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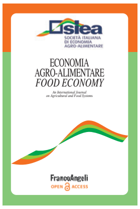

AI and Consumer Perception of Expertise: A Conceptual Framework for Studying Algorithmic Trust in Wine Recommendations

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Abstract

Artificial intelligence (AI) is transforming how consumers in credence-based markets search for, interpret, and trust product information. In the wine sector, where authenticity and quality depend on symbolic and experiential cues, AI-driven recommendation systems increasingly act as new intermediaries. This paper develops a conceptual framework explaining how consumers perceive algorithmic expertise and form trust in AI-generated wine recommendations. Integrating theories of information asymmetry, signalling, source credibility, and trust in automation, the framework identifies AI transparency and source framing as key drivers of perceived expertise and trustworthiness. These perceptions, moderated by literacy, cultural orientation, and risk, influence purchase intention and reliance on AI advice. The study highlights AI as both a signalling and screening institution that can reduce but also redistribute information asymmetries in agri-food markets. The paper concludes with methodological and policy directions for ensuring transparent and consumer-centred AI adoption in the food and wine industries.

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Introduction

The rapid digitalisation of agri-food markets is transforming the way consumers search for, evaluate, and select products. Artificial intelligence (AI) systems increasingly act as intermediaries between producers and consumers by generating product recommendations, quality predictions, and personalised advice. From e-commerce platforms suggesting "wines you may like" to AI-driven chatbots capable of mimicking sommelier expertise, algorithmic agents are becoming key actors in shaping consumption decisions (Festa *et al.*, 2025; Cao, 2025). At the same time, AI systems not only transform the channels through which consumers access products but also transform the nature of expertise and trust that underpin consumer decisions (Glikson & Woolley, 2020; Longoni & Cian, 2022). These technologies analyse vast datasets, predict preferences, and personalise communication at a scale and speed previously unattainable, thereby redefining how value and meaning are co-created between producers, intermediaries, and consumers (Paschen *et al.*, 2020; Pizzi *et al.*, 2021).

In the agri-food sector, where authenticity, quality, and provenance are essential to consumer choice, AI-driven recommendation systems introduce both opportunities and risks. Beyond its role as a technological tool for information processing, AI increasingly operates as a quasi-social actor, shaping how consumers perceive expertise, authority, and trust. Through conversational interfaces, recommendation narratives, and anthropomorphic cues, AI systems actively participate in the social construction of expertise rather than merely transmitting information (Lindgren & Holmström, 2020; Munnuka *et al.*, 2022; Mariani *et al.*, 2023).

This means that, on the one hand, algorithms can reduce information asymmetries by helping consumers navigate complex product assortments and interpret multidimensional quality cues, such as origin, sustainability, or expert ratings (Akerlof, 1970; Darby & Karni, 1973). On the other hand, they may create new forms of opacity and dependence, as consumers often cannot verify how or why a particular product is recommended (Miller, 2019). The resulting "black-box" effect raises questions about transparency, fairness, and accountability in digital decision environments (Glikson & Woolley, 2020; Von Eschenbach, 2021).

In agri-food and wine markets, such opacity is particularly problematic because authenticity, origin, and quality are central credence attributes that cannot be independently verified by consumers (Caswell & Mojduszka, 1996; Charters, 2006). When recommendation logic remains opaque, consumers may struggle to assess whether algorithmic advice reflects genuine product characteristics, commercial incentives, or hidden biases, potentially undermining confidence in digital intermediaries and trust in food systems more broadly (McCluskey & Loureiro, 2003; Reitano *et al.*, 2024).

Trust therefore becomes a central determinant of consumer acceptance of algorithmic advice, particularly because AI systems operate simultaneously as technical decision tools and as socially perceived sources of expertise. Previous research on trust in automation demonstrates that transparency, perceived expertise, and perceived benevolence are critical antecedents of user trust (Hoff & Bashir, 2015). In recommendation systems, trust formation is further complicated by the dual nature of AI as both a technological tool and a social actor (Castelo *et al.*, 2019; Lee & See, 2004). Consumers may anthropomorphize digital assistants, attributing human-like competence or warmth, yet simultaneously fear loss of control or bias. Such ambivalence gives rise to phenomena of algorithm aversion – a tendency to reject algorithmic output after observing error – and, conversely, algorithm appreciation, where algorithms are perceived as more objective and consistent than humans (Dietvorst *et al.*, 2015; Logg *et al.*, 2019; Pizzi *et al.*, 2021).

Understanding this transformation is particularly important in markets characterised by information asymmetries and credence attributes, such as the wine sector. Many of a wine's quality attributes – such as terroir, craftsmanship, or cellar ageing – cannot be fully assessed prior to purchase or even after consumption (Hanf, 2000; Cardebat & Livat, 2016). Consumers traditionally rely on expert ratings, origin labels, and storytelling to infer quality (Orth *et al.*, 2007; Ashton, 2013; Mora & Livat, 2013; Kaimann *et al.*, 2023). Today, digital recommendation systems, blockchain traceability platforms, and AI-enhanced virtual sommeliers increasingly mediate these signals, raising questions about how algorithmic expertise is perceived relative to human expertise (Wien & Peluso, 2021; Kramer *et al.*, 2024; Kopsacheilis *et al.*, 2024; Velasco *et al.*, 2024; Tassiello *et al.*, 2025). Recent systematic reviews further confirm that consumer responses to AI in agri-food systems are shaped by perceptions of transparency, fairness, and expertise attribution, rather than by technical performance alone (Reitano *et al.*, 2024; Reitano *et al.*, 2025).

Wine quality, authenticity, and origin cannot be verified before purchase and are difficult to assess even after consumption (Hanf, 2014). Consequently, consumers have historically relied on human experts and established reputation mechanisms to infer quality and reduce uncertainty. With AI systems assuming advisory and evaluative functions traditionally held by experts, a new question arises: How do consumers perceive and construct trust in algorithmic expertise?

Addressing this question requires re-examining the foundations of consumer trust in digital contexts. While marketing research has long recognised trust as a key driver of online purchase behaviour (Gefen *et al.*, 2003), little is known about how trust operates when the source of information is a non-human, algorithmic system.

Prior research on trust in AI and recommendation agents remains conceptually fragmented, often treating cognitive evaluations (such as accuracy or competence) and affective responses (such as comfort, warmth, or anxiety) in isolation rather than as jointly shaping trust formation (Benbasat & Wang, 2005; McKnight *et al.*, 2011; Glikson & Woolley, 2020). As a result, existing studies offer limited conceptual guidance on how these cognitive and affective mechanisms interact in algorithmic recommendation contexts, or on how such processes can be empirically examined in a systematic manner.

The introduction of AI therefore challenges established constructs of credibility, authenticity, and authority in markets traditionally grounded in human expertise and narrative mediation. In sectors such as wine – where emotional, cultural, and symbolic values coexist with technological innovation – understanding this transformation matters not only for theory but also for managerial and policy decision-making (De Toni *et al.*, 2022; Pizzi *et al.*, 2021). It remains unclear whether AI systems are perceived as expert, objective, or alien sources of advice, and how these perceptions shape purchasing behaviour, willingness to pay, and perceived authenticity.

The purpose of this paper is to address this gap by developing a conceptual framework for analysing consumer perceptions of expertise and trust in AI-based wine recommendation systems. Drawing on theories of information asymmetry, signalling, and source credibility, the paper proposes that consumers interpret algorithmic advice through both cognitive (perceived competence, transparency) and affective (trust, authenticity) dimensions. It also discusses how methodological innovations – ranging from digital experiments and vignette studies to eye-tracking and sentiment analysis – can enhance our understanding of consumer responses to AI-generated recommendations. By integrating theoretical and methodological insights, the paper aims to contribute to the growing debate on how digital technologies reshape consumer behaviour in the agri-food sector, highlighting the need for responsible and transparent use of AI in guiding consumer choice.

1. Theoretical Background

Understanding consumer behaviour toward AI-driven recommendation systems in the agri-food sector requires integrating insights from multiple theoretical traditions. The literature on information asymmetry, signalling, source credibility, and trust in automation provides a complementary foundation for analysing how consumers assess expertise and develop trust in digital intermediaries. This chapter outlines the conceptual premises of these theories and explains how they converge in the context of algorithmic mediation.

1.1. *Information Asymmetries and Credence Goods in the Agri-Food Sector*

Markets for agri-food and wine products are often characterised by information asymmetries between producers and consumers (Akerlof, 1970). Consumers cannot directly observe critical quality attributes such as production methods, sustainability practices, or authenticity before purchase. These credence attributes remain uncertain even after consumption (Darby & Karni, 1973). As a result, purchasing decisions rely heavily on indirect signals – labels, certifications, expert scores, or price – as proxies for underlying quality.

The wine sector exemplifies this dynamic. Although intrinsic attributes like taste or aroma can be experienced, much of wine's perceived value stems from extrinsic cues such as reputation, origin, or expert evaluation (Lockshin *et al.*, 2005; Cardebat *et al.*, 2014; Ashton, 2014; Livat *et al.*, 2019). Because these signals function as quality heuristics, their credibility depends on consumers' trust in the institutions or individuals who provide them. Traditionally, wine critics, sommeliers, and guides have played a crucial role in reducing uncertainty and aligning perceptions between producers and consumers. In economic terms, these experts act as information intermediaries who perform screening and signalling functions, thereby mitigating market inefficiencies caused by asymmetric information.

AI-based recommendation systems increasingly function as additional algorithmic signals, complementing or partially substituting traditional cues by aggregating and interpreting multiple quality indicators on behalf of consumers. Recent studies also show that algorithmic transparency improves user confidence and acceptance, especially when explanations are simple and human-centric (Miller, 2019; Longoni & Cian, 2022). However, when signals are overly technical or inconsistent, they can increase skepticism or cognitive fatigue (Pieters, 2008). From this perspective, AI systems act as new signalling institutions, shaping perceptions of trustworthiness in markets where traditional human intermediaries are being replaced or augmented by digital ones.

1.2. *Source Credibility and Perceived Expertise in Consumer Decision-Making*

Within consumer behaviour theory, source credibility has long been recognised as a determinant of persuasion and trust (Hovland & Weiss, 1951; Ohanian, 1990). The perceived expertise, trustworthiness, and attractiveness of the information source shape consumers' evaluations and willingness to act on recommendations. When the source of advice is an algorithm rather than a human expert, these dimensions translate into assessments of system competence (accuracy, domain knowledge) and reliability (consistency, transparency, and fairness), which jointly determine whether AI-based advice is perceived as credible (Lee & See, 2004; Hoff & Bashir, 2015; Shin, 2021).

In the wine market, where symbolic and experiential dimensions intertwine, the expert's authority often substitutes for direct knowledge or experience (Ashton, 2013; Cardebat & Livat, 2016; Kaimann *et al.*, 2023). The consumer's confidence in a rating or recommendation is therefore closely tied to the expert's perceived legitimacy and competence.

However, the growing digitalisation of food and wine communication has blurred traditional boundaries of expertise. Online reviews, peer platforms, and algorithmic recommender systems increasingly complement – or even replace – human experts (Dubois, 2025). This shift challenges the conventional understanding of expertise as a function of human judgement and professional training. Instead, expertise becomes algorithmically mediated, shaped by data-driven models that emulate human evaluation processes. The consequence is a redefinition of what constitutes credible expertise and how consumers perceive authority in digital environments.

As such, AI-based recommendation systems represent a novel type of communicator – non-human, data-driven, and adaptive. Consumers evaluate such systems using similar psychological heuristics to those they apply to human experts (Dietvorst *et al.*, 2015; Castelo *et al.*, 2019; Logg *et al.*, 2019). When the AI system displays consistent accuracy, appropriate reasoning, and domain-specific knowledge, it is perceived as competent; when it demonstrates fairness, ethical behaviour, and transparency, it is perceived as trustworthy (Glikson & Woolley, 2020). In the agri-food sector in general, and the wine sector in particular – where emotional and cultural associations play an essential role, source framing affects consumer reactions (Kim & Sundar, 2012).

In the agri-food sector in general, and the wine sector in particular, where emotional and cultural associations play an essential role, source framing – whether an AI is presented as a neutral tool or as a "virtual sommelier" – affects consumer reactions (Kim & Sundar, 2012; Moeskops, 2022; Beverland, 2006).

1.3. *Algorithmic Trust and AI Explainability*

Recent research on trust in AI extends traditional notions of credibility to encompass the perceived reliability, transparency, and fairness of algorithmic systems (Glikson & Woolley, 2020). Trust in AI differs from interpersonal trust in that it is grounded less in social relationships and more in cognitive evaluations of system performance, predictability, and alignment with user goals (Lee & See, 2004; Verma *et al.*, 2021). In human-machine interaction, trust develops when users perceive an automated system to be competent, reliable, and appropriately aligned with human intentions, while excessive trust can lead to complacency and insufficient trust can result in underuse or outright rejection (Hancock *et al.*, 2011; Hoff & Bashir, 2015).

In consumer decision contexts, these dynamics manifest as algorithm aversion and algorithm appreciation. Consumers may reject algorithmic advice after observing small mistakes – even when the system performs objectively better than humans (Dietvorst *et al.*, 2015) – yet in other situations they prefer algorithmic recommendations for tasks perceived as objective, data-driven, or analytical (Logg *et al.*, 2019). The balance between these tendencies depends heavily on transparency, framing, and user experience (de Visser *et al.*, 2018; Longoni & Cian, 2022).

A central challenge underlying these divergent responses is the opacity of machine learning systems, which limits users' ability to understand how recommendations are generated and to assess whether algorithmic outputs align with their preferences, values, or expectations (Miller, 2019; von Eschenbach, 2021). To mitigate this "black-box" problem, the field of Explainable AI (XAI) seeks to translate complex algorithmic operations into intelligible, human-understandable explanations that support user understanding, perceived control, and appropriately calibrated reliance (Ribeiro *et al.*, 2016; Lee & See, 2004; Shin, 2021). Experimental studies demonstrate that the framing and transparency of AI-generated advice critically shape user acceptance: recommendations presented as collaborative or human-augmented ("AI-assisted expert") tend to elicit higher trust and adoption than those described as fully autonomous (Langer *et al.*, 2023; Longoni & Cian, 2022; Kim & Sundar, 2012). Transparent explanations also serve as cognitive aids, reducing uncertainty and increasing the perceived fairness and control of automated systems (Eiband *et al.*, 2018; Verma *et al.*, 2021).

Trust in automation is therefore context-dependent and co-evolutionary as it evolves over time through interaction, feedback, and performance consistency (de Visser *et al.*, 2018; Hoff & Bashir, 2015). In the agri-food sector, and particularly in the wine industry, trust in AI intersects with emotional, cultural, and moral dimensions such as authenticity, provenance, and sustainability – elements that historically underpinned human expertise and artisanal value (Beverland, 2006; Pizzi *et al.*, 2021).

In these settings, consumers may simultaneously value efficiency, precision, and personalization while seeking the reassurance of human-like judgment, narrative, and taste. The interaction between algorithmic precision and perceived human warmth thus becomes central to the formation of trust in AI-mediated experiences (Kim & Sundar, 2012; Moeskops, 2021). As recommendation systems evolve from impersonal databases to "virtual sommeliers" capable of storytelling and contextual reasoning, they redefine what counts as expertise in markets where emotion, culture, and identity are integral to consumption (Arakawa *et al*., 2024).

1.4. *Gaps and Conceptual Opportunity*

Despite growing attention to AI in marketing and consumer research, empirical and conceptual studies focusing on algorithmic trust in credence goods remain scarce. The wine sector provides an especially fertile ground for such investigation: it combines high symbolic value, multi-dimensional quality attributes, and deep-rooted traditions of expert mediation. These characteristics amplify the relevance of trust and expertise attribution, as consumers must navigate complex sensory, cultural, and reputational cues when evaluating wine quality.

The integration of AI recommendation systems into this domain raises novel questions about how consumers form perceptions of algorithmic expertise, how trust operates in digital decision environments, and how transparency and framing influence behavioural outcomes.

This paper therefore builds on the theoretical intersections between information asymmetry, source credibility, and algorithmic trust to develop a conceptual framework explaining consumer responses to AI-generated wine recommendations. In particular, the framework focuses on cognitive effort, perceived expertise, and perceived trustworthiness as the core mechanisms through which consumers evaluate algorithmic advice in a credence-goods context. Cognitive effort captures the information-processing costs associated with interpreting AI outputs, perceived expertise reflects competence attributions toward the system, and perceived trustworthiness represents the relational acceptance of algorithmic recommendations under conditions of uncertainty. The next section presents this framework and outlines the key constructs and relationships that support the formation of trust and perceived expertise in algorithmic contexts.

2. Conceptual Framework: Algorithmic Expertise and Consumer Trust

2.1. *Overview*

The emergence of artificial intelligence (AI) in consumer decision environments has transformed how individuals evaluate information, attribute expertise, and form trust. In agri-food markets – consumers frequently rely on intermediaries to interpret complex quality cues and reduce uncertainty (Akerlof, 1970; Darby & Karni, 1973) – in particular in a credence-based category such as wine. As AI systems increasingly replace or complement traditional experts, understanding the antecedents and mechanisms of algorithmic trust becomes paramount.

Building on the theoretical foundations of information asymmetry, signalling theory, source credibility, and trust in automation, the framework proposed here explains how consumers perceive AI-based recommendation systems as competent, trustworthy, or reliable sources of advice. Specifically, it suggests that AI transparency and source framing shape consumer perceptions of expertise, trustworthiness, and ease of understanding, which together determine behavioural outcomes such as purchase intention, reliance on AI advice, and satisfaction. These relationships are moderated by individual and contextual factors including digital literacy, product knowledge, cultural orientation, and perceived risk (Gefen *et al.*, 2003; Hoff & Bashir, 2015; Awad *et al.*, 2020).

2.2. *AI Transparency and Explainability*

Transparency refers to the degree to which an AI system communicates how its recommendations are generated. Research in human-AI interaction shows that transparent systems elicit greater perceived competence and fairness, provided that explanations are understandable and matched to user expertise (Miller, 2019; Glikson & Woolley, 2020). In recommendation systems, explainability enhances user trust when it helps consumers form a coherent "mental model" of how the algorithm functions (Verma *et al.*, 2021; Kunkel *et al.*, 2019). Conversely, excessive or overly technical detail can create confusion, raise cognitive effort, and paradoxically reduce trust (Longoni & Cian, 2022; Angelov *et al.*, 2021).

In the context of credence goods, AI transparency performs a function analogous to quality signals in traditional signalling theory (Spence, 1973; Connelly *et al.*, 2011). A transparent algorithm effectively signals the reliability of its data sources and decision logic. Consumers interpret this signal as an indicator of expertise and integrity – attributes that mitigate uncertainty about product authenticity or suitability (Schnackenberg & Tomlinson, 2016; Macready *et al.*, 2020). Thus, transparency and explainability are not simply ethical imperatives but also strategic trust-building mechanisms.

2.3. *Source Framing and the Human-AI Comparison*

How the source of a recommendation is framed strongly influences perceived expertise and trust. Studies in algorithmic decision-making demonstrate that consumers evaluate identical advice differently depending on whether it is presented as coming from a human expert or an AI system (Dietvorst *et al.*, 2015; Logg *et al.*, 2019). After witnessing algorithmic error, users tend to show algorithm aversion, preferring human judgment despite equal or superior algorithmic accuracy (Dietvorst *et al.*, 2015). However, when algorithms are framed as collaborative or human-augmented, consumers often exhibit algorithm appreciation, perceiving such systems as both competent and objective (Longoni & Cian, 2022).

This framing effect aligns with classical source-credibility theory, which states that perceived expertise and trustworthiness are the primary determinants of persuasive impact (Hovland & Weiss, 1951; Ohanian, 1990). Anthropomorphic framing, i.e., portraying the AI as a "virtual sommelier" or "digital assistant", can elicit warmer responses and greater engagement, while highly mechanical framing may signal cold precision but lower empathy.

Such framing choices highlight a fundamental competence–warmth trade-off: while anthropomorphic cues enhance emotional engagement and approachability, more mechanical framing may reinforce perceptions of analytical precision and objectivity. This trade-off is central to consumer acceptance of AI systems, as framing cues shape expectations about whether algorithmic advice should be evaluated primarily in terms of human-like warmth or technical competence (Cuddy *et al.*, 2008; Castelo *et al.*, 2019; Kim & Sundar, 2012).

2.4. *Perceived Expertise, Trustworthiness, and Cognitive Effort*

Perceived expertise represents consumers' beliefs about the AI system's competence and depth of knowledge. It is influenced by prior experience, system performance, and the quality of explanations (Glikson & Woolley, 2020). In recommendation contexts, expertise is often inferred from accuracy, personalization, and data diversity – attributes associated with analytical power rather than social experience (Paschen *et al.*, 2020).

Perceived trustworthiness extends beyond competence to include integrity and benevolence (Gefen *et al.*, 2003). Consumers trust AI systems when they believe that algorithms act in their best interest and make consistent, unbiased decisions (Hoff & Bashir, 2015). Trust is thus the mediating construct linking system attributes (e.g., transparency, framing) to behavioural outcomes.

Cognitive effort, or the mental resources required to process explanations, also affects these perceptions. Studies in information-processing theory show that when explanation formats match the consumer's literacy level, cognitive fluency enhances trust and satisfaction; when explanations are complex or contradictory, cognitive strain triggers skepticism (Miller, 2019; Pieters, 2008; Alter & Oppenheimer, 2009). This balance is particularly relevant for wine consumers, whose expertise ranges widely – from novices relying on heuristic cues to connoisseurs who may critically assess algorithmic reasoning (Mueller Loose & Lockshin, 2013; Danner *et al*., 2016).

Conceptually, these mediators are interrelated rather than independent. Lower perceived cognitive effort reduces information-processing costs, facilitating comprehension and confidence in system outputs. This, in turn, supports higher attributions of expertise, as systems that are easy to understand and interpret are more likely to be perceived as competent. Perceived expertise then functions as a key antecedent of trustworthiness, as users are more inclined to trust recommendations when they believe the underlying system is knowledgeable and reliable. Conversely, high cognitive effort may undermine expertise attributions and weaken trust formation.

2.5. *Behavioural Outcomes and Moderating Factors*

Trust and perceived expertise jointly determine key behavioural outcomes such as purchase intention, reliance on AI, and user satisfaction. Experimental studies indicate that transparent recommendation systems increase decision confidence, reduce perceived risk, and enhance satisfaction (Longoni & Cian, 2022; Shin, 2021). When consumers perceive AI systems as both competent and fair, they are more likely to follow algorithmic suggestions and report positive post-purchase experiences (Pizzi *et al*., 2021).

However, these relationships are moderated by several contextual factors. Digital and AI literacy strengthens the positive effect of transparency on trust because consumers with higher literacy can better interpret explanations and identify algorithmic logic (Shin, 2022). Product knowledge plays a similar role: expert wine consumers rely more on their own judgments and are therefore less influenced by algorithmic cues (Cardebat & Livat, 2016). Cultural orientation also affects algorithmic trust; cross-cultural studies demonstrate that societies with high uncertainty avoidance tend to exhibit lower acceptance of automation (Awad *et al*., 2018). Finally, perceived risk influences reliance: when purchase stakes are high, consumers may revert to human expertise even if they trust the algorithm (Hoff & Bashir, 2015; Madhavan, Wiegmann, & Lacson, 2006).

Together, these moderators highlight that algorithmic trust is not universal but contingent on cognitive, experiential, and cultural conditions – an insight essential for tailoring AI design and communication strategies in agri-food markets.

2.6. *Conceptual Framework and Theoretical Integration*

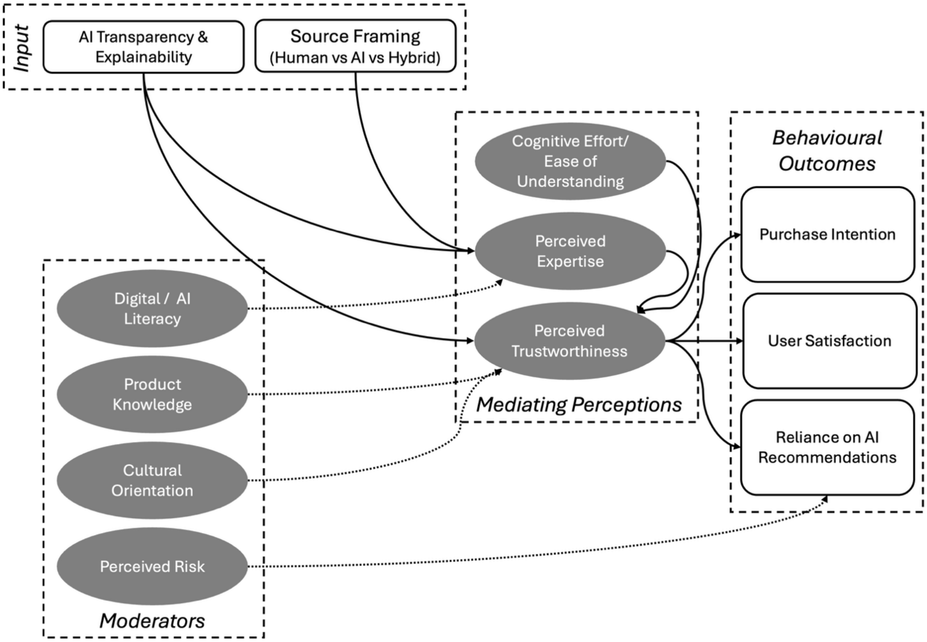
The proposed framework conceptualises AI-based recommendation systems as signalling mechanisms that reduce information asymmetry in credence-based markets (Spence, 1973; Connelly *et al.*, 2011). In this view, algorithmic design features – such as transparency and source framing – function as *input signals* that communicate reliability and competence. Consumers interpret these signals through perceptions of expertise and trustworthiness, which, moderated by individual characteristics (e.g., literacy, cultural orientation, product knowledge), lead to behavioural outcomes such as purchase intention, reliance, and satisfaction (Gefen *et al.*, 2003; Glikson & Woolley, 2020). Over time, consistent performance and ethical behaviour allow algorithms to accumulate what can be termed digital trust capital – that is, a reputational asset built through repeated, reliable, and transparent AI-user interactions that strengthens long-term credibility in credence-based markets (Ransbotham *et al.*, 2021; Schnackenberg & Tomlinson, 2016).

In the wine sector, where authenticity, storytelling, and expertise are central to consumer choice, AI-driven recommendation tools can either reinforce or erode trust. Transparent, human-augmented systems that explain reasoning and reflect wine culture can complement traditional sommeliers, while opaque or overly technical systems risk alienating consumers who associate authenticity with human judgement (Dietvorst *et al.*, 2015; Beverland, 2006; Caputo & Reardon, 2025; Shin, 2021). Digital transparency thus acts not merely as a functional feature but as a symbolic signal of integrity and authenticity, bridging the cognitive and cultural dimensions of trust in agri-food consumption.

Accordingly, the framework advances existing trust and signalling theories by positioning AI as a dual-role actor as both a signalling device communicating quality and a screening mechanism filtering information where information asymmetry persists.

The model (see below Figure 1: Conceptual Model of Algorithmic Expertise and Consumer Trust Formation) illustrates the hypothesised relationships among variables (AI transparency and source framing), mediating perceptions (expertise, trustworthiness, and cognitive effort), moderating factors (digital literacy, product knowledge, cultural orientation, and perceived risk), and behavioural outcomes (purchase intention, reliance, satisfaction). Over time, these interactions contribute to the accumulation of digital trust capital, representing the sustained credibility of algorithmic systems in credence-based markets such as wine.

Figure 1 - Conceptual Model of Algorithmic Expertise and Consumer Trust Formation



3. Methodological Approaches for Studying Algorithmic Trust

Understanding how consumers perceive algorithmic expertise requires research methods that go beyond traditional surveys or preference studies. Because trust and credibility often operate at an implicit or subconscious level, new tools from behavioural, digital, and neuroscientific research can reveal the cognitive and emotional mechanisms underlying consumer responses to AI-generated recommendations. For this reason, below methodological strategies are outlined that can be either individually or in combination applied to empirically test the conceptual framework proposed above:

3.1. *Experimental Approaches*

Controlled experiments offer a robust means of identifying causal relationships between AI design features (e.g., transparency, framing) and consumer responses (Dietvorst *et al.*, 2015; Logg *et al.*, 2019). Experimental manipulation of these variables allows researchers to isolate effects on perceived expertise, trust, and behavioural intention.

1. Scenario-based (vignette) experiments
Participants are exposed to short, realistic descriptions of shopping or recommendation scenarios that vary in framing (e.g., "AI sommelier" vs. "human sommelier"). Such designs are efficient for exploring framing and transparency effects on perceived trustworthiness (Longoni & Cian, 2022; Castelo *et al.*, 2019; Langer *et al.*, 2023).

2. Conjoint or Discrete Choice Experiments (DCEs)
Respondents choose among hypothetical wine offerings with systematically varied attributes (price, origin, recommendation source, transparency). The resulting data enable estimation of part-worth utilities for each attribute (Louviere *et al.*, 2010; Mueller Loose & Lockshin, 2013), revealing trade-offs between trust-related and product-related factors.

3. Online behavioural experiments
Simulated e-commerce interfaces record real-time behaviour – click patterns, dwell time, and recommendation acceptance – providing behavioural indicators of trust that complement stated preferences (Pizzi *et al.*, 2021; Shin, 2021). These designs are particularly suited to examining algorithm aversion (Dietvorst *et al.*, 2015) and algorithm appreciation (Logg *et al.*, 2019) phenomena in digital purchase contexts.

3.2. *Digital and Neuroscientific Methods*

Because trust formation often involves non-conscious emotional processes, methods from consumer neuroscience and biometrics can provide richer insights than purely declarative measures (Plassmann *et al.*, 2012; Ramsøy, 2019). Together, these methods allow researchers to connect cognitive evaluations (perceived expertise) with affective reactions (emotional trust), yielding a holistic picture of consumer-AI interaction.

1. Eye-tracking
Measures visual attention to AI-related cues (logos, transparency icons, explanations). Fixation duration and gaze transitions indicate cognitive processing and scepticism or confidence (Pieters, 2008).

2. Facial expression and emotion recognition
Automated facial-coding systems can detect micro-expressions (e.g., surprise, confusion, satisfaction) during AI-consumer interaction, serving as affective markers of trust (Lewinski *et al*., 2014; Ramsøy, 2019).

3. Electroencephalography (EEG) and galvanic skin response (GSR)
These physiological measures capture arousal and emotional valence linked to trust and decision confidence. For instance, higher frontal alpha asymmetry correlates with positive engagement toward transparent algorithms (Vecchiato *et al*., 2014).

3.3. *Data Analytics and Machine Learning for Trust Measurement*

Digital ecosystems such as online wine platforms, social media, and AI chat interfaces generate vast behavioural and textual data that can be harnessed to study trust at scale. Computational methods enable both descriptive and predictive analysis. Text mining and sentiment analysis.

User reviews, social media discussions, or chatbot conversations can be analysed using natural language processing to identify trust-related sentiment, perceived fairness, or authenticity concerns (Camacho *et al*., 2020; Pizzi *et al*., 2021).

1. Network analysis
Examines how trust and influence propagate within digital communities (Jerez-Villota, 2025). This is especially relevant for recommendation ecosystems where peer and algorithmic signals interact.

2. Predictive modelling
Machine learning approaches such as random forests or gradient boosting can model determinants of algorithmic trust and forecast consumer engagement patterns (Paschen *et al*., 2020). Combining predictive models with behavioural experiments allows for iterative testing of design interventions.

These analytical approaches move beyond self-reported trust, offering evidence from actual behaviour and longitudinal engagement.

3.4. *Integrative and Mixed-Method Designs*

Given the multifaceted nature of algorithmic trust, multi-method designs are particularly valuable (Venkatesh *et al*., 2013).

- Sequential mixed-methods can begin with qualitative interviews exploring consumers' perceptions of AI expertise, followed by experimental validation.

- Parallel designs can combine biometric measures (e.g., eye-tracking) with psychometric trust scales, providing both depth and generalizability (Plassmann *et al.*, 2012).
- Cross-cultural comparative studies – building on Hofstede (2001) – can reveal how cultural dimensions (e.g., uncertainty avoidance, power distance) shape reactions to AI transparency and framing (Awad *et al.*, 2020; Awad *et al.*, 2020).

Mixed-method approaches thus enhance both the ecological validity and interpretive richness of consumer behaviour research in digital environments.

3.5. *Methodological Contribution*

These approaches represent a significant shift from traditional consumer research methods that rely primarily on surveys and post-hoc evaluations. Combined, these methods provide empirical means to observe how algorithmic systems operate as screening mechanisms by processing and prioritising informational cues that consumers use to interpret quality. In doing so, they allow direct testing of how AI-generated signals may reduce or reshape information asymmetries between producers and consumers. Innovative digital and experimental tools make it possible to:

- Capture real-time decision processes and emotional dynamics;
- Measure implicit trust indicators beyond conscious awareness;
- Test design interventions (e.g., transparency wording, AI-human framing) in ecologically valid settings.

For credence-based products such as wine, integrating these methods enables a more precise analysis of how algorithmic transparency and expertise framing influence trust, authenticity perception, and purchase behaviour.

Methodologically, this approach allows the core mechanisms of signalling and screening to be observed directly rather than inferred, allowing for empirically grounding of research rather than a theoretical debate.

4. Implications and Future Directions

4.1. *Theoretical Implications*

The conceptual framework developed in this paper contributes to the growing literature on consumer trust and digital transformation by extending classical theories of information asymmetry and source credibility into the domain of algorithmic mediation. Based on the combination of information asymmetry, and instruments to address it – signalling, and screening – the framework interprets AI transparency and framing as new market signals, through which digital intermediaries communicate credibility and competence. It suggests that AI-based systems function not only as technical tools for product recommendation but also as new signalling institutions that influence consumer perceptions of quality, expertise, and authenticity.

First, by applying signalling theory to algorithmic contexts, the framework positions transparency and explainability as digital analogues of traditional trust signals such as certification labels or expert endorsements. The algorithm itself becomes a signal carrier, communicating the reliability of the underlying data and the competence of its design. This redefines how trust capital is generated in markets for credence goods, shifting from personal or institutional reputation toward data-driven credibility.

Second, the model enriches the understanding of expertise in consumer behaviour research. Expertise is no longer confined to human knowledge and sensory experience but emerges as a hybrid construct, blending human curation, machine learning, and data aggregation. This "hybrid expertise" challenges traditional hierarchies of authority in the wine sector and other agri-food domains where craftsmanship and authenticity have long been associated primarily with human judgement.

Finally, by conceptualising trust capital as a measurable and transferable construct, the paper links consumer behaviour research with broader debates in institutional and digital economics, where trust is increasingly recognised as a strategic resource. The framework thus bridges behavioural, economic, and technological perspectives on how information systems shape consumer confidence and market efficiency.

4.2. *Managerial Implications*

For practitioners in the agri-food and wine sectors, the framework translates into concrete design and governance choices that directly shape consumer trust, perceived expertise, and acceptance of AI-based recommendation systems. Rather than treating AI adoption as a purely technical implementation, the framework highlights how managerial decisions regarding transparency, framing, personalization, and human-AI integration function as strategic signals that consumers use to screen and interpret algorithmic advice under conditions of uncertainty.

Each managerial principle outlined below reflects a practical manifestation of signalling and screening dynamics that are directly shaped by managerial design and communication choices: transparency communicates credible signals of reliability, while framing determines how effectively consumers screen and interpret AI-based advice.

1. Transparency as a trust-building feature: Systems that disclose how recommendations are generated – through simple, comprehensible explanations – are more likely to elicit trust and engagement. Transparency should be framed as empowerment, not technical detail. When positioned in this way, transparency enables consumers to engage more confidently with algorithmic advice, supporting autonomy rather than passive reliance.
2. Framing and anthropomorphism: Consumers respond differently depending on whether an AI is presented as a neutral algorithm, a virtual sommelier, or a collaborative assistant. Designing interfaces that balance competence with warmth can humanise technology without sacrificing perceived expertise.
3. Personalisation and fairness: Algorithmic recommendations must be perceived as both relevant and unbiased. Excessive personalisation can trigger privacy concerns, while opaque filtering criteria may undermine trust. Ethical data practices and consumer control options are essential.
4. Integrating AI with human storytelling: Especially in the wine sector, where narratives of terroir, craftsmanship, and heritage drive emotional value, AI systems should complement – not replace – human expression. Hybrid models that embed digital precision within authentic storytelling may offer the strongest trust cues.
5. Continuous monitoring of consumer responses: AI systems evolve through feedback loops. Monitoring user sentiment, engagement metrics, and cross-cultural differences allows producers and platforms to adapt recommendations dynamically and sustain long-term credibility.

Taken together, these implications suggest that effective AI deployment in wine markets depends less on maximizing algorithmic sophistication than on aligning system design with how consumers cognitively process information and attribute expertise and trust. Managers who actively shape these dimensions are better positioned to harness AI as a credibility-enhancing tool rather than a source of skepticism.

4.3. *Policy and Societal Implications*

At the policy level, ensuring the integrity of these new algorithmic signalling institutions is essential to prevent renewed information asymmetries between digital platforms and consumers and to safeguard transparency, fairness, and accountability. The European Commission's AI Act (2024) already classifies recommendation systems influencing consumer choices as requiring transparency and explainability. Similar principles are echoed in broader discussions on trustworthy AI (European Commission, 2020; Floridi *et al.*, 2018).

For policymakers, this implies three main priorities:

1. Establish clear transparency standards for algorithmic recommendation and data use in agri-food contexts.
2. Encourage industry codes of conduct for responsible AI design and consumer communication.
3. Invest in digital literacy programmes that empower consumers to interpret algorithmic information critically.

The wine sector, where authenticity, quality, and regional identity are central, can serve as a model case for implementing responsible AI practices that balance innovation with heritage and consumer protection. Ultimately, policy should safeguard the integrity of information signals whether emitted by human experts or algorithms to preserve transparency as a public good in digital markets, a principle increasingly recognised in recent governance initiatives on algorithmic transparency and accountability (Council of Europe, 2023).

4.4. *Directions for Future Research*

Future research should build more direct empirical bridges between the concepts of information asymmetry, signalling, and screening in algorithmic environments. While this paper conceptualises AI as a new signalling institution, the next step is to operationalise this function empirically. AI technologies themselves can serve as both object and instrument of study.

First, researchers could apply AI-driven text and sentiment analysis to social-media content related to wine brands, recommendation platforms, or virtual sommeliers. Tracking discussions, for instance, on Instagram or Vivino would allow identification of emotional tone, expressions of trust, and consumer interpretations of algorithmic versus human expertise. Such analyses could reveal how credibility signals circulate and evolve in digital communities and how consumers evaluate authenticity or bias in AI-based recommendations.

Second, machine-learning models can be used to detect and classify consumer signals (e.g., endorsement, scepticism, perceived fairness) and to study how firms respond through their own signalling behaviour. This approach would align methodological innovation directly with the theoretical roots of signalling and screening theory – AI acting simultaneously as an analytical tool and as the phenomenon under investigation.

Cross-cultural investigations examining how factors such as uncertainty avoidance and technology acceptance moderate algorithmic trust would deepen understanding of AI adoption in global agri-food markets. Longitudinal research tracking how trust in AI systems evolves with prolonged exposure and user feedback could reveal learning effects and adaptation processes over time. Extending the analysis to other credence goods – such as olive oil, spirits, or specialty coffee – would help assess the generalisability of the model beyond wine and highlight product-specific trust dynamics. Moreover, future work should explore human-AI collaboration models, examining how hybrid forms of expertise – for instance, AI supporting human sommeliers or agricultural advisors – influence both consumer perceptions and organisational decision-making.

By integrating these research directions, scholars can advance a new methodological and conceptual agenda for consumer behaviour research in the digital age that combines behavioural insight with technological understanding and ethical awareness.

Conclusion

Artificial intelligence is transforming how information asymmetries are managed in credence-based markets. In the wine sector, where authenticity and quality are inferred through reputation and expert judgement, AI now functions as both a screening mechanism, processing complex data on quality cues, and a signalling device, communicating reliability, origin, and taste predictions to consumers.

This paper has proposed a framework linking these classical economic theories with emerging digital technologies. By situating AI within the logic of signalling and screening, it reinterprets algorithmic transparency, framing, and explainability as modern equivalents of certification labels and expert endorsements. In doing so, it shows how algorithmic systems participate in the co-creation of credibility and trust, potentially reducing – but also redistributing – information asymmetries among producers, platforms, and consumers.

Future empirical work, particularly through AI-enabled analysis of social-media discourse and emotional responses, can test how these new signals operate in practice. Such methods make it possible to observe trust formation dynamically, capturing how consumers react to algorithmic advice and how digital trust capital accumulates or erodes over time. These techniques allow researchers to capture cognitive, affective, and behavioural dimensions of consumer-AI interaction that are often inaccessible through conventional surveys. In doing so, they help bridge the gap between technological innovation and behavioural insight, enabling more nuanced analyses of consumer decision-making in increasingly automated environments.

For practitioners, the framework highlights that trust is not automatically granted to algorithms; it must be designed, communicated, and maintained.

The combination of transparency, fairness, and human-like empathy will likely determine the long-term success of AI-driven recommendation systems in the agri-food industry. For policymakers, the findings underline the importance of developing ethical and transparent governance mechanisms for algorithmic advice, in order to ensure that digitalisation enhances rather than undermines consumer autonomy.

Finally, understanding AI as an institutional actor that produces and filters quality signals anchors digital transformation within information economics theory, ensuring that innovation serves transparency, authenticity, and consumer trust.

Declaration of Generative AI Use

During the preparation of this article, the author used ChatGPT (OpenAI, GPT-5) to support language refinement, structural editing, and consistency improvements. After using this tool, the author thoroughly reviewed and edited all content and takes full responsibility for the final version of the manuscript.

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