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ALGORITHMIC FOOD SECURITY, AGRICULTURAL DATA GOVERNANCE, AND SMALLHOLDER INCLUSION: A GOVERNED CAPABILITY-CONVERSION FRAMEWORK

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Abstract:

Artificial intelligence (AI) is transforming agriculture, yet its contribution to smallholder food security depends on more than just access to or adoption of technology. This conceptual paper develops a governed capability-conversion framework explaining how AI-mediated opportunities translate into multidimensional household food security. Drawing on an integrative, theory-driven review, the framework explains how AI and data conditions interact with governance and substantive inclusion to shape livelihood capabilities and, ultimately, multidimensional household food security. It integrates the Capability Approach, Data Justice, and Resource Dependence Theory through conversion freedom, defined as smallholders' substantive institutional capacity to transform algorithmically mediated opportunities into livelihood capabilities while retaining meaningful agency and viable alternatives. The framework distinguishes a governed capability-conversion pathway from a dependency-constrained pathway and identifies enabling data-governance quality and algorithmic dependency as opposing moderators. The framework advances agricultural AI scholarship by explaining why comparable digital participation can yield divergent developmental outcomes and by providing a testable foundation for future empirical research.

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Keywords:

Agricultural Artificial Intelligence; Algorithmic Food Security;
Conversion Freedom; Data Governance; Smallholder Inclusion;
Livelihood Capabilities; Algorithmic Dependency



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Introduction

Artificial intelligence (AI) is increasingly embedded in agriculture through precision farming, crop monitoring, predictive analytics, digital extension, automated decision support, and data-driven resource management. These applications can improve productivity, resource efficiency, risk management, and agricultural decision-making (Benos et al., 2021; Rejeb et al., 2022; Tzachor, Devare, et al., 2022; Tzachor, Richards, & Jeen, 2022). Yet their developmental value cannot be inferred from technological sophistication, predictive accuracy, or adoption alone. As AI increasingly influences how farmers are represented, classified, and evaluated, it also affects access to information, finance, insurance, inputs, markets, and public support. The critical question is therefore not simply whether AI improves agricultural efficiency, but whose capabilities are expanded through AI-mediated allocation and under what institutional conditions.

This question is of great importance for smallholders who, while making up a substantial share of farms and food output globally, often struggle with finance, infrastructure, market, and institutional issues (Lowder et al., 2021). New technologies can mitigate some of the challenges faced by smallholders due to growing access to information and services but still constrain the extent of their use across different socio-economic strata and farming conditions (Hoang & Tran, 2023). Hence, farmers who are poorly connected, poorly documented, or poorly represented in agricultural data systems may face not only barriers to adoption but also reduced algorithmic visibility. The developmental consequences of agricultural AI thus depend in part on the adequate representation of heterogeneous smallholders and their farming conditions within the data infrastructures that inform consequential decisions.

But access to technology does not necessarily translate into meaningful inclusion. Farmers can supply production, transactional, spatial, or behavioral data but maintain some limited control over how these data are accessed, reused, combined, or commercialized. Thus, agricultural data governance encompasses access, control, privacy, contracts, and decision-making authority beyond mere legal ownership of the data (Atik, 2022; Reissig et al., 2024; Jouanjean et al., 2020). Data sovereignty, privacy, security, and benefit-sharing are also likely to affect confidence and participation in farmer data-transfer relational arrangements (Sullivan et al., 2024). The intrinsic conceptual challenge is the concurrent access opportunity enabled by the technology system and the reliance it may generate on agents to handle data flows, algorithms, infrastructure, or marketplace interfaces for data control. Digitalization plausibly implies

participation but is associated with weak bargaining power, limited options, and limited ability to translate entry into tangible outcomes. The present research makes useful contributions to each challenge, but the rationale for the conversion method is missing. Much of the existing research on digital agriculture focuses on access and use of the technology, as well as research in the area of responsible AI that emphasizes on fairness, transparency, accountability and autonomy and of the data governance sector that emphasizes the access to rights, participation, governance and powers of the different actors and entities in general (Mallinger & Baeza-Yates, 2024; Jouanjan et al., 2020; Ruder & Wittman, 2025). These streams rarely explain, sequentially, how data quality shapes algorithmic representation, how representation affects resource allocation, how allocation translates into substantive inclusion, and how inclusion translates into livelihood capabilities and multidimensional household food security. The unresolved gap is therefore not the absence of research on AI, governance, or inclusion individually, but the absence of an integrated causal explanation of conversion freedom—the institutional capacity of smallholders to transform algorithmically mediated opportunities into livelihood capabilities. The novelty of the framework, therefore, lies not in proposing another account of digital inclusion but in theorizing the institutional conditions under which algorithmic participation becomes convertible into livelihood capabilities while distinguishing exclusion from participation-based dependency.

Accordingly, this paper asks: Under what data-governance conditions does AI-mediated agricultural allocation strengthen smallholder livelihood capabilities and household food security, and under what conditions does it generate exclusion or dependency? It develops a governed capability-conversion framework connecting datafication quality, algorithmic representation adequacy, allocation fairness, substantive inclusion, livelihood capabilities, and multidimensional food security. The framework distinguishes a governed capability-conversion pathway, in which enabling governance preserves freedom of conversion, from a dependency-constrained pathway, in which asymmetric control and limited alternatives weaken capability conversion despite digital participation. The paper makes three theoretical contributions. First, it advances conversion freedom as the central explanatory principle that connects agricultural AI to household food security. Second, it specifies a theoretically ordered architecture in which the Capability Approach explains resource-to-capability conversion, Data Justice explains the governance conditions surrounding representation and allocation, and Resource Dependence Theory explains how asymmetric control and restricted alternatives constrain conversion. Third, it develops a multilevel and testable causal architecture separating representation, allocation, institutional inclusion, household capabilities, and achieved food-security outcomes. The contribution, therefore, lies not merely in integrating three theories but in explaining why similar levels of digital participation or AI-mediated access to resources can yield divergent developmental outcomes.

Literature Review

Agricultural digitalization presents a fundamental development dilemma: technologies that can improve information, productivity, resource management, and market coordination do not necessarily distribute these gains evenly. Smallholder participation is still influenced by infrastructure, digital skills, socioeconomic factors, institutional support, and access to enabling resources (Gumbi et al., 2023; Abdulai et al., 2023; Hassim et al., 2024). Empirical evidence also points to considerable heterogeneity in the actual uptake of digital agricultural services by smallholders, highlighting the relevance of socioeconomic and institutional conditions surrounding technology use. Thus, agricultural AI must be understood as both a

technological innovation and a sociotechnical system in which data, institutional arrangements, and power shape who participates and who ultimately benefits.

Agricultural AI and Multidimensional Food Security

Ahmad et al. (2024), describe that applications of artificial intelligence can provide support for crop monitoring, forecasting, resource optimization, disease control, climate adaptation, and agricultural decision making. These applications can also provide prospective approaches to boost productivity and build resilience in the food system. However, the choice of technology is constrained by infrastructure, accessibility, implementation, and socio-economic factors, which can hinder the realization of potential benefits for smallholder farmers (Hassim et al., 2024; Miine et al., 2023). These restrictions can limit the potential benefits smallholder farmers can realize. This is a critical distinction because household food security is a multimodal outcome achieved through availability, access, consumption, and stability, rather than a simple technological output. The best approach to conceptualizing agricultural AI is to view it as an upstream information and decision-making infrastructure. The developmental outcomes of agricultural AI are contingent on the downstream distribution and translation of technology-derived resources and opportunities at the institutional and household levels.

Datafication, Algorithmic Representation, and Allocation

Agricultural AI focuses on transforming farmers, farms, environmental conditions, transactions, and production activities into machine-readable information. Therefore, the significance of datafication in development is contingent not only on the volume of available data but also on whether agricultural data are accurate, comprehensive, timely, interoperable, and sufficiently representative to support valid inferences and decisions. Weaknesses that characterize agricultural data infrastructures, including data quality issues, poor interoperability, governance challenges, and unequal data-sharing arrangements, can limit digital systems' ability to capture the complexity of the agricultural context (Jouanjean et al., 2020; Sullivan et al., 2024). Poor data infrastructures make certain farmers and agricultural practices or local peculiarity less transparent to digital decision-making systems, while algorithms inherently compress complex realities into binary classifications, scores, and predictions. Studies on algorithmic fairness indicate that bias and discrimination arise from the informational and institutional characteristics of algorithmic decisions rather than merely from a lack of technical expertise (Demirchyan, 2025). This representational challenge is important in smallholder agriculture, as access to agricultural services and markets is increasingly mediated by digital technologies. Thus, smallholders can become data-visible without being appropriately represented in the decisions derived from such data, especially when externally constructed infrastructures prioritize institutional purposes over farmers' informational and governance needs (Amar et al., 2026). Algorithmic representation, therefore, supplies the conceptual bridge between datafication and allocation: what becomes legible to the system defines the informational basis on which consequential resources can subsequently be assigned.

Substantive Inclusion and Capability Conversion

Having access to digital tools does not ensure real inclusion. Research shows that farmers' use of digital agriculture services varies with their socio-economic conditions, access to technologies and networks, and other factors that affect acceptability and level of use (Miine et al., 2023). On a deeper level, gaining participation does not guarantee that farmers have an

equal voice or authority in the process. Recent research has revealed that small farmers may be major producers of agricultural data but remain passive in decision-making processes related to its use (Amar et al., 2026). Substantive inclusion then refers to effective institutional standing, not just connectivity or platform enrolment. However, inclusion is not the same as livelihood capability: information, finance, insurance, market access, or institutional support are only developmentally valuable if households can translate these opportunities into effective capability to produce, earn income, manage risk, exercise market choice, and adapt to shocks. This distinction defines the conceptual space of conversion freedom between institutional inclusion and developmental outcomes.

Data Governance, Platform Power, and Dependency

Data governance conditions this transformation, determining how agricultural data are accessed, controlled, interpreted, shared, and translated into consequential decisions. Thus, farmer-centered governance is more than formal ownership or consent, but includes participation, transparency, opportunities for redress, meaningful control, and the allocation of value derived from the data. Data sharing-related research to the area of agriculture demonstrates that both interoperability and data sharing exist together with various concerns regarding privacy, control, governance, security, and trust (Jouanjean et al., 2020; Sullivan et al., 2024), whilst research conducted recently in the area of smallholders indicated that provision of data does not automatically go along with the opportunities of governance participation and value creation (Amar et al., 2026). These asymmetries open a second possibility: dependence can be combined with digital participation. Farmers could remain connected to economically valuable platforms and services, but become dependent on externally controlled data histories, algorithms, infrastructure, or market interfaces. Dependency is thus analytically distinct from exclusion: exclusion prevents meaningful participation, while dependency can be created through participation when critical resources are controlled externally, and the scope for viable alternatives or exit is limited.

These streams of literature, taken together, explain different stages of agricultural digital transformation, but are insufficiently integrated. Digital-agriculture scholarship explains adoption and technological opportunity; algorithmic-fairness research identifies representational and distributive risks; data-governance scholarship reveals questions of participation, control, and power; and capability-oriented reasoning explains why access to resources need not generate equivalent developmental outcomes. What remains insufficiently specified is the sequential mechanism connecting datafication → representation → allocation → substantive inclusion → livelihood capabilities → household food security, together with the governance and dependency conditions that strengthen or constrain this process. Thus, prevailing views do not address two theoretical discontinuities: the first is between algorithmic representation and distributive allocation, and the second is between institutional inclusion and households' ability to transform available resources into valued livelihood opportunities. To address these discontinuities, an explanation of the governance conditions that enable conversion and the dependency conditions that constrain conversion is needed. The missing theoretical link is therefore conversion freedom: the institutional capacity through which smallholders convert algorithmically mediated opportunities into substantive livelihood capabilities. The unresolved mechanism underlies the capability-conversion framework described below.

Review Methodology

Review Design and Search Strategy

This research adopted an integrative, theory-based review to synthesize diverse scholarship on agricultural AI, data governance, smallholder inclusion, livelihood capabilities, and food security. This is the right approach because the aim is not to aggregate comparable effect sizes but to link fragmented concepts, identify explanatory mechanisms, and develop a theoretically coherent framework (Paul & Criado, 2020; Kraus et al., 2022). The search was conducted on 6th August 2026 through Scopus and the Web of Science Core Collection; Google Scholar was used only for backward and forward citation chaining. The main search window was January 2015–6 August 2026, although earlier seminal works were retained when necessary for theoretical attribution. Table 1 describes the search strategy and eligibility criteria.

Table 1: Search Strategy

Component	Specification
Databases	Scopus and Web of Science Core Collection; Google Scholar used only for backward and forward citation chaining
Search period	January 2015–6 August 2026; earlier seminal works retained where theoretically indispensable
Module A	Agricultural AI, smallholders, and food security
Module B	Agricultural data governance, rights, access, and control
Module C	Digital agricultural platforms, agency, capabilities, power, and dependency
Module D	AI governance, fairness, equity, accountability, and inclusion
Inclusion criteria	English-language peer-reviewed articles, scholarly books, and authoritative institutional publications addressing agricultural digitalisation together with socioeconomic, governance, inclusion, livelihood, power, or food-security implications
Exclusion criteria	Purely technical AI studies without socioeconomic or institutional relevance; non-agricultural studies; non-scholarly commentary; duplicate records
Synthesis approach	Theory-driven, concept-centric synthesis focusing on constructs, causal mechanisms, contradictory evidence, governance conditions, and boundary conditions

Note: The literature search was completed on 6 August 2026.

Evidence Selection and Concept-Centric Synthesis

Relevant publications were evaluated in terms of their substantive contribution to construction definition, causal mechanisms, governance arrangements, empirical patterns, contradictory evidence, or theoretically relevant boundary conditions. The synthesis was divided into a core analytical body of literature used directly to build the framework and additional literature on theory, methodology, and context used to ground the concepts. Core sources were included when they made a substantive contribution to the specification or refinement of constructs, causal relationships, governance mechanisms, dependency conditions, or boundary conditions, but citations of contextual information were not treated as evidence directly informing the development of the framework. Evidence was organized in a concept-centric matrix that covered AI functions, data features, algorithmic representation, allocation implications,

inclusion mechanisms, governance dimensions, livelihood dimensions, food-security dimensions, power relations, levels of analysis, and contextual conditions. We compared concepts across sources iteratively to identify convergence, contradictions, causal mechanisms, and boundary conditions. The search and citation chaining continued until no new eligible evidence materially altered the identified constructs, relationships, governance mechanisms, or boundary conditions, which served as the operational criterion for theoretical saturation. The synthesis that emerged informed the seven propositions developed in the conceptual framework.

Conceptual Framework

Theoretical Foundations and Integrative Logic

The framework synthesizes the Capability Approach, Data Justice, and Resource Dependence Theory (RDT) through an intentionally asymmetrical theoretical architecture in which each lens explains different parts of the causal process rather than being treated as an interchangeable account of digital inclusion. The Capability Approach (Sen, 1999) provides the normative underpinning for the distinction between resources, substantive opportunities, and realized functioning. When considering digital agriculture, this implies that access to AI-mediated information, finance, insurance, inputs, markets, or advisory services cannot be equated with development. The question is whether smallholders have the substantive freedom to transform these resources into valued livelihood opportunities. Recent work applying a capabilities lens to farmers' use of digital technologies reasserts the need to focus on what farmers can do with digital resources rather than on technical access per se (Hidalgo et al., 2024).

Data Justice relies on this and extends the argument to identify the conversion of capability in institutional arrangements surrounding data, representation, participation, and distribution. Thus, it makes both a normative and an explanatory contribution. The quality of data governance shapes the degree to which smallholders are represented, treated fairly in algorithmically mediated allocation, meaningfully participate in consequential processes, and contest decisions that affect their opportunities (Taylor, 2017; Ruder & Wittman, 2025). In this sense, formal access to digital systems or data-derived services does not guarantee substantive inclusion when farmers lack transparency, voice, contestability, or meaningful input on the governance of data and algorithmic judgments.

Even if digital services are still helpful, RDT gives us another reason why participation may not lead to equal capabilities. Smallholders may find themselves dependent on resources over which they have little influence when algorithms, infrastructures, market interfaces, or complementary assets are in the hands of agricultural platforms, service providers, or other external actors that control critical data histories (Pfeffer & Salancik, 1978). Such dependency might restrict viable options, increase switching costs, and weaken exit capacity, thereby reducing farmers' ability to convert involvement into substantial livelihood prospects. Thus, RDT reveals that asymmetric control can constrain capability conversion even without formally excluding farmers from digital systems.

We integrate the three views through the lens of freedom of conversion, which we define here as the substantive institutional capacity of smallholders to convert algorithmically mediated resources and opportunities into livelihood capabilities while preserving sufficient agency and viable alternatives. Conversion freedom is not being offered as a fourth theory, a new causal

construct, or mediator. Instead, it is the integrative explanatory principle that unites the three theoretical lenses: the Capability Approach tells us what needs to be converted, Data Justice provides the governance conditions under which conversion becomes substantively possible, and RDT explains how asymmetric control and dependency can limit that conversion. The theoretical division of labor forms the basis for the sequential constructions and the moderating criteria below.

Construct Boundaries and Levels of Analysis

The framework identifies six sequential constructs that operate at interrelated levels of analysis. Datafication quality refers to the completeness, accuracy, timeliness, granularity, representativeness, and interoperability of data that allows smallholders and farming conditions to be digitally observed. Algorithmic representation adequacy is the extent to which these data allow artificial intelligence systems to represent heterogeneous farmers, production conditions, risks, and constraints without systematic distortion or omission. Conversely, AI-mediated allocation fairness concerns the distributive consequences of algorithmically informed decisions: whether consequential resources, including information, credit, insurance, inputs, market access, and public support, are distributed without systematic disadvantage from irrelevant or distorted informational differences (Ntoutsis et al., 2020; Mehrabi et al., 2021). And so, these constructs are analytically distinct from one another: the quality of datafication pertains to informational inputs, the adequacy of representation to algorithmic legibility, and the fairness of allocation to distributive decisions.

The downstream constructs identify institutional position, substantive opportunity, and achieved outcome. Substantive smallholder inclusion refers to farmers having an effective institutional position in AI-mediated agricultural arrangements with meaningful participation, and the capacity to understand, respond to, and contest consequential decisions. Rather, livelihood capabilities are the substantive opportunities households have to produce, earn income, manage risk, exercise market choice, and adapt to shocks, capturing what farmers are effectively able to do, rather than their institutional participation per se. Finally, the developmental outcome achieved in terms of availability, access, utilization, and stability is multidimensional household food security. Thus, the framework moves from the data-system level (datafication and representation) to the institutional level (allocation and inclusion) and the household level (capabilities and food security), while maintaining a conceptual separation between the conditions, opportunities, and achievements represented at each level.

Figure 1 integrates these constructs into a sequential governed capability-conversion architecture and identifies the two theoretically specified moderating conditions.

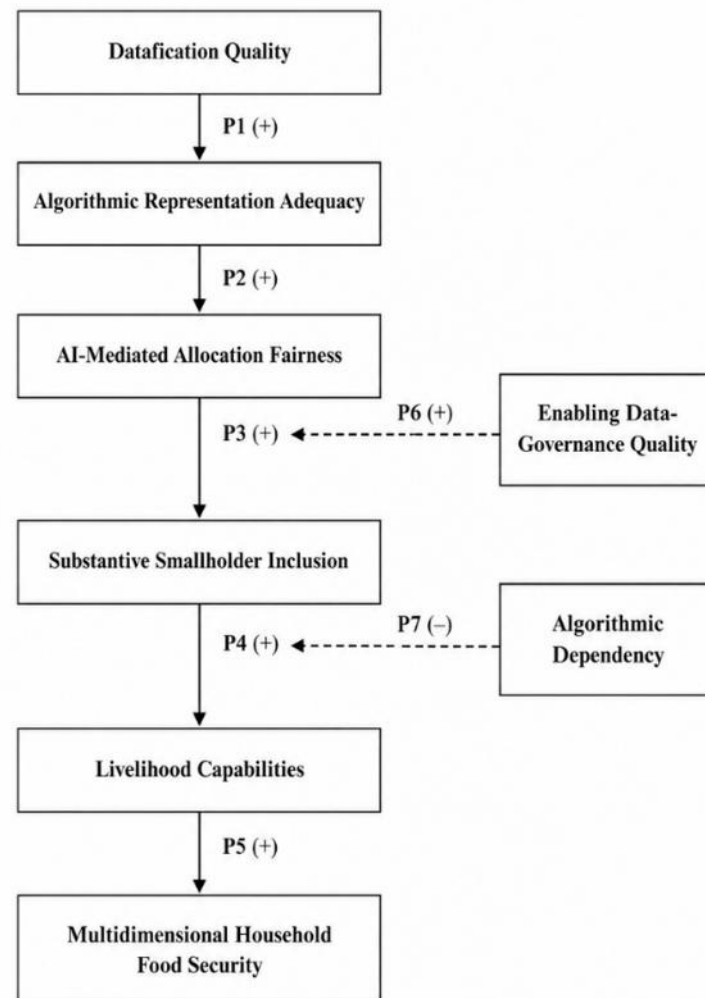


Figure 1. Governed Capability-Conversion Framework for Smallholder Algorithmic Food Security

Note. Solid arrows represent the sequential capability-conversion pathway (P1–P5). Dashed arrows represent moderating effects. Enabling data-governance quality positively moderates the relationship between AI-mediated allocation fairness and substantive smallholder inclusion (P6), whereas algorithmic dependency negatively moderates the relationship between substantive smallholder inclusion and livelihood capabilities (P7).

Proposition Development

Datafication, Representation, and Allocation

The informativeness of AI-mediated agricultural decisions is limited by the data through which smallholders and their farming conditions become digitally legible. Incomplete, inaccurate, outdated, or systematically unrepresentative data may fail to capture relevant heterogeneity, leading to discrepancies between farmers' actual circumstances and their algorithmic representations. This problem goes beyond the usual data quality issues, as biases in selection, measurement, and representation can be propagated through machine-learning systems and systematically affect their outputs (Ntoutsis et al., 2020; Mehrabi et al., 2021). Thus, in

heterogeneous smallholder settings, where farms vary in scale, location, production systems, resource endowments, and risk exposure, higher quality data should improve the extent to which relevant farmer and farm characteristics are captured, rather than systematically obscured or distorted. This makes datafication quality an informational precursor to representation, rather than a direct driver of allocation or food security. Accordingly:

P1. Higher datafication quality is positively associated with greater algorithmic representation adequacy of smallholders and their farming conditions.

Algorithmic representation is distributivity significant when classifications, predictions, rankings, or scores serve as input for obtaining limited agricultural resources. Representational problems may continue to emerge when algorithmic results determine the provision of credit, insurance, advisory services, inputs, market opportunities, or state support. Nonetheless, fair distribution does not mean that all farmers should be treated the same; they might have legitimate differences in their qualifications or needs, and this should be considered in the decision-making process. The core question remains whether distributions unfairly disadvantage some farmers due to under- or misrepresentation of their situation. Research on algorithmic justice also demonstrates that seemingly neutral solutions resulting in disadvantages are associated with biased or limited representation (Liao & Naghizadeh, 2023; Das, 2022). Hence, improved representation should provide a stronger basis for making distributional decisions and minimizing the negative consequences of misrepresentation. Thus:

P2. Greater algorithmic representation adequacy is positively associated with greater fairness in AI-mediated agricultural resource allocation.

Allocation, Inclusion, and Capability Conversion

Fair allocation does not automatically constitute substantive inclusion because receiving algorithmically mediated resources and being institutionally included within the decision system are analytically distinct. Allocation processes acquire greater inclusive significance when affected actors are not only treated fairly in distributive terms but are also able to understand, question, and contest consequential algorithmic decisions. Research on algorithmic allocation demonstrates that fairness involves competing distributive considerations rather than a purely technical optimization problem (Dix et al., 2020), while scholarship on contestable AI highlights the importance of enabling affected actors to challenge decisions that shape their opportunities (Lyons et al., 2021). In smallholder agriculture, fairer allocation should therefore strengthen substantive inclusion by reducing systemic disadvantage and improving farmers' effective institutional standing within AI-mediated resource systems. Accordingly:

P3. Greater fairness in AI-mediated agricultural resource allocation is positively associated with greater substantive smallholder inclusion.

Substantive inclusion becomes developmentally consequential only when improved institutional standing expands what farmers can effectively do. Access to information, finance, insurance, markets, or institutional support does not automatically generate livelihood capability because households differ in their ability to transform available resources into productive and adaptive opportunities. This distinction reflects the Capability Approach's separation between resources and substantive freedoms (Sen, 1999) and establishes conversion freedom as the explanatory mechanism connecting institutional inclusion with capability

expansion. Inclusion should therefore strengthen livelihood capabilities by enabling smallholders to convert institutionally accessible opportunities into enhanced production, income generation, risk management, market choice, and adaptive capacity. Thus:

P4. Greater substantive smallholder inclusion in AI-mediated agricultural systems is positively associated with stronger livelihood capabilities.

Livelihood Capabilities and Food Security

Livelihood capabilities constitute the proximate household-level mechanism by which institutionally accessible opportunities can contribute to food security achievements. Stronger production capabilities can support food availability; income-generating and market capabilities can improve economic access; and risk-management, diversification, and adaptive capabilities can protect consumption and livelihoods against climatic or economic shocks. Empirical research on smallholders associates market participation, livelihood diversification, and adaptive capacity with food security outcomes, while demonstrating that these relationships vary across households and dimensions of food security (Usman & Callo-Concha, 2021; Matsuura et al., 2023; Bitana et al., 2023). Capabilities should therefore be distinguished from food security itself: they represent substantive opportunities through which households may achieve valued outcomes rather than the achievements themselves. Accordingly:

P5. Stronger livelihood capabilities are positively associated with greater multidimensional household food security.

Enabling Data-Governance Quality

The positive relationship between fair allocation and substantive inclusion should depend on the governance conditions surrounding AI-mediated decisions. Even comparatively equitable allocations may remain institutionally shallow when farmers lack meaningful participation, intelligible decision processes, mechanisms for contesting adverse outcomes, practical data mobility, or reasonable opportunities to share in data-derived benefits. These factors can be understood together in terms of their role in ensuring the quality of data governance, as they enhance farmers' real agency within institutions, rather than merely controlling data processing. Contestability is especially important, as it enables the parties affected by relevant decisions to challenge them and participate in decision-making rather than merely receive the results (Alfrink et al., 2023; Lyons et al., 2021). Consequently, these governance values directly pertain to the processes of allocation and inclusion: they clarify the extent to which data justice yields real institutional fairness. Accordingly:

P6. Enabling data-governance quality positively moderates the relationship between AI-mediated allocation fairness and substantive smallholder inclusion, such that the positive relationship is stronger under higher-quality governance conditions.

Algorithmic Dependency

Substantive inclusion may also produce uneven gains in capability if participation engenders dependence on critical resources controlled by external actors. Algorithmic dependence is the degree to which smallholders rely on externally controlled data histories, algorithms, digital infrastructure, services, or market interfaces for economically consequential opportunities and

have few viable alternatives or exit capacity. This construction is contrasted with digital exclusion, in which excluded farmers do not participate meaningfully, and dependent farmers may participate extensively yet remain constrained by asymmetric control over resources. It is not the same as market concentration either; the latter is only theoretically relevant in terms of limiting substitutability, switching, or bargaining alternatives. According to RDT, dependence is important when strategic resources are externally controlled and alternatives are limited. High dependence on algorithms must therefore curtail conversion freedom, limit farmers' capacity to switch providers, negotiate, adapt, or deploy resources autonomously, and weaken the capability gains of substantive inclusion. Thus:

P7. Algorithmic dependency negatively moderates the relationship between substantive smallholder inclusion and livelihood capabilities, such that the positive relationship is weaker at higher levels of dependency.

Discussion

The theory in this study argues that the effect of agricultural AI on people's lives does not depend on whether they use these technologies. It's about how people can take advantage of the opportunities AI presents and make them work for them. If small farmers get fair treatment and a voice on critical issues. We must ask ourselves whether small farmers are being treated fairly and have a say in crucial issues. We need to examine if small farmers are being treated fairly, and whether they have a voice on the big issues. We must evaluate if they can use the resources. They must establish a life for themselves." The crucial question is not only whether they are employing AI. The fundamental issue is whether they are included and can convert their resources into possibilities to earn a living. Agriculture & AI matter. We need to think about how this affects small farmers and whether they are adequately represented. The point is that technical access, representational adequacy, distributive justice, institutional inclusion and capability growth are conceptually different phases, not interchangeable signals of successful digitalization. The main theoretical contribution is hence conversion freedom, which explains how similar AI-mediated opportunities can lead to different developmental outcomes. The framework does not see the Capability Approach, Data Justice and Resource Dependence Theory as competing perspectives, but rather each has a role to play in explaining how it complements the other two. The Capability Approach outlines the conversion of resources into capabilities. Data Justice identifies the institutional conditions that define representation, allocation and participation. RDT shows that conversion can be constrained because of asymmetrical control over essential resources and limited options. This combination further enhances the existing information in two other aspects. First, it theorizes algorithmic representation as distributive and consequential, demonstrating how problems about who and what can be legible to AI may cascade into future resource allocation, not only reduce predicted accuracy. Second, it distinguishes digital exclusion from algorithmic dependency. Exclusion implies the absence of meaningful participation, yet reliance can be produced despite participation, when farmers are placed in a position of dependence on externally controlled digital resources and limited alternatives for switching, bargaining or leaving. "Agricultural AI governance needs to be more than just using the technology and making sure the models are accurate. It's about making the conditions that give people the freedom to make decisions. Policymakers, development agencies, farmer organizations, and technology companies should be asking questions like: Who gets to decide, and who is being wronged by machine decisions? They should also ask whether farmers know what is going on and whether they can speak up

about choices that affect them. They should be questioning whether people have real options and choices.

Being open and honest, involving people, questioning decisions, and using tools and services can help ensure that everyone is included and not overly dependent on one thing. Agricultural AI governance is critical. We should be talking about this kind of stuff.

Empirically, the framework offers a testable architecture to examine where the conversion chain strengthens or weakens across crops, platforms, farmer groups, and institutional contexts. The relevant question is therefore not whether agricultural AI improves food security per se, but for whom, through which conversion mechanisms, and under what governance and dependency conditions

Conclusion

In this conceptual paper, we develop a governed capability-conversion framework to explain how agricultural artificial intelligence can shape multidimensional household food security through datafication quality, algorithmic representation adequacy, AI-mediated allocation fairness, substantive smallholder inclusion, and livelihood capabilities. Its central theoretical contribution is conversion freedom, which explains why access to algorithmically mediated resources does not necessarily lead to equivalent developmental outcomes. The framework distinguishes a governed capability-conversion pathway from a dependency-constrained pathway by assigning different explanatory roles to the Capability Approach, Data Justice, and Resource Dependence Theory, and articulates seven testable propositions. The limitations of this paper are its conceptual nature, the selective approach to integrative reviews, the English-language evidence base, and the lack of empirical validation across heterogeneous agricultural and institutional contexts. Future research should operationalize and test the proposed relationships using longitudinal, multilevel, comparative, and mixed-method designs, with special attention to heterogeneity across farmers, technologies, governance arrangements, platform structures, and regulatory environments.

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