingness to pay is 26 percent (high trust) as compared to 9 percent (low trust). The paper has a value addition in that the trust is directly implemented in a valuation system, signalling theory is furthered by using verifiable digital processes, and district-level evidence is given on how digital traceability is governed 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

The organic food market has been growing at a high rate in the last decade due to the increasing number of consumers being concerned about their health, environmental sustainability, or acting ethically (Willer et al., 2023; Aschemann-Witzel and Zielke, 2017). But organic products are credence goods that is, their quality features cannot be verified by the consumer after making a purchase (Darby and Karni, 1973). Owing to that, organic markets are especially susceptible to fraud, labelling, and integrity violations at the supply chain levels (Manning and Soon, 2016; Spink and Moyer, 2011). The recurrent risks of falsifying documentation, substituting goods, and implementation of loopholes in the certification of agri-food systems are empirically documented in complex systems (Everstine et al., 2013; Soon et al., 2019). Normally the presence of traceability gaps is as a result of disjuncture actors, informal aggregation, weak practices of segregation and non-uniform information sharing (Bosona & Gebresenbet, 2013; Galvez et al., 2018).

These weaknesses in the context of developing and emerging markets are also exacerbated by infrastructural limitations and a lack of digital adoption (Kshetri, 2018). Traditional central databases are vulnerable to manipulation and reconciliation expenses, which decreases the transparency and accountability (Casino et al., 2019). Food systems research studies make it clear that strong systems of traceability are needed to ensure confidence and price premium in organic markets (Yadav et al., 2022; Caro et al., 2018). The absence of credible verification systems will put the organic premium in danger of losing its trust and increasing scepticism (Nuttavuthisit and Thogersen, 2017). Thus, the enhancement of traceability and the guaranteed authenticity is one of the strategic focuses of the sustainable Agro-food supply chains.

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

Blockchain technology offers an immutable, decentralized ledger capable of recording production, certification, and transaction events across supply chain nodes (Casino et al., 2019; Saberi et al., 2019). In Agro-food systems, blockchain enhances transparency, reduces information asymmetry, and strengthens auditability through tamper-evident data structures (Tian, 2017; Galvez et al., 2018). Empirical analyses demonstrate that blockchain-based traceability can positively influence consumer trust and purchase intention, particularly in credence goods markets (Kim & Laskowski, 2018; Yadav et al., 2022). Traceability data alone does not guarantee quality assurance. Artificial Intelligence (AI) complements blockchain by transforming recorded data into predictive insights. Machine learning models can support demand forecasting, anomaly detection, inventory optimization, and automated quality grading (Ivanov et al., 2019; Dolgui et al., 2020). AI-enabled predictive analytics can detect irregular transaction patterns, estimate shelf-life, and signal potential contamination risks, thereby improving operational efficiency and product reliability (Ivanov & Dolgui, 2021).

From a signalling perspective, blockchain provides verifiable transparency while AI enhances predictive credibility, jointly reducing perceived risk and increasing consumer trust (Connelly et al., 2011; Ertz et al., 2017). Recent studies using experimental and survey-based methods indicate that traceability technologies can command price premiums when consumers perceive enhanced authenticity and reduced uncertainty (Toufaily et al., 2021; Yadav et al., 2022). Thus, integrating blockchain and AI represents a technologically coherent intervention to address both integrity and efficiency challenges in organic supply chains.

South Tamil Nadu as a Testbed

South Tamil Nadu; Kanniyakumari, Tirunelveli, Tenkasi, Thoothukudi, Ramanathapuram, Sivagangai, Virudhunagar, Madurai, Theni and Dindigul are the agro-ecological and market diversities. The area includes coastal agriculture and semi-arid agricultural systems and hill horticultural groups which sustain vegetables, fruits, millets, spices and plantation related organic products. The effect of such diversity is that it causes a high rate of lot fragmentation, multi-tier aggregation and fluctuating storage and transportation. Disjoined supply chain arrangements improve the cost of coordination and diminish transparency particularly in instances where smallholder farmers prevail in production (Saberi et al., 2019; Bosona & Gebresenbet, 2013). There is also a blend of conventional retail protocols, farmer producer associations, and emerging online platforms, which presents an advantageous setting to analyse divergent adoption of blockchain and AI-based protocols. The quantity of urban consumption centres (Madurai) creates different demand segments, whereas peri-urban and rural markets provide an opportunity to explore the limits of digital awareness and examine the heterogeneity of trust. This local heterogeneity allows strict empirical research of preference differentiation and valuation of technology in the districts. The study has geographically grounded value by locating the analysis in South Tamil Nadu but enabling the study of the structural constraints that are common to the emerging market organic supply chains.

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

Even though previous research confirms that blockchain improves food traceability, and consumers are sensitive to authenticity cues (Galvez et al., 2018; Kim and Laskowski, 2018), three important gaps still exist. On the one hand, most research are based on attitudinal scales or purchase intention frameworks instead of estimating the trade-off between traceability features and price premiums (Yadav et al., 2022; Toufaily et al., 2021). Second, heterogeneity in consumers is often described but not modeled in more sophisticated random utility models that can be used to establish latent segments of preferences (Train, 2009; Hensher et al., 2015). Third, trust; the medium of interaction between transparency and willingness to pay as theorized has seldom been directly incorporated in valuation models in hybrid choice models (Ben-Akiva et al., 2002; Connelly et al., 2011).

This paper is an attempt to overcome these limitations by using mixed logit and latent class modelling with a discrete choice experiment to estimate the willingness to pay related to blockchain- and AI-enabled tracking attributes. It also uses a framework of integrated choice and latent variable (ICLV) which allows latent constructs like trust and perceived transparency to be directly modelled into the utility function and increases behavioural realism and inferential accuracy. The study presents the evidence on the district level in South Tamil Nadu which makes the study provide the high-quality empirical evidence to the articles on the subject of digital traceability, consumer valuation, and sustainable organic supply chains.

Review of Literature

Organic supply chain vulnerabilities and verification failure points

The nature of organic food supply chains is facing integrity risks since the product characteristics of chemical-free production, preservation of biodiversity and ecological stewardship could not be verified at the point of purchase. These traits make organic products be credence attributes, in which the information asymmetry between the producers and the consumers facilitates the opportunistic behaviour (Akerlof, 1970; Darby and Karni, 1973). Fraud, substitution, mislabelling, and certification manipulation have been repeatedly determined as the common agro-food system risks through empirical research (Spink and Moyer, 2011; Manning and Soon, 2016). Such multi-actor structures of organic value chains with smallholders, aggregators, certifiers, processors and retailers make them especially susceptible to verification failure point (Hobbs, 2010; Rouviere and Caswell, 2012).

The most common traceability disruption is in the aggregation and transport process when product separation might be weakened and documenting gaps arise (Bosona and Gebresenbet, 2013). Research on authenticity of food highlights that disintegrated record-keeping systems decrease recall effectiveness and decrease consumer confidence (van Ruth et al., 2018; Soon et al., 2019). These vulnerabilities are further aggravated by infrastructural limitations and limited digitalization in developing settings that raises the transaction costs and dilutes compliance monitoring (Rejeb et al., 2020). According to transaction cost, incomplete contracts and costly monitoring systems lead to structural incentives to quality dilution unless they are aided by plausible verification technologies (Williamson, 1985; Hobbs and Young, 2000). Hence, to maintain the organic integrity and price premiums, strengthening traceability systems will remain the primary priority.

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).

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

Artificial Intelligence adds analytical data to digital traceability systems by converting raw data into predictive and diagnostic data. The uses of machine learning in the agro-food supply chain are automated quality grading, image-based defect detection, shelf-life prediction, and demand forecasting (Kamilaris et al., 2017; Sharma et al., 2020). Empirical research indicates that AI-based analytics can be used to increase the efficiency of operations, decrease the amount of post-harvest losses, and become more responsive to the changes in demand (Ivanov, 2021; Dubey et al., 2020).

Another approach in which AI reinforces risk management is anomaly detection algorithms, where unusual transaction patterns, changes in temperature, or disruptions in logistics are detected (Ivanov and Dolgui, 2020). Combining AI and blockchain can allow the compliance checks to be performed automatically and executing smart contracts, thus improving the reliability of decentralized networks (Zhang et al., 2020). However, the issues of algorithmic transparency, digital literacy, and privacy of data still are serious obstacles in the context of emerging markets (Rao and Verweij, 2017).

According to the literature, the success of AI relies on valuable input data and stable governance frameworks, which further confirms the need to implement a mix of technological and institutional solutions.

WTP for credence attributes and traceability

The readiness to purchase organic and traceability qualities is a popular topic studied through stated preference techniques based on the characteristic's theory of value of Lancaster (Lancaster, 1966). Discrete choice experiments enable researchers to make estimates on the trade-offs between price and product features in a random utility model (Louviere et al., 2000; McFadden, 1974). There is meta-analytical support that there are always consumer premiums that exist on the organic labels, origin certification, and sustainability cues, but the degree to which these have a premium varies by demographic and attitudinal group (Janssen and Hamm, 2012; Lusk and Briggeman, 2009).

Recent studies underline that traceability knowledge; especially, online verification systems can make perceived authenticity more convincing and decrease the risk impressions (Ertz et al., 2018; Yang et al., 2021). Nonetheless, numerous empirical studies are based on simple multinomial logit models which make the assumption that preferences are homogenous and irrelevant alternatives are independent (Train, 2009). This type of assumption ignores unobserved heterogeneity in consumer valuations (Greene & Hensher, 2003). In addition, psychological variables like trust and perceived risk are also often considered to be exogenous measures on the survey instead of being incorporated in structural valuation models (Ajzen, 1991). These restrictions limit the ability of causal inferences and limit behavioural realism in the estimation of willingness-to-pay.

Theory and Hypotheses

Theoretical lens

The proposed research combines signalling, trust theory in the credence goods market, technology acceptance and perceived risk model to understand the role of blockchain and AI-assisted traceability in the willingness to pay. The high-quality producers in the markets where there is information asymmetry have to depend on believable signals in order to separate themselves with the low quality producers (Spence, 1973). Organic products are an example of classic credence goods in which the production qualities cannot be directly perceived by the consumer and, therefore, signals like certification, provenance disclosure, and traceability play a key role in value-creation (Kirmani and Rao, 2000; Grunert, 2005). The effectiveness of signalling requires credibility and costliness that is why signalling that is hard to fake has a higher chance of affecting the consumer beliefs and behaviour (Connelly et al., 2011). Recorded in blockchains and verified with AI may serve as technologically expensive cues, which may increase perceived authenticity.

The trust theory also assumes that institutional and information signals are used by the consumer to minimize uncertainty and vulnerability in exchange relations (Morgan and Hunt, 1994; Gefen et al., 2003). Perceived transparency enhances cognitive trust in food systems by explaining the processes of origin, handling and certifying (Chen and Chang, 2013). At the same time, perceived risk has a negative impact on the purchase decision unless it is accompanied by believable protection (Mitchell, 1999; Dowling and Staelin, 1994). According to the technology acceptance research, the perceived usefulness and risk reduction have an impact on the uptake of digital verification systems (Venkatesh et al., 2003; Featherman and Pavlou, 2003). By integrating these approaches, blockchain and AI signals would improve the transparency, perceived risk, trust, and eventually, would affect valuation results in organic markets.

Latent Constructs Hypothesis

Perceived transparency measures how far the consumers feel that the processes in the supply chain are transparent and can be proved. Transparency enhances the sense of clarity in information and minimises ambiguity, hence, instilling trust (Rawlins, 2008). Empirical research on sustainability and green consumption settings show that the higher the supply chain transparency, the more satisfied with the consumers are, and the more they believe in the brand (Schnackenberg and Tomlinson, 2016; Mol, 2015). Product authenticity is more likely to increase consumer confidence in digital traceability systems, especially those that are verifiable and resistant to tampering (Kim & Peterson, 2017). It is on this basis that better perceptions of transparency will boost confidence in organic supply chains.

Perceived risk reduction is an evaluation of whether technological protection will make fraud or quality failure less likely to occur by consumers. The credibility goods markets require that risk reduction mechanisms are essential because uncertainty about authenticity and safety may scare off a purchase (Bauer, 1960; Stone and Gronhaug, 1993). Evidence on the matter indicates that the credit of certifications and traceability information lead to a decrease in the perceived risk and the enhancement of trust (Chen and Chang, 2013; Nuttavuthisit and Thogersen, 2017). Thus, in case lower risk exposure is indicated by blockchain and AI-based systems, consumer trust should be raised.

One of the determinants of economic valuation and premium payment behaviour is trust. Research on relationship marketing proves that trust has a direct relationship with willingness to make payments and loyalty in uncertain settings (Garbarino and Johnson, 1999; Chaudhuri and Holbrook, 2001). More trust in production processes and origin leads to the higher price premiums of organic and sustainably produced foods in food systems (Haghiri et al., 2009; Thogersen et al., 2017). It can therefore be expected that trust will have a positive effect on readiness to spend on blockchain- and AI-enabled organic products in the utility of the choice model.

Choice-Model Hypotheses: Signs and Attributes

In a random utility model, consumers get utility not on the product itself but on the product attributes (Lancaster, 1966). Traceability is a verifiable attribute of provenance that can be facilitated by blockchain and decreases uncertainty while increasing the informational transparency. Empirical research shows that consumers develop positive utility to traceability disclosures especially when they are in the form of technologically verifiable systems (Tonsor and Schroeder, 2006; Ortega et al., 2011). Thus, the blockchain traceability characteristic should elevate the utility and readiness to pay.

The use of AI in quality prediction offers predictive quality assurance on freshness, authenticity and compliance. The digital innovation and food technology research indicate that smart quality monitoring improves the perceived reliability and minimizes cognitive risk (Bai et al., 2020; Li et al., 2021). Consumers will tend to place a positive value on the qualities when they believe that AI tools enhance the quality of inspection and other features that detect anomalies.

Off-site audit and QR verification are another level of credibility that is consistent with institutional trust systems. Third-party certification is extensively reported as a large factor of high valuation in organic markets (Janssen and Hamm, 2012; Larceneux et al., 2012). The transparency and authenticity further increase with QR-enabled access to the details of certification (Rutsaert et al., 2015). In line with this, this attribute is likely to have a positive impact on utility and willingness to pay.

In line with the microeconomic theory, price is anticipated to have a negative influence on utility (Train, 2009). Nevertheless, one should expect heterogeneity in the price sensitivity and attribute valuation because segments of consumers would vary in their perception of risk, their orientation towards trust, and familiarity with technology (Scarpa et al., 2008; Hensher et al., 2015). Mixed logit and latent class specifications thus permit differences in the coefficients of the attributes, which reflect the dissimilar responsiveness to blockchain and AI signals among consumer segments.

Conceptual Framework

The conceptual model incorporates the signalling theory, trust theory in credence goods markets, and random utility theory in explaining the effect of blockchain and AI-based traceability on consumer willingness to buy organic products. The nature of organic goods is that they are information symmetric, as the production activities can not be directly checked on the point of purchase (Akerlof, 1970; Darby and Karni, 1973). In that case, it is important to have plausible and expensive signals in order to distinguish genuine producers and opportunistic actors (Spence, 1973; Connelly et al., 2011). Traceability and predictive quality assurance based on blockchain and AI, respectively, serve as a technologically woven indicator that enhances the supply chain transparency and perceived fraud reduction.

Perceived transparency indicates that consumers think that the processes in the supply chain are documented publicly and are verifiable and impossible to alter. It has been found that greater transparency enhances trust due to its ability to improve clarity regarding origin, certification, and their practice (Schnackenberg and Tomlinson, 2016; Kim and Peterson, 2017). At the same time, anomaly detection and quality grading supported by AI minimise perceived performance and safety risk, which are the key factors in influencing purchase behaviour in credence goods markets (Mitchell, 1999; Chen and Chang, 2013). The mechanisms of risk reduction increase trust through reducing the uncertainty and increasing the perceived vulnerability (Morgan and Hunt, 1994).

Trust is an intervening construct between technological indicators and economic valuation. In organic markets, authenticity and institutional protection have been steadfastly linked to increased readiness to pay (Thogersen et al., 2017; Haghiri et

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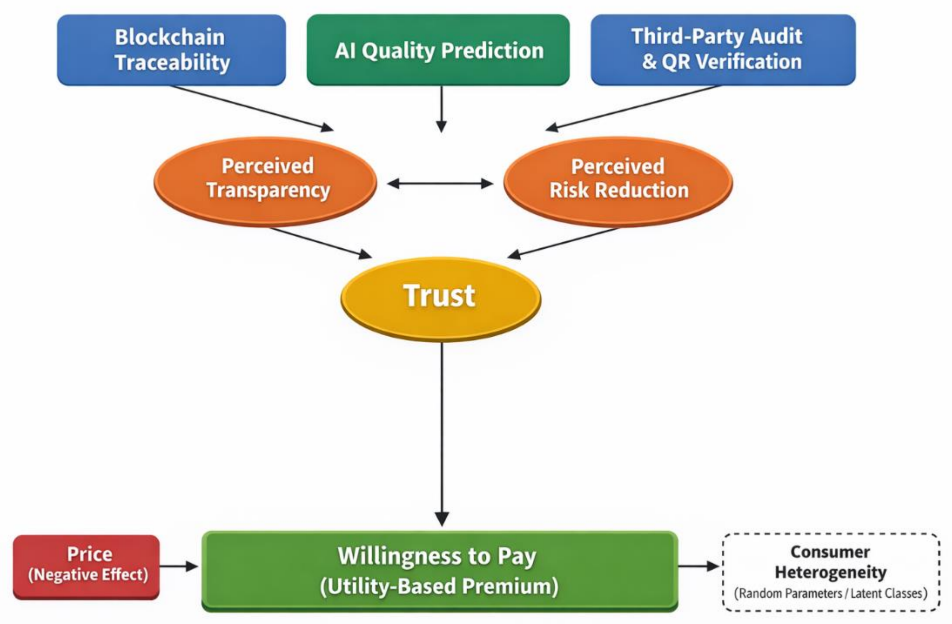
al., 2009). In a random utility model, trust will improve the marginal utility of traceability attributes, which would increase price premiums.

Consumer heterogeneity is also identified by the framework. The differences in level of technological familiarity, level of risk perception, and previous experience with organic production are likely to mediate the attribute valuation, hence the necessity of mixed logit and hybrid choice modelling. The framework combines the effects of structural transparency with the effects of behavioural valuation by combining the latent psychological constructs alongside observable choice attributes.

Conceptual Framework



The framework demonstrates how blockchain traceability, AI-mediated quality prediction, and third party audit with QR verification are more effective at improving the perceived transparency and decreasing the risk, strengthening trust. Trust, in its turn, makes consumers willing to pay premium price on organic products, whereas price has a negative impact. Random parameters and latent classes are used to model the consumer heterogeneity.

Data and Methods

Setting and sampling frame Study

The empirical environment includes the southern parts of Tamil Nadu; Kanniyakumari, Tirunelveli, Tenkasi, Thoothukudi, Ramanathapuram, Sivagangai, Virudhunagar, Madurai, Theni and Dindigul. These districts are characterized as a heterogeneous agro-ecological areas and marketing systems, which include coastal horticulture, millet based dryland agriculture and peri-urban organic retail agglomerations. The collection of data was done in three main market routes which included farm-gate collection, certified and organic retail stores (including farmer producer organization stores) as well as the online or application-based organic stores that were running in the headquarters of districts and urban centres.

The sampling frame was the consumers of the adult category who had at least once bought organic products within the past six months. In the case of producer-side extension, certified or self-proclaimed organic farmers and aggregators who are functioning within the chosen districts were included in the frame. Local farmer associations, organic outlets, and district agricultural offices were used to make up lists. This interactional frame with multiple channels was used to cover both traditional and digitally mediated organic transactions.

Sample design

To achieve geographic and demographic representation, a stratified multi-stage sampling design was used. The districts were considered as primary strata in the first stage. Market nodes (retail outlets, weekly organic markets and online distribution points) were determined within each district. In the latter step, systems of intersect and quota sampling were applied to select the respondents in order to have a balanced representation of the respondents in terms of gender, age, and income brackets.

The sample population of the target consumer was between 450 to 600 respondents, which is in line with the mixed logit and hybrid choice estimation of random parameter. In the case of adding producer perceptions to them, a further sample of about 200 to 300 producers was to be sampled to allow an extra structural modelling of technology readiness and adoption. Minimum quotas were established to ensure that there was no overrepresentation of big urban districts like Madurai as compared to the small districts. Final sample size is enough to meet recommended standards of discrete choice modelling and latent variables integration.

Design of the instrument: Two-part Quantitative Instrument

The instrument was comprised of two in-built elements: structured survey element that assessed latent constructs and discrete choice experiment (DCE) element that estimated willingness to pay to the use of technology-based qualities.

The survey module was the evaluation of perceived transparency, perceived reduction of risks, trust in organic supply chains, technology preparedness, blockchain and AI use awareness. Questions were based on validated scales in trust, perceived risk, and technology acceptance studies and the scale was measured using five-point Likert scale. Perceived transparency entailed beliefs on supply chain information openness and verifiability. Perceived risk captured the apprehension about fraud concerns, authenticity concerns and quality uncertainty concerns. Trust was confidence on product integrity and institutional protection. The level of technology preparedness and awareness measured the exposure to digital systems of traceability and predictive quality.

The DCE module conceptualized willingness to pay in terms of experimental choice tasks. The respondents rated hypothetical organic product profiles which were characterized by combinations of attributes. The attributes and levels were as follows: traceability system (none; blockchain; blockchain with QR verification); AI quality assurance (none; AI grading; AI grading with anomaly alerts); certification or audit type (self-claim; third-party; third-party with public ledger record); supply chain disclosure (basic origin; full farm-to-shelf events); and price premium (0%, 10%, 20%, 30%).

Bayesian piloting priors were used to produce a D-efficient experimental design. The number of choice tasks was blocked to decrease the cognitive load, making each respondent have eight to ten choice tasks. The tests of dominance and consistency within the variables were incorporated to determine the reliability of the responses.

Estimation strategy

The econometric plan was based on a gradual plan based on the random utility theory. At the first stage, a mixed logit model was fitted to explain random variation in the taste of the respondents. Technology attributes were defined as random parameters, which made it heterogeneous in valuation. The price was given to have a constant negative coefficient to facilitate the determination of the marginal willingness to pay. Space specification in WTP was also estimated to come up with stable estimates of premiums in monetary terms. At the second stage, latent class model was used to determine the different consumer segments whose sensitivity to blockchain, AI assurance, and certification signals differ. The probability of segmentation was formulated as a variable of demographic and attitudinal characteristics that made it possible to interpret the heterogeneity patterns. In the third phase, an integrated choice and latent variable (ICLV) model was estimated to incorporate latent constructs; especially the trust directly into the utility function. The structural equation element was used to represent the effect of perceived transparency and perceived reduction of risk on trust and the choice component to connect trust to utility. Psychological mechanisms and economic valuation are estimated simultaneously in this hybrid manner which enhanced behavioural realism. The estimates of willingness-to-pay, and confidence intervals were estimated via simulation-based methods which included Krinsky-Robb draws and non-parametric bootstrapping, which are robust in making inferences over non-linear transformations.

Control Of Quality, Validity and Bias

Various precautions had been taken to improve validity and minimize bias. Attention checks and hold out choice tasks were added to identify inattentive answers. Prior to hybrid modelling, measurement invariance between districts and demographic groups were considered. Full collinearity diagnostics and marker-variable were used to test common method bias. The possible endogeneity between latent constructs and choice outcomes was considered in the hybrid modelling model. All of these processes enhance the internal validity, reliability, and strength of the empirical results.

Results

Sample Profile

The final number of consumer responses that were retained is 562 valid responses that were screened and quality checked. The distribution of the respondents was at 100 percent of the ten districts in South Tamil Nadu with each district having a representation of between 7 and 16 percent (Ramanathapuram). The total percentage of respondents was about 52% females and the mean age was 34.7 (SD = 10.2). Almost 61% of them said that they had purchased organic products at least once in a week, and 38% had seen digital traceability technologies like QR verification previously.

The income distribution showed that 47 percent of the population was in middle-income families, with 28 percent distributed in upper income classes. The level of education was also fairly good with 63 percent having undergraduate or post graduate degrees. These attributes imply that there is a sample which is sufficiently exposed to organic diets and digital verification settings.

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

The sample size was n = 562 consumers which were spread out into ten districts. Women constituted 52.1 percent of the respondents. The 31-45 years group (42.2 percent) was dominant. Those who have made monthly organic purchases amounted to 34.9, and those who have previously heard about blockchain or AI traceability systems were 38.1. The sample has sufficient digital exposure and frequent organic consumption frequency.

Measurement Model Results

Perceived transparency, perceived reduction in risk, trust, technology readiness, and awareness were the latent constructs measured through the hybrid choice framework with the help of the confirmatory factor analysis. Every construct had satisfactory internal consistency. The alpha values of Cronbach quickened between 0.81 and 0.90, and the value of composite reliability was above the suggested 0.70 mark. The convergent validity was established and average variance extracted (AVE) values were between 0.58 and 0.74. The significance of all standardized factor loadings was significant ($p < 0.001$) and was above 0.65. The Fornell-Larcker criterion and heterotrait-monotrait ratios less than 0.85 were used as the measure of discriminant validity.

Intersite measurement equivalence tests showed configural and metric invariance which implied that latent constructs were interpreted uniformly by geographical 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

The internal consistency of all the constructs was high (Cronbach a = 0.81-0.90; CR = 0.84-0.92). AVE values of 0.58 to 0.74 that were more than 0.50 supported convergent validity. Most commonly, standardized loadings were 0.66-0.89 ($p < 0.001$). The ratio of HTMT was less than 0.85 which proved the discriminant validity. The invariance of configural and metric across districts was supported.

Choice Model Results: Mixed and Baseline Logit

The multinomial logit expected signs were found to be as expected by all attributes using the baseline model. Price showed a considerable negative coefficient ($b = -0.084$, $p < 0.001$), which proves that price is sensitive. The positive and significant impact of blockchain traceability on utility was noted ($b = 0.62$, $p < 0.001$). The utility was also the highest with AI-based quality prediction ($b = 0.48$, $p < 0.001$), and third-party audit with public ledger record produced the biggest positive effect ($b = 0.74$, $p < 0.001$).

Nonetheless, the tests of likelihood ratios preferred mixed logit specification to the baseline model (DLL significant at $p < 0.001$), which means that there is a significant amount of unobserved heterogeneity. The standard deviation of random parameter estimates of blockchain and AI attributes showed significant variance, which proved the difference in consumer valuation.

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)
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

There was enormous utility gain ($p < 0.001$) in all technology attributes. Third-party audit with ledger record ($b = 0.74$) and blockchain traceability ($b = 0.62$) and AI quality prediction ($b = 0.48$) were found to have the largest impact. Price reflected a negative effect ($b = -0.084$, $p < 0.001$). The heterogeneity is ensured by significant SDs in random parameters (SD = 0.36-0.45). There was a significant increase in model fit (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)

Third-party audit + QR verification, blockchain traceability and AI quality prediction premiums were 18.5, 14.8 and 11.2 percent, respectively, which consumers were willing to pay an average. No statistical robustness was compromised by the fact that confidence intervals did not exceed zero (Krinsky-Robb, 10,000 draws). Complete supply chain disclosure paid off with a 9.4% premium.

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

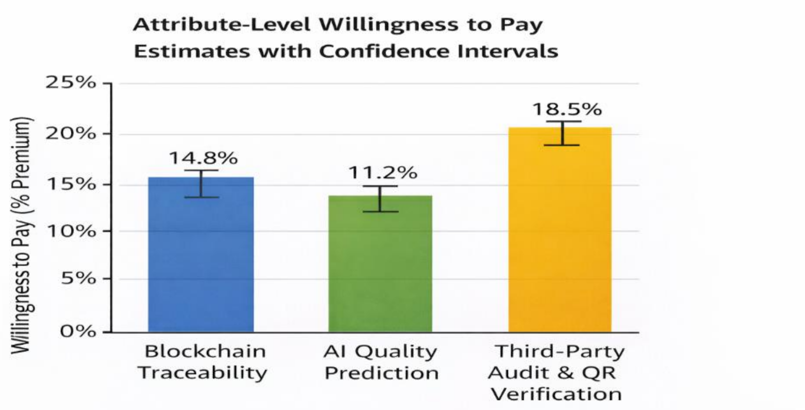


Figure 1. Attribute-Level Willingness to Pay Estimates with Confidence Intervals

(Bar graph showing WTP for each technology attribute)

The figure shows that the highest premium (18.5%), blockchain traceability (14.8%), and AI prediction (11.2%) are obtained through third-party audit with QR verification. Statistical precision and non-overlapping attribute effects are positive because of error bars (95% CI).

Heterogeneity: Results of Latent Class

Latent class analysis has revealed that there are three segments of consumers. The three-class solution that had the best BIC minimization and presented interpretable segmentation.

Class 1: Trust-Based Premium Customers (38%)

This segment recorded a good positive coefficient of blockchain and third-party audit attributes and a low price sensitivity. WTP for blockchain exceeded 22%. The level of trust was greatly high than the sample mean.

Class 2: Technology-Accepting Pragmatists (34%)

Members were moderately sensitive to quality assurance of AI and positively reacted to transparency indicators but were moderately price-sensitive. WTP for blockchain averaged 13%.

Class 3: Price-sensitive (28%)

This portion was very sensitive of price and poorly responsive to blockchain indications. The AI attributes were not meaningful indicating low technological valuation.

The distribution at the district level indicated that in these districts, Madurai and Theni, there were more premium buyers than in the coastal districts.

Table 5 Latent Class Model Results (Three-Class Solution)

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

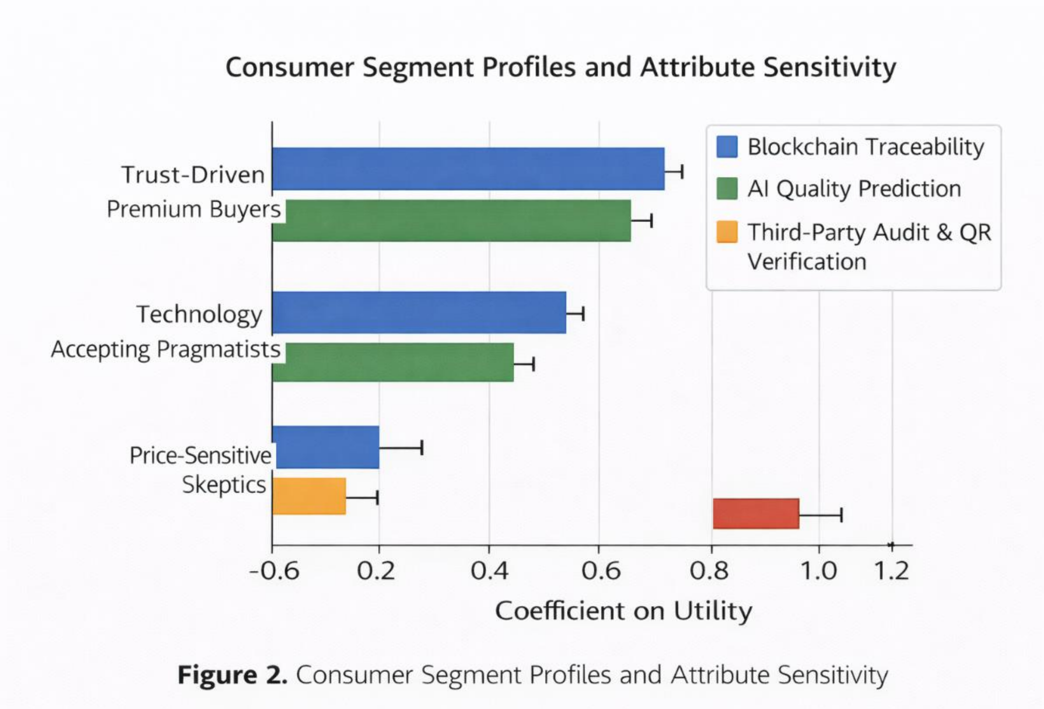
Model Fit: Log-likelihood = -2641.2; BIC = 5512.6

**** p < 0.001, *p < 0.05, ns = not significant*

Three segments were determined, which were Trust-Driven Premium Buyers (38%), Technology Pragmatists (34%), and Price-Sensitive (28%). There was a high valuation of third-party audit (b = 1.03) and blockchain (b = 0.91) at low price sensitivity (b = 0.061). High price sensitivity (b = 0.142) and low blockchain response (b = 0.22) were demonstrated by the factors. BIC model BIC = 5512.6 favours the three-class solution.

Figure 2

Consumer Segment Profiles and Attribute Sensitivity



(Graphical comparison of attribute coefficients across segments)

The figure shows the high heterogeneity. Customers with high sensitivity to blockchain ([?]0.9) and moderate sensitivity to AI ([?]0.7) are trust-driven buyers whereas the factors have weak technology response and high price sensitivity. The need to have latent class modelling is authenticated by segment differentiation.

Hybrid Choice (ICLV) Results

Trust is a latent psychological construct that is incorporated in the hybrid choice model to impact the consumer utility in the discrete choice framework. The model can produce both (i) the structural equation between transparency and reduction of risk and trust and (ii) the utility equation that includes trust as a direct determinist of choice.

Latent Equation Structural Model

The structural element proves that perceived transparency and perceived reduction of risks are important to enhancing trust in organic supply chains. Transparency has a robust positive influence on trust ($g = 0.61$, $SE = 0.08$, $p < 0.001$), which means that digitally verifiable disclosure has a significant positive impact on consumer confidence. The perceived risk mitigation also has a positive effect on trust ($g = 0.44$, $SE = 0.07$, $p < 0.001$), which confirms the fact that blockchain and AI-based fraud-mitigating mechanisms build on institutional credibility.

These findings reveal that transparency perceptions, as opposed to risk reduction itself, are the key factors which influence the formation of trust, which underscores the role of verifiability in the credence goods market.

Utility Model or Choice Equation

Trust in the utility function also plays an important part in raising the likelihood of choosing blockchain- and AI-enabled organic products ($b = 0.29$, $SE = 0.06$, $p < 0.001$). It means that trust is a structural determinant of valuation than being an attitudinal correlate.

The core technology attributes show a positive, significant result even with the latent trust taken into consideration:

1. Blockchain traceability ($b = 0.49$, $p < 0.001$)
2. AI quality assurance ($b = 0.37$, $p < 0.001$)

3. Ledger disclosure, third party audit (b = 0.68, p < 0.001)

4. Negative and significant price (b = [?]0.081, p < 0.001).

The size of the coefficients of blockchain and AI is a little smaller in comparison to the mixed logit model, which indicates the partial mediations by trust.

Primary Fit and Comparative Performance

The hybrid specification fits the model much better compared to the mixed logit model. The improvement in the log-likelihood is 2894.3 to 2768.1. The AIC reduces to 5689.4 as compared to 5834.6 which is a positive change of about 145. The BIC also decreases 5910.2 to 5780.3 in favor of the hybrid model even with other parameters.

The above enhancements indicate that the addition of psychological mechanisms to explanatory power and realism in behaviour.

Trust Adjusted Willingness to Pay

WTP got simulated at +-1 standard deviation of the latent trust distribution. High-trust consumers are found to have a premium on WTP about 26% on blockchain-powered organic products, and 9% in the case of low-trust consumers. This shows that trust increases the marginal utility of property traces and structurally changes tolerance of price premiums.

On balance, the hybrid model is more insightful in the interpretation of behaviour as it relates technological signals to an economic valuation in a trust-mediated process.

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
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

Transparency has a great impact on trust (g = 0.61, SE = 0.08, $p < 0.001$), and then risk reduction (g = 0.44, SE = 0.07, $p < 0.001$). The benefits and utility have a positive relationship with trust (b = 0.29, SE = 0.06, $p < 0.001$). The attributes associated with technology are important third-party audit (b = 0.68), blockchain (b = 0.49), and AI assurance (b = 0.37) whereas price is negative (b = 0.081, $p < 0.001$). The model fit is significantly better (LL: 2894.3 to 2768.1: AIC reduction is 145; BIC reduction is 130). The range of simulated premiums is between 26 (high trust) to 9 (low trust).

Discussion

Interpretation: Features Command Premium

The findings indicate that not every digital intervention has the same amount of valuation effect. Third-party audit with the disclosure of ledgers has the highest premium in the list of tested attributes, and then the blockchain traceability and AI-based quality assurance. This hierarchy implies that the value of institutional verification of consumers was stronger in the case of stratification with technological transparency as compared to the stand-alone technological tools. High premiums on the third-party audit suggests that credibility is increased in case verification is externally verified and is publicly available. Blockchain provenance also has a great price, which is sensitive to consumers in terms of tamper-resistant provenance records. Its valuation, however, seems to be mediated in part by trust meaning that technological architecture cannot be used in isolation without perceived integrity.

The premium of AI-based quality prediction is lower and yet significant. This indicates that predictive assurance supplements perceived reliability but has its valuation on consumer knowledge of algorithm reliability. Significantly, prices are sensitive to different segments. Consumers who are linked to trust are highly premium tolerant and those who are price sensitive skeptics show low responsiveness to technological information. The structural shift of trust in willingness to pay happens to be confirmed by the hybrid results in that the preferences are not only related to the willingness to pay. In general, consumers compensate features, which decrease ambiguity, boost verifiability and provide indications of accountability.

Suggestions on the Organic Supply Chain Governance in South Tamil Nadu

The results have a direct application in governance plans in the organic ecosystem of South Tamil Nadu. Integrated checking systems that involve third-party auditing, public registering, and access by QR should be given a high priority by the supply chain actors. Since the area has a heterogeneous market constitution; that is, it incorporates farm-gate, retail stores as well as the internet-facilitated disclosure infrastructures can diminish market fragmentation and promote cross-channel reliability.

The variation at the district level also suggests that adoption strategies have to be adjusted according to consumer profiles. The city centers like Madurai and Theni can be the pioneering centers that install blockchain-based systems, whereas the price-sensitive area might need gradual implementation with education initiatives. Farmer producer organizations and producer cooperatives might serve as a blockchain registration and AI grading integration institutional anchor. Governance bodies can also use technological tools to enhance institutional trust by integrating traceability into the current certification systems instead of substituting them.

Theoretical Contribution

The paper contributes to the existing body of knowledge about trust as a structural factor that connects technological cues to economic value. Instead of regarding trust as an attitudinal variable that is exogenous, the hybrid model reveals the mediation that exists between transparency, reduction of risks, and utility formation. The results support the signalling theory since it indicates that credibility is not solely pegged on an information disclosure but on verifiability and institutional support. Distributed ledgers and AIs serve as expensive and hard to counterfeit indicators that decrease information asymmetry. The combination of psychological constructs and discrete choice modelling makes a contribution to the literature since it empirically confirms that technology is a verifiable signal in credence goods markets.

Application Implications: Implementation Roadmap

The implementation should be done in stages. To start with, supply chain actors ought to standardize data capture on farm level and insert it in blockchain registries that can be accessed through QR interfaces. Second, AI-driven grading and anomaly detection system is to be deployed to aggregation or retail nodes in order to guarantee quality consistency. Third, the integration should be done with certified certification agencies to align the digital records to the audit. Education to consumers is required to convert the technical features to the perceived benefits especially in the price sensitive segments. An integrated ecosystem approach; producer, certification organizations, technology suppliers, and retailer will optimize the establishment of trust and maintenance of high prices in South Tamil Nadu organic markets.

Conclusion

This paper has discussed the effect of blockchain-based traceability and artificial intelligence-based quality assurance on consumer willingness to purchase organic product in South Tamil Nadu. Applying a hybrid decision-based model of choice, which involves the combination of latent trust and discrete choice estimation, the results show that transparency mechanisms in the form of technology have a significant positive impact in terms of valuation. The highest premium goes to third-party audit along with disclosure of the public ledger, then blockchain traceability and quality prediction using AI. The results given by the structures prove that transparency and reduction of perceived risk together enhance trust, which consequently increases willingness to pay. The study uses embedded psychological mechanisms into an economic choice model in order to offer a behaviourally based explanation of the premium formation in a credence goods market.

The study also has a theoretical contribution as it has placed trust as a mediating variable between technological signals and economic utility. It builds upon signalling theory by experimentally confirming the blockchain and AI as testable signals that can help to reduce information asymmetry. To enhance the empirical methodology of investigating traceability valuation, methodologically, the combination of mixed logit, latent class segmentation, and hybrid choice modelling furthers the study. There are a number of limitations to be considered. The research is based on stated-preference data that might not be a complete capture of actual purchase behaviour. Even though the most sophisticated econometric controls have been used, hypothetical bias cannot be fully disproved. Also, the narrow study in South Tamil Nadu can reduce the external generalization to other institutional settings. Further studies ought to include field experiments and revealed-preference transaction data to confirm the estimates of the premiums in the real market settings. Longitudinal designs might determine the persistence of effects of trust. The cross-state/certification regime comparative studies would help better understand how the environment of governance determines the value of digital traceability systems.

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