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Artificial Intelligence in Agriculture: Capturing Stakeholders' Perspectives with a Q Methodological Approach

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1. Introduction

The application of artificial intelligence (AI) to agricultural production is receiving growing attention as a means to enhance efficiency and competitiveness in the agri-food sector (Bresciani *et al.*, 2025). As global agriculture faces increasing pressure (including climate change, population growth, and resource constraints technological innovation is increasingly presented as a strategic response to future-proof food systems (Ben Ayed and Hanana, 2021; John *et al.*, 2023). Among emerging solutions, AI is widely regarded as a key enabler of precision agriculture, capable of optimising input use, forecasting yields, and supporting decision-making (Kamilaris, Kartakoullis and Prenafeta-Boldú, 2017; Chu *et al.*, 2019; Jain and Choudhary, 2022; Ryan, van der Burg and Bogaardt, 2022; Ryan, Isakhanyan and Tekinerdogan, 2023; Wang and Doudna, 2023; Aijaz *et al.*, 2025). For example, Darlan et al. (2025) demonstrated that AI, through deep learning models, can accurately identify strawberry growth stages in greenhouses, enabling more precise and efficient crop management. Other studies have shown its potential to improve crop breeding and food security under changing climate conditions (Wang and Doudna, 2023; Aijaz *et al.*, 2025). Despite these opportunities, AI adoption in agriculture remains limited due to concerns regarding ethics, economics, and social implications. Key issues include data governance, labour displacement, and equity of access (Bronson, 2018; Rotz *et al.*, 2019; Ryan, van der Burg and Bogaardt, 2022; Ryan, Isakhanyan and Tekinerdogan, 2023; Wang and Doudna, 2023; Tascione *et al.*, 2024; Aijaz *et al.*, 2025). High costs, uneven value distribution along the supply chain further constrain uptake (Yang *et al.*, 2025). Iliopoulos et al. (2025) highlighted strong scepticism toward data ownership and dependence on technology providers. A lack of trust among farmers, policymakers, and technology providers - exacerbated by doubts over whether government strategies accurately reflect real on-farm conditions - also acts as a barrier (Gardezi and Stock, 2021; Iliopoulos *et al.*, 2025). Additional obstacles, primarily involving direct users, include limited time, limited skills, and insufficient infrastructure (Iliopoulos *et al.*, 2025). Beyond these concerns, Iliopoulos et al. (2025) show that farmers' scepticism can be mitigated when relationships among governments, technology providers, and advisors are transparent and grounded in long-term support rather than one-off sales interactions. Similarly, Li et al. (2017) and Ryan et al. (2023) suggest that AI in agriculture should be developed through an interdisciplinary approach that jointly addresses technological, economic, and social dimensions. Importantly, smart farming does not automatically lead to improved environmental benefits; without appropriate management, advanced technologies may relocate impacts (Tascione *et al.*, 2024; Reitano, Segovia and Nayga, 2025).

While much of the literature focuses on technical and structural barriers, less is known about how different stakeholders perceive AI's opportunities and risks, often overlooking the diversity of views and value-laden concerns that shape adoption processes (Trabelsi *et al.*, 2023; Chowdhury *et al.*, 2024). Understanding stakeholders' perceptions is essential to bridging the persistent trust gap and ensuring more inclusive innovation pathways. This study focuses on the Italian agricultural sector, a relevant context given the sector's structural importance to the national economy and the prevalence of small and medium-sized farms, which often face greater challenges in adopting advanced digital technologies. Although interest in digital transformation is growing and the sector is increasingly integrating technologies such as IoT, robotics, and AI, research examining innovation networks and the digital transition in Italian agriculture remains limited

(Cuomo et al., 2024; Moussaoui, Ghelfi, and Viaggi, 2025). In this evolving yet uneven landscape, exploring stakeholder perceptions is essential to understanding how technological change is socially interpreted and negotiated. To address this gap, this study employs Q methodology (Brown, 1993; Stephenson, 1936) to explore how stakeholders perceive the opportunities and risks of integrating AI into agriculture. Q methodology is a participatory approach designed to systematically capture and interpret subjectivities. This method has been increasingly used to study perceptions of environmental and technological issues (Walder and Kantelhardt, 2018; Mandolesi *et al.*, 2024; Solfanelli *et al.*, 2025). To our knowledge, only one study has focused specifically on stakeholder perspectives on AI in agriculture (Wising, Sandström, and Lidberg, 2024).

This study identifies shared viewpoints among key stakeholders, including farmers, nutritionists, journalists, and healthcare professionals, about AI in agriculture. By systematically mapping these perspectives, the paper seeks to clarify how perceived benefits, risks, and values are socially constructed and negotiated across different professional and institutional domains. By doing so, this study contributes to a more nuanced understanding of technological change that moves beyond deterministic or purely economic interpretations. By empirically mapping structured stakeholder subjectivities, this study advances the literature in different ways. First, it complements dominant technology adoption models by revealing how normative, ethical, and institutional considerations shape AI acceptance beyond instrumental utility. Second, it operationalises the Social Construction of Technology framework through Q methodology, offering a structured yet interpretative lens to capture contested technological meanings. Third, by focusing on the Italian agri-food context, the study provides context-sensitive insights into how structural constraints, such as farm size and digital infrastructure, mediate innovation pathways. For practitioners and policymakers, these findings highlight that AI adoption cannot be approached as a purely technical upgrade, but requires capacity-building measures, inclusive stakeholder engagement, and governance frameworks attentive to distributive and institutional implications.

2. Literature Review

Research on AI in agriculture has often drawn on technology adoption frameworks, particularly the Technology Acceptance Model (TAM) (Davis, 1989) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh *et al.*, 2003). These models focus on instrumental drivers, perceived usefulness, perceived ease of use, and behavioural intention to explain technology adoption. TAM-based studies in agriculture have examined farmers' attitudes towards digital tools and automation (Aubert, Schroeder and Grimaudo, 2012), yet they have been criticised for overlooking broader ethical, institutional and social dimensions relevant to complex and transformative technologies such as AI. More recent sociotechnical acceptance models seek to incorporate elements such as trust, regulation, ethical concerns, and social norms (Dwivedi *et al.*, 2019). Nevertheless, they often remain limited in capturing the *subjective constructions of meaning* that shape technological acceptance or resistance. This limitation is particularly salient for AI, where questions on data privacy, labour displacement, environmental sustainability, and power asymmetries are not easily reducible to utility calculations.

Interpretative frameworks such as the Social Construction of Technology (SCOT) argue that technologies are shaped through negotiation among "relevant social groups" (Bijker, Hughes and Pinch, 2012). In agriculture, this implies that farmers, policymakers, scientists, and citizens interpret AI differently based on their values, interests, and experiences. Technologies stabilise when consensus emerges, or dominant actors impose closure; until then, meanings remain fluid and contested. The literature on responsible innovation (Kaack et al., 2022) and participatory agri-tech development (Bronson, 2018) further underscores the importance of inclusive and reflexive processes aligned with societal values. However, empirical studies that systematically capture stakeholder subjectivities remain limited.

This study addresses this gap by applying the Q methodology, an interpretative, mixed-methods approach that enables the creation of maps of stakeholder perspectives (Ramlo, 2016; Walder and Kantelhardt, 2018; Mandolesi *et al.*, 2024; Soriano Longarón *et al.*, 2025). By combining the strengths of qualitative and quantitative approaches, the Q method enables a deeper exploration of key perspectives than traditional surveys, while also providing more structure to qualitative data (Solfanelli et al., 2025; Watts and Stenner, 2005). It is purposely used for its effectiveness in revealing patterns of agreement and disagreement within a socio-technical context (Walder and Kantelhardt, 2018; Mandolesi *et al.*, 2024; Rizzo *et al.*, 2025). Unlike surveys, Q does not aim to generalise the set of perspectives to a broader population, but rather to map coherent viewpoints and the reasoning that underpins them (Stephenson, 1953; Solfanelli *et al.*, 2025). This makes it particularly suited to contested innovations such as AI (Lehrer and Sneegas, 2018; Wising, Sandström and Lidberg, 2024; Soriano Longarón *et al.*, 2025). Furthermore, it enables the generation of meaningful insights from small yet diverse participant samples, making it well-suited to exploratory research aimed at capturing multiple stakeholder viewpoints rather than quantifying attitudes (Steelman and Maguire, 1999; Walder and Kantelhardt, 2018). For this reason, due to its intensive, in-depth orientation, Q studies typically rely on a carefully constructed, small participant sample (P sample) designed to encompass the full range of perspectives and attitudes relevant to the research topic (Brown, 1980). Hence, its abductive nature supports the exploration of underlying motivations, providing a rich and structured view of stakeholders' subjectivity, even when only a limited group of experts in specialised fields can be engaged (Brown, Rhoads and Wolf, 2018; Rizzo *et al.*, 2025).

Within this theoretical landscape, the study offers a novel contribution. While TAM/UTAUT focuses on individual behavioural intentions, SCOT emphasises the social construction of meaning; Q provides a structured empirical lens on stakeholder subjectivities, revealing consensus and disagreement that are difficult to capture with existing approaches. In doing so, the study contributes to a more nuanced understanding of agricultural digitalisation and its governance challenges, supporting more democratic, inclusive, and context-aware innovation pathways (Wising, Sandström and Lidberg, 2024; Reichenspurner and Matzdorf, 2025).

3. Methodology

Q methodology offers a systematic approach to measuring an individual's subjective viewpoints on a specific topic (Stephenson, 1936; Brown, 1993). It is particularly useful for providing a structured 'snapshot' of the reality in terms of shared views. This method identifies attitudes by engaging participants with a carefully selected set of self-referent statements, the Q sample (Brown, 1980, 1993). As a participatory approach, it actively involves participants in the structuring and prioritising of their perspectives, allowing their subjective views to shape the results (Lehrer and Sneegas, 2018; Mandolesi, Naspetti and Zanoli, 2022). By asking participants to rank-order the statements into a quasi-normal distribution (e.g., from "least agree" to "most agree"), Q sorts are generated (Brown, 1993). Then, by correlating these Q sorts, which are a formal expression of individuals' viewpoints, an inverted factor analysis is applied to group people with similar viewpoints into the same 'group' (commonly referred to as 'factors') (Stephenson, 1936). This process reveals shared viewpoints based on the relative ranking of statements, as well as the key similarities and distinctions between the identified factors. Although the Q uses quantitative factor analysis, its primary focus remains subjectivity, making it both communicable and systematically investigable (Brown, 1993). A Q study typically comprises five steps: 1) creating the concourse of statements, 2) selecting a representative Q sample, 3) identifying participants, 4) collecting Q sorts and interviews, and 5) factor extraction and interpretation (Figure 1).

Figure 1: Q steps undertaken in this study (Source: Author's elaboration, 2025)

Step 1: Creating the concourse of statements

A Q study starts with the collection of the concourse, which is the *"flow of communicability surrounding any topic"* (Brown, 1980). During this step, the researcher sought to collect all possible opinions surrounding the topic to cover the potential infinite debate. Starting from the scientific literature, researchers first identified key themes regarding the adoption of new technologies in the agricultural and food sectors. Additional information on this topic was obtained from the web and social media (for example, online magazines, forums, and existing interviews). Finally, the concourse included over 160 subjective statements on the social debate over new technologies, with a focus on artificial intelligence.

Step 2: Selecting a representative Q sample

Subsequently, the concourse was refined into a smaller subset of statements - the Q sample - (Brown, 1980). The Q sample should offer a miniature of the original concourse, aiming to provide sufficient representativeness and variety, while avoiding redundancy (Brown, 1993). To narrow the initial concourse to a manageable number of statements, we followed a structured, systematic approach (Brown, 1980). Statements were classified across three theoretical dimensions: A) ethics, responsibility, and privacy; B) impact on work and economy; and C) sociocultural and environmental impact. To obtain a balanced Q sample, the ten most relevant and diverse statements for each category were selected, resulting in a 30-statements Q sample (Table IV).

Step 3: Defining the P sample

In Q methodology, participants are selected to represent the diversity of views, rather than to be statistically representative of a population (S. Brown, 1980; Mandolesi et al., 2022; Watts & Stenner, 2005). A theoretical and purposive sampling strategy ensured inclusion of stakeholders positioned at different points in the agri-food system where AI technologies have direct or indirect impacts. The goal was not to capture all possible opinions, but to ensure that relevant and contrasting perspectives were present in the participant sample (P sample). Additionally, a typical Q study employs a small number of participants (Brown, 1980). The P sample comprises 20 stakeholders from four groups: farmers (5), journalists (4), health specialists (5), and nutritionists (6) (see Table II). Farmers were included as they are the primary users of agricultural technologies. Health specialists and nutritionists were involved due to the potential impact of AI-driven changes in agricultural practices on food quality and public health. Journalists, all specialised in agri-food reporting, were included as they play a key role in shaping public narratives and mediating the circulation of knowledge about technological innovations. The selection of these groups aligns with the study's objective to capture perspectives along the agri-food chain, including both direct users and professionals who interpret or are indirectly influenced by technological change.

Table I: Characteristics of participants.

Step 4: Collecting Q sorts and interviews

Between October and November 2024, email invitations were sent to various stakeholders and organisations representing different communities of practice, from which volunteers were recruited. Ultimately, 20 stakeholders completed the sorting process. Participants ranked the 30 statements in a quasi-normal distribution ranging from "+4" (most agree) to "-4" (least agree) (Figure 2). Neutral statements were placed in the middle of the distribution. Participants were allowed to rearrange the statements as many times as needed until they were satisfied with their final ranking. After sorting, each participant completed a short interview to provide additional comments on the extremes of their distribution. Post-sort interviews were used to enrich and contextualise the findings derived from the sorting task.

Figure 2: Q sorting distribution

Factor extraction and interpretation of the emerging views

Once collected, Q sorts were cross-correlated and subjected to factor analysis (Stephenson, 1936; Brown, 1980). Data were analysed using KADE statistical software (Banasick, 2019). The centroid method was used for data reduction and for "grouping" participants into factors based on the similarity of their Q-sorts. The adoption of this statistical method reduces the complexity of individual perspectives (i.e., the Q sorts, which are the variables in a Q study) and transforms them into a set of coherent factors, from which key similarities and distinctions can be identified. According to this method, it is important to define the number of factors to retain for interpreting the results. There are different ways to define the factors to be extracted (Lehrer and Sneegas, 2018). In this study, the Kaiser-Guttman criterion (i.e., eigenvalues greater than 1) was employed. Brown's rule retains the following four factors: according to Brown (1980), a factor with at least two statistically significant factor loadings should be retained (Brown, 1980). Factor loadings are correlation coefficients that represent the degree to which a Q-sort correlates with a factor. In this study, significant factor loadings were selected to be ±0.357 (obtained as follows: it must exceed 1.96 x SE with $p<0.05$, where SE is the standard error and is given by SE = $1/\sqrt{n\ of\ statements}$) (Brown, 1980). The four factors were then rotated using a combination of varimax and manual rotation. All the factor loadings are listed in Table II. The table identifies how Q sorts 'load' or is correlated with each factor.

Table II: Factor loadings and defining sorts.

Note: in bold are indicated defining sorts with p<0.05, in italic sorts not assigned

Table III: Factor scores correlations for each factor

4. Results

The analysis revealed four dominant factors that explained 44% of the study's variance, distributed as follows: 9% for Factor 1, 6% for Factor 2, 18% for Factor 3, and 11% for Factor 4. The solution was also characterised by low factor correlations (see Table III). For each factor, distinguishing statements and their corresponding factor scores, calculated as weighted averages of the scores from the flagged Q sorts, were used to interpret participants' diversity (Brown, 1980). For each factor, the factor scores, which identify how the statements correlate with each factor, are reported in Table IV. The signs preceding each factor score denote the direction of agreement: a positive sign (+) indicates agreement, whereas a negative sign (-) indicates disagreement. Post-sort interviews were included in the analysis to support the observed factors and confirm the accuracy of the factor interpretation. Participants were assigned anonymous identification codes based on their professional role: F = Farmer, J = Journalist, N = Nutritionist, HS = Health Specialist. A number was then added to indicate each participant's unique ID within the sample (e.g., F10 = Farmer number 10).

*Table IV: Distinguishing statements for each factor (those marked with ** significance at p<0.01; with * p<0.05).*

4.1 Interpretation of Factors

Factor 1. "The Concerned Sceptic" viewpoint

Factor 1 accounted for three Q-sorts (one farmer and two journalists). This viewpoint expresses a sceptical and critical attitude towards the adoption of artificial intelligence in agriculture, emphasising concerns about potential unintended consequences and broader regulatory and ethical implications. Given the lack of clear standards, establishing specific rules for data governance is essential (**27**, +4)[1]. Regarding this point, one participant affirmed, *"Technological innovations without new rules become dangerous"* (J3). This perspective places great importance on AI's impact on privacy and fundamental rights, with particular concern for the processes of personal data collection, profiling, and management (**9**, +4**; **22**, +3). One participant added: *"AI has no protected end users, so it is difficult to define the 'economic advantage' as they contribute now"* (F10). This view reflects a clear opposition to the optimistic discourse that emphasises the prospective economic and productive benefits of AI in agriculture. In addition, the implementation of AI will potentially disadvantage smaller producers and primarily benefit larger farmers (**23**, +3*; **10**, -3*). Finally, scepticism surrounds the sustainability of AI production to meet growing food demand (**18**, -4**).

Factor 2. "The Critical Adopter" viewpoint

This view accounted for two Q-sorts (one from a farmer and one from a nutritionist). This perspective highlights the concerns regarding the practical applicability of AI in the agricultural sector. Proponents acknowledge the potential value of innovation (for example, in terms of productivity and traceability) while asserting that the adoption of AI must take place in compliance with the principles of inclusiveness, sustainability, and accessibility for all stakeholders within the agricultural sector. In this view, concerns centre on the idea that AI can diminish human decision-making and thinking abilities, potentially affecting agricultural businesses (**2**, +4**). Regarding this, one participant stated, *"Relying too much on technology means a future lack of independent decision making"* (F17). In addition, for representatives of this perspective, simply replacing human operators with automation or AI technology is insufficient to fully address safety risks and prevent deaths associated with interactions with agricultural machinery (**21**, -3*). The position is clarified by the following comment: *"In all sectors, the human operator should never be replaced; AI should only serve as a support for humans*" (N15). This view places great emphasis on the economic implications of adopting these technologies. They acknowledge that not all farmers are inclined to invest in AI and automation because of the lack of immediate financial returns (**24**, +4*). This could deepen existing socioeconomic inequalities in agriculture (**7**, +2). Moreover, the digital gap, which characterises, for example, different countries and small vs. large farmers, could represent another significant barrier to the widespread adoption of AI technologies (**25**, +3). Contrary to the first perspective, this view is not concerned with the risks that AI poses to privacy and fundamental rights (**9**, -3).

Factor 3 "The Responsible Environmentalist"

This view accounted for six Q sorts (two farmers, one journalist, two health specialists, and one nutritionist). From this perspective, AI is a fundamental asset for agricultural advancement, particularly for environmental sustainability. Representatives of these perspectives contend that technological progress is both inevitable and necessary to maintain competitiveness in global trade (**28**, +4**) and to address the challenges faced by the agricultural sector, including the sustainable management of natural resources. More specifically, the perspective highlights AI's potential to conserve crucial resources such as water and soil (**13**, +3**), and to reduce agriculture's environmental footprint by optimising

[1] In brackets from this point on, the statement number (in bold) and related factor scores.

inputs such as water, fertilisers, and pesticides (**14**, +3). Positive attitudes towards AI are also associated with the belief that it will neither supplement human decision-making or reasoning (**2**, -3**) nor eliminate agricultural jobs, as fears about worker replacement are deemed to be overstated (**26**, -4**). Two participants were included in the study. *"On the contrary, I believe that specialised figures in this sector could emerge"* (HS8) and *"I believe that AI will never surpass human critical capacity and intuition"* (F19). Some participants stated, *"It is impossible to refuse progress and evolve"* (F9) and *"I am convinced that the competition will overwhelm those who do not adapt to the use of AI in different sectors"* (HS4). However, it is important to emphasise that proponents of this perspective, more than others, believe that political systems must establish the conditions necessary for the effective and beneficial use of AI (**1**, +4). Finally, in accordance with the second perspective, the view acknowledges that a significant digital divide in agriculture could pose a challenge for adopting AI-based technologies (**25**, +3) and that not all farmers could be ready to invest in AI and automation due to delayed returns (**24**, +2*).

Factor 4 "The Technological Optimist"

This view accounted for five Q sorts (one journalist, one health specialist, and three nutritionists). This viewpoint is characterised by a predominantly positive attitude towards the adoption of AI and automation in agriculture. The proponents appeared to have no doubts about the implementation of AI and the potential issues associated with its adoption. First, there is a strong belief that rejecting technological advancements is counterproductive. Consequently, AI is perceived as having significant potential to enhance farmers' productivity, facilitate their work, and increase overall agricultural efficiency (**5**, +4**; **18**, +3). Participants stated that *"AI will help make better choices that will improve productivity and therefore the economy of the sector"* (N16); *"In my opinion, the use of AI and human labour is complementary to gain greater benefits in terms of productivity"* (N11); and *"Skilled labour will be increasingly necessary"* (J1). Moreover, this viewpoint highlights AI's capacity to improve product traceability throughout the agricultural supply chain, thereby enhancing food security (**19**, +4). Additional advantages associated with AI technologies include addressing growing demand while promoting sustainable practices, such as a circular economy and reducing food waste (**15**, +3; **18**, +3). However, this view tends to underestimate potential socioeconomic risks, particularly inequalities that may arise from the widespread adoption of AI in global agriculture (**7**, -3**). This perception is also influenced by stakeholders' concerns regarding the possibility of occupying marginal roles in international trade if adequate government measures or policies do not support AI investments (**1**, +1).

Shared points between perspectives

Across all perspectives, only a limited number of areas of consensus emerged. A shared concern is the perception that AI may exacerbate the digital divide in agriculture (**25**, +1, +3, +3, +1), reflecting unequal access to digital infrastructure, connectivity, and technological literacy. Stakeholders consistently view this gap as a structural barrier to the adoption of inclusive AI. Another partial convergence relates to technological vulnerabilities. Most views (Factors 1, 3 and 4) attribute low concern to risks such as cyberattacks or data theft (**29**, -2, 0, -2, -3). This relative confidence suggests that these risks are considered manageable or secondary compared to broader structural challenges, and that stakeholders generally trust existing security measures despite the sector's increasing digitalisation.

5. Discussion

This study systematically examined stakeholder attitudes toward AI adoption in agriculture using Q methodology within the Italian context, identifying four distinct viewpoints. Overall, the results confirm that AI is framed not as a neutral technology but as a socially constructed and contested innovation, consistent with the SCOT framework (Bijker, Hughes and Pinch, 2012). Stakeholders' perceptions are shaped by institutional, cultural and socio-economic conditions rather than by technical features alone. This aligns with SCOT, which emphasises that technological meanings emerge through negotiation among multiple social groups, each with distinct values, interests, and technological frames (Bijker, Hughes and Pinch, 2012). Scholars advocating for participatory and responsible approaches (Bronson, 2018; Kaack *et al.*, 2022) build on this insight, highlighting that the sustainable and equitable deployment of AI in agriculture requires inclusive governance, active stakeholder engagement, and the integration of social and ethical values into design and regulation. Therefore, the variety of viewpoints revealed by the present Q study reflects the expected diversity arising from the social construction of AI as a contested socio-technical object, providing a richer understanding of consensus, disagreement, and normative tensions.

Factors 1 and 2 predominantly reflect critical perspectives. While Factor 2 is less overtly negative, both express concerns about human-AI integration, ethical implications, and the absence of a clear regulatory framework. These concerns align with recent evidence showing that trust is a strategic barrier to digitalisation in agriculture (Iliopoulos et al., 2024). In Factor 1, distrust is primarily institutional and ethical, as participants question who controls the data, who benefits from AI, and whether adequate regulatory safeguards are in place, especially for smaller producers. This resonates with SCOT, which shows how different social groups may construct technologies as threats when institutional protections are weak (Gardezi and Stock, 2021). By contrast, Factor 2 adopts a more pragmatic orientation, highlighting feasibility constraints, high costs, and the risks associated with diminishing human judgment. This aligns with evidence showing that infrastructural limits, uneven digital skills, and organisational culture constrain AI adoption in Italian farms (Cuomo *et al.*, 2024). This view critiqued reductionist framings of automation, reflecting broader concerns about job displacement and the loss of tacit knowledge (Li *et al.*, 2017). Notably, farmers were present in both of these critical factors. Although this does not imply that all farmers perceive AI in this way, it suggests that those most directly involved in production may be particularly sensitive to both the ethical and practical risks of AI integration (Iliopoulos et al., 2024).

In contrast, Factors 3 and 4 articulate more positive interpretations. Factor 3 emphasises the environmental potential of AI, particularly regarding resource optimisation, but stresses that such benefits depend on infrastructure, supportive regulation, and farmers' financial capacity. This finding is consistent with Tascione et al. (2024), who argue that new technologies alone do not guarantee environmental improvements. This perspective also recognised practical barriers already identified in the Italian context, such as high adoption costs, technical complexity, and data interoperability challenges (Moussaoui, Ghelfi and Viaggi, 2025). To overcome these obstacles, stakeholders recommended targeted policy measures, including financial incentives, training programs and technical support. The view reflects principles of responsible innovation, emphasising that technological progress must be supported by governance and participatory design processes (Bronson, 2018; Markoff-Legrand, Bocquet and Gandia, 2024).

A key tension emerges between the conditional pragmatism of Factor 2 and the eco-modernism optimism of Factor 3. While both acknowledge AI's potential, Factor 2 remains more attuned to issues of human displacement, socio-economic inequality, and limited incentives for smaller farms. In contrast, Factor 3 positions AI as a necessary tool for ecological transition and resource conservation, emphasising its potential to reduce environmental footprints. This divergence reflects broader debates in sustainability innovation, where trade-offs between social resilience and technological ambition frequently arise. What distinguishes these perspectives is not merely how they evaluate AI's utility, but the normative conditions they attach to its legitimacy. This highlights the need for governance frameworks that treat innovation not as a linear, one-size-fits-all process, but as a path-dependent, value-sensitive trajectory. Concepts such as innovation pathway governance (Pereira *et al.*, 2021; Salazar Morales, 2025) advocate for inclusive, anticipatory, and reflexive approaches that align technological development with plural societal goals. Similarly, value-sensitive design (Garst *et al.*, 2022) emphasises embedding ethical, environmental, and social values directly into the design and deployment of technologies. Applying these lenses to agricultural AI suggests that policy and industry actors should facilitate pathways that are responsive to both structural barriers (as voiced by Factor 2) and aspirational sustainability goals (as promoted by Factor 3), thereby avoiding the marginalisation of stakeholder needs in favour of technocentric visions.

Factor 4, by contrast, expresses confidence in AI's ability to enhance efficiency and competitiveness and tends to perceive AI adoption as both inevitable and desirable. Notably, this perspective is largely held by stakeholders outside primary production (nutritionists, journalists and health professionals), who do not bear the direct financial and operational burdens of implementation. As a result, compared with Factor 3, this view tended to downplay potential socio-economic barriers, including the digital divide and investment constraints (Cuomo *et al.*, 2024; Moussaoui, Ghelfi and Viaggi, 2025). This view aligns with broader narratives of technological inevitability and innovation-driven progress (Bronson, 2018; Rotz et al., 2019), framing AI as a necessary step rather than a socio-technical transition that requires tailored support, governance, and safeguards to ensure fair outcomes. In their study, views ranged from scepticism, often linked to concerns about autonomy, experiential knowledge, and trust in institutions, to more optimistic perspectives framing technology as a support for sustainable resource management.

Across all viewpoints, a recurrent theme is the digital divide, which stakeholders perceive as a critical barrier to inclusive AI adoption (Tzachor *et al.*, 2022). This structural divide reflects the digital divide in Italian agriculture, driven by limited connectivity and uneven digital literacy (Cuomo *et al.*, 2024). Without targeted support, especially for small-scale farmers, AI may exacerbate socioeconomic disparities. A second, albeit weaker, area of convergence concerns digital vulnerabilities, which were perceived as less urgent than structural and operational challenges, an interpretation consistent with prior work (Rotz et al. 2019).

6. Conclusion

This study examined how AI is interpreted within sustainable agriculture by identifying shared viewpoints through Q methodology. Four distinct perspectives emerged, revealing that AI adoption is a negotiated process shaped by diverse technological frames rather than a neutral or linear trajectory. Q methodology proved particularly effective in surfacing this plurality, including non-dominant viewpoints that are often overlooked by conventional surveys (Rizzo *et al.*, 2025). Based on the empirical insights, three structured implications emerge for research, practice, and policy. First, addressing the digital divide is a prerequisite for equitable AI adoption. Across viewpoints, stakeholders identified structural inequalities in infrastructure, skills, and financial capacity as major barriers. Digitalisation strategies must therefore incorporate targeted capacity-building measures, training programmes, and financial support mechanisms, particularly for small and medium-sized farms. Second, AI integration requires co-design and stakeholder engagement. The divergence between cautious and optimistic viewpoints demonstrates that technological implementation cannot follow a one-size-fits-all trajectory. Inclusive, participatory processes are essential to align AI deployment with farmers' experiential knowledge, ethical concerns, and sustainability expectations. Third, governance frameworks must be inclusive, anticipatory, and value-sensitive. The findings show that trust, legitimacy, and perceived fairness significantly influence acceptance. Policymakers should therefore move beyond techno-centric narratives and develop regulatory and institutional safeguards that ensure transparency, accountability, and equitable benefit distribution.

From a scholarly standpoint, the study advances the literature by empirically operationalising SCOT through Q methodology, demonstrating how structured subjectivities shape technological acceptance, and exposing the limits of traditional technology acceptance models when applied to value-laden and contested innovations such as AI in agriculture.

Some limitations should be acknowledged. Because the study was conducted within the Italian context, the configuration of perspectives may vary in settings characterised by alternative cultural or institutional environments. Future applications of Q methodology could therefore broaden the scope by exploring whether - and how - viewpoints converge or diverge across countries or in other agricultural and policy environments. Furthermore, this exploratory study focused intentionally on professional viewpoints to capture informed, experience-based subjectivities. Consumers were excluded for two reasons: first, the statements used contained technical language and sector-specific concepts that would likely be difficult for a general lay audience to interpret reliably; second, the study aimed to explore expert interpretations rather than general attitudes. Nonetheless, consumer trust and acceptance are widely recognised as critical to the uptake of emerging agri-food technologies. Future research could therefore integrate consumer viewpoints to develop a more comprehensive picture of how expectations toward AI unfold across the entire food system.

In conclusion, AI adoption in agriculture emerges as a value-sensitive and governance-dependent process, shaped by ethical concerns, socio-economic conditions, and institutional arrangements. Issues such as data governance, labour displacement, and algorithmic bias intersect with regulatory frameworks and influence the perceived legitimacy of technological change. By making visible the diversity of stakeholder interpretations, Q methodology provides a structured and transferable approach for examining contested innovations across contexts. While viewpoint configurations remain context-specific, the methodological framework can be systematically applied to other agri-food systems to support context-aware innovation governance.

Ethical Statement

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CRediT authorship contribution statement

All Authors contributed to the conceptualisation of the study. Gabriella Esposito contributed to the implementation of several Q sorts and supported the data collection process. In collaboration with Serena Mandolesi, she co-authored the original draft and contributed to the discussion and development of both theoretical and practical implications. Serena Mandolesi led the methodological design, including the construction of the Q sample and sorting tool, and was responsible for data curation, formal data analysis and visualisation. She also contributed significantly to the validation of results and to writing, reviewing, and editing the manuscript. Raffaele Zanoli supervised the entire research process, guiding the methodological design, and validation. He also coordinated project administration and provided ongoing support for the interpretation of results and final editing of the manuscript.

Declaration of competing interest

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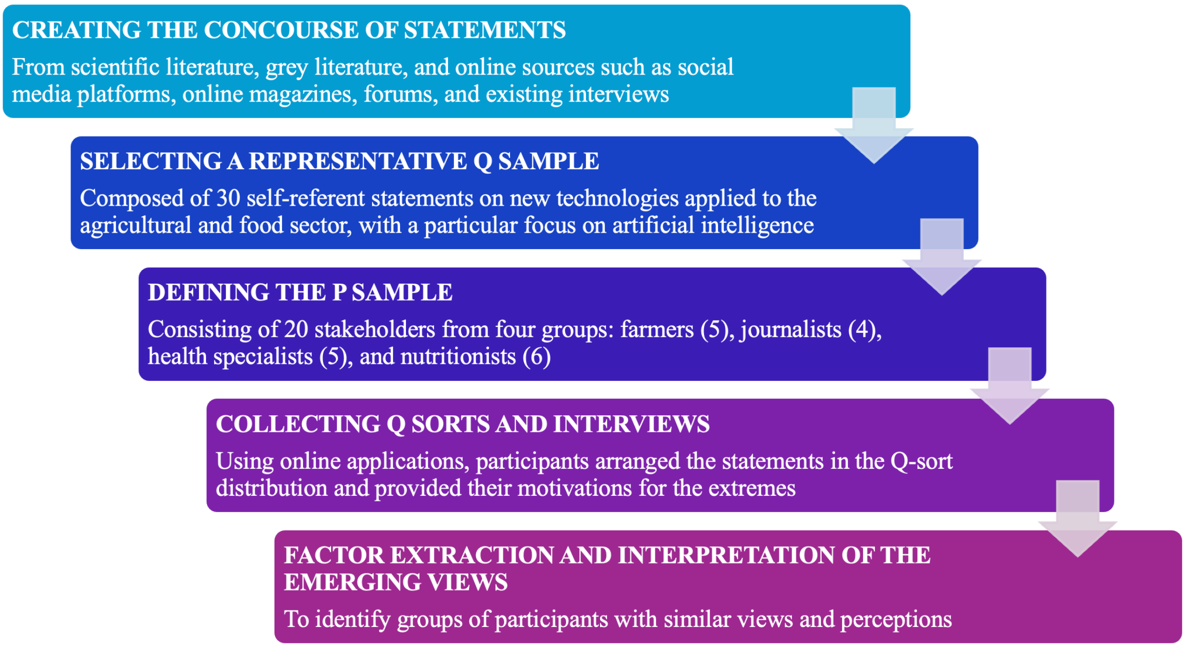

Figure 1 Q steps undertaken in this study (Source: Author's elaboration, 2025)

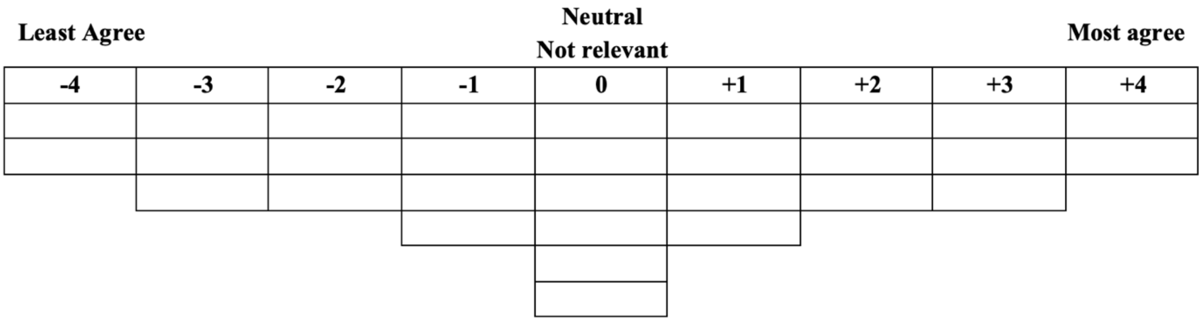

Figure 2 Q sorting distribution

Table 1 Characteristics of participants

		Gender			Age		Total
Type	Male	Female	N/A	25-30	31-59	Over 60	
Farmer	3	2			4	1	5
Journalist	2	1	1		2	2	4
Health specialist	2	3		2	2	1	5
Nutritionist	1	5		5	1		6

Table 2 Factor loadings and defining sorts (in bold are indicated defining sorts with p<0.05, in italic sorts not assigned)

n	Work	Factor 1	Factor 2	Factor 3	Factor 4
1	Journalists	0,2495	0,3097	0,3092	**0,6291**
2	Journalists	-0,1093	0,0537	**0,8478**	0,0579

3	Journalists	**0,3635**	-0,0234	0,1203	-0,0396
4	Health specialists	0,3097	-0,2028	**0,8034**	0,0231
5	Health specialists	*-0,0772*	*0,1612*	*0,2365*	*-0,3483*
6	Health specialists	*0,3495*	*0,129*	*0,0011*	*-0,0303*
7	Health specialists	0,2351	-0,3547	0,1446	**0,4012**
8	Health specialists	0,2409	0,0766	**0,8146**	0,3082
9	Farmers	0,0198	-0,097	**0,6553**	0,3008
10	Farmers	**0,7482**	-0,0111	-0,2615	-0,0884
11	Nutritionists	0,1112	0,0939	0,2312	**0,6106**
12	Nutritionists	0,2561	0,0672	**0,4831**	-0,0035
13	Nutritionists	*0,0997*	*-0,2075*	*0,3415*	*-0,1559*
14	Nutritionists	0,3483	0,201	-0,2366	**0,4081**
15	Nutritionists	0,2535	**0,411**	-0,2233	-0,0118
16	Nutritionists	0,1973	-0,2928	0,2554	**0,5414**
17	Farmers	0,0162	**0,6688**	0,171	0,3695
18	Journalists	**0,5182**	-0,2129	0,1669	-0,0972
19	Farmers	-0,177	-0,1284	**0,4273**	0,3554
20	Farmers	*0,218*	*0,2612*	*-0,1265*	-0,3532

Table 3 Factor scores correlations for each factor

	Factor 1	Factor 2	Factor 3	Factor 4
Factor 1	1	0,0693	0,0351	0,2194
Factor 2		1	0,1554	0,3265
Factor 3			1	0,4058
Factor 4				1

Table 4 Distinguishing statements for each factor (those marked with ** significance at p<0.01; with * p<0.05)

N	Statement	Category	F1	F2	F3	F4
1	I believe that politics must create the conditions for the good use of AI to be possible and fruitful.	Ethics, responsibility and privacy	+2	+1	+4	+1
2	I believe that AI risks replacing the human ability to think and make decisions, which will invariably impact agricultural businesses.	Ethics, responsibility and privacy	+2	+4**	-3**	+1
3	I believe that due to AI and automation in agriculture, wealth risks are becoming more concentrated than how already it is.	Socio-cultural and environmental impact	0	-2	-1	0
4	We need rules, especially regarding managing data derived from AI, sensors and other autonomous machines.	Ethics, responsibility and privacy	+3	+2	+2	0
5	I believe that AI and automation can facilitate the work of our farmers and breeders, increasing their productivity.	Impact on work and economy	-1	-1	0	+4**
6	I believe that AI can increase animal welfare and mitigate the effects of climate change.	Socio-cultural and environmental impact	-1	-2	0	-2
7	I believe that AI and automation will only increase the socioeconomic inequalities currently rooted in global agriculture.	Socio-cultural and environmental impact	+1	+2	0	-3**

N	Statement	Category	F1	F2	F3	F4
8	I believe that the current EU regulation on AI is not sufficient to guarantee privacy and ethical use of technology.	Ethics, responsibility and privacy	+1	+1	0	0
9	I fear that the impact of AI on privacy and fundamental rights will be enormous (e.g., collection of personal data, consent management, profiling).	Ethics, responsibility and privacy	+4**	-3	-3	-2
10	I think automation and AI could be the keys to a more profitable agricultural future for producers.	Impact on work and economy	-3*	0	0	-1
11	I believe that the large-scale deployment of AI is not sustainable at all because huge amounts of water are required to cool data centres.	Socio-cultural and environmental impact	-4*	0	-3	-2
12	For me, AI and automation cannot create new job opportunities in the agricultural sector.	Impact on work and economy	0**	-4	-4	-4
13	I believe that AI in agriculture can help preserve vital resources such as water and soil.	Socio-cultural and environmental impact	-1	-1	+3**	-1
14	AI can reduce the environmental impact of agriculture by optimising the use of water, fertilisers and pesticides.	Socio-cultural and environmental impact	0	-1	+3	+2
15	I believe that AI can be an effective tool to improve the circular economy and fight food waste.	Socio-cultural and environmental impact	+2	0	+1	+3
16	I believe that AI and automation will help farms of all sizes to produce more using fewer natural resources.	Impact on work and economy	-2	0	+1	-3
17	I think that, thanks to AI, the adoption of autonomous tractors will help reduce the costly need for specialised labour.	Impact on work and economy	-2	-4	-1*	-4
18	AI can increase agricultural productivity, meeting the growing demand for food globally in a more sustainable way.	Socio-cultural and environmental impact	-4**	+1	+1	+3
19	I think AI can improve the traceability of products along the agricultural supply chain, providing greater food security for the population.	Socio-cultural and environmental impact	0	+3	+2	+4
20	AI can help us create a more equitable and fair agri-food system, ensuring everyone has access to healthy and nutritious food.	Socio-cultural and environmental impact	-1	+1	0	-1
21	The elimination of human operators, thanks to automation, could prevent injuries and deaths related to agricultural machinery.	Impact on work and economy	0	-3*	-1	0
22	I am concerned about the risk of exploitation of data derived from AI (e.g., by insurers setting premiums for crop losses or flood damage).	Ethics, responsibility and privacy	+3	+2	-2	-1
23	I believe that only large farms can benefit from AI and automation to the detriment of small producers.	Ethics, responsibility and privacy	+3*	-2	-2	+1*
24	I believe that not all farmers are willing to invest in AI and automation because the investments may not have an immediate return.	Impact on work and economy	-3**	+4*	+2*	0**
25	I believe that the digital gap in agriculture is a significant obstacle to the adoption of AI-based technologies today.	Ethics, responsibility and privacy	+1	+3	+3	+1
26	While autonomous tractors fill the agricultural labour deficit, there is still the fear that they could replace the already few remaining agricultural workers.	Impact on work and economy	0**	+3	-4**	+2
27	The biggest disadvantage is the lack of standards that dictate the rules for the development of these systems and a legislative framework that regulates their applications.	Ethics, responsibility and privacy	+4	0	+1	+3
28	I believe that rejecting technological progress leads nowhere. There is a risk of being marginalised from world trade.	Impact on work and economy	+1	-1**	+4**	+2

N	Statement	Category	F1	F2	F3	F4
29	I believe that AI could make the agricultural sector more vulnerable to technological problems of any nature (e.g., cyberattacks, data theft).	Ethics, responsibility and privacy	-2	0	-2	-3
30	I think that AI can foster the vertical and horizontal integration of agricultural supply chains.	Impact on work and economy	-3	-3	-1	0