

Sustainable Career Pathways in Digital Agriculture: Conceptualizing AI-Driven Agri-FinTech Ecosystems

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ABSTRACT

Purpose-The purpose of this conceptual paper is to theorize the development of sustainable career pathways for artificial intelligence (AI) and financial technology (FinTech) in the context of digital agriculture, and to develop a theoretical framework of the skills, roles and institutional design required for sustainable, resilient careers in AI-enabled Agri-FinTech environments.

Design/methodology/approach-The paper adopts a conceptual approach, drawing on sustainable careers theory and literature on digital agriculture, career sustainability, financial technology and human capital development, and presents this in a person -context-time framework using a narrative review of secondary sources and industry reports, and based on the success of the case studies.

Findings-The paper ideates the nature of hybrid roles that are required to meet the need of multidisciplinary skillsets in the field of agronomy, data science, and financial risk management, within the context of AI in Agri-FinTech. The key elements for sustainable career pathways include continuous worker upskilling, policy supportive linkages between the education system and industry, and governance flexibility to overcome digital divides in smallholder and rural settings.

Research Limitation/Implications-The framework is a conceptual paper and thus needs to be empirically validated in different geographic and socioeconomic contexts, preferably with longitudinal and cross-sectoral data to evaluate the career sustainability of AI-Agri-FinTech practice. Practical Implication- The model provides guidance for policymakers, educational institutions and agribusiness companies to create training, reskilling and organizational structures which remain relevant to the rate of agricultural finance change.

Social Implication-Inclusive access to digital skills and financial technologies are crucial to promote equitable rural development and economic resilience, while reducing technological marginalization. Originality/ Value- This paper integrates the existing seminal theory of career sustainability into the AI-FinTech-agriculture nexus, an under-explored topic, and lays the groundwork for further empirical and policy studies in this space.

Keywords: Agriculture, Agri-FinTech, Artificial intelligence, Digital Agriculture, Sustainable Careers, Workforce Development

1. Introduction

There has been a fourth agricultural revolution, in which sensors, satellites, robotics and artificial intelligence (AI) are merging with mobile connectivity to transform the production, financing and marketing of food and agricultural products (Klerkx et al., 2019). In this transformation, Agri-FinTech companies leverage AI-based data analytics, data sources, and mobile technologies to provide credit, insurance, and payment services to farmers who have been traditionally excluded from formal financial systems (Köster et al., 2025; Mahbubi et al., 2024). The role of Agri-FinTech in the digital agriculture transition is becoming more and more recognized as an infrastructural precondition, as access to capital is a key constraint on the transition to sustainable agriculture (Köster et al., 2025). Alongside this change, the human aspect of agricultural change has been the subject of relatively scant systematic and theoretical reflection. Digital agriculture is not just automating jobs; it is generating new types of jobs across the agri-food value chain (AFVC), such as data-driven agronomists, agri-fintech enabled rural entrepreneurs, agri-finance credit officers and drone-data technicians, which barely existed a decade ago (Khanna et al., 2024). Despite this, it remains a challenge to theorise how such change relates to sustainable, durable careers, especially in the smallholder and rural setting where most of the world's agricultural labour resides (Food and Agriculture Organization (FAO) 2021. This gap is significant for 4 reasons. Firstly, agriculture continues to be a key source of employment in low- and middle-income countries (LMICs), and digital transformation is likely to have a tangible impact on livelihoods and out-migration from rural areas (Solutions for Youth Employment (S4YE) 2021. Second, access is also extremely uneven the digital and financial infrastructure that supports AI-based farming practices are far less accessible for smallholder farms than for large commercial farms, meaning that the same technologies that provide employment for one farm may be absent for another (Mehrabi et al., 2021). Third, sustainable careers theory, which was developed mainly in urban and organisational, knowledge-economy environments, has not been transferred to contexts where production of the context involves a technological infrastructure, financial intermediaries, and agricultural institutions, but not a single employer (De Vos et al., 2020; Van der Heijden & De Vos, 2015). Fourth, the hybrid positions this literature comes with can just as well give

rise to new precarious arrangements (gig-like; see Rani & Furrer, 2021; Wood et al., 2019), as to careers that last. Fourth, neither should the hybrid positions that this literature is beginning to identify be seen as uniformly good in and of themselves, nor should they be dismissed as nothing more than precarious arrangements. In this paper, the gaps are addressed by focusing on a single theoretical lens: sustainable careers theory (De Vos et al., 2020; Van der Heijden & De Vos, 2015) to bring together the fields of digital agriculture and Agri-FinTech scholarship and the career literature. The paper does not appeal to an alternative ecosystem theory, but rather considers the technological and financial environment of AI-based agriculture as an elaboration of the part of the context dimension in the sustainable careers theory, in which the context is not just an organization but the result of the joint work of several technological and institutional actors, and is still described within the same person context time language as in the previous theory. Career pathways are, therefore, considered as the product of technology, financial context and individual competency (person) and time (continuous re-skilling), aligning with the original formulation by De Vos et al. (2020). The paper makes three contributions. First, it adapts the theory of sustainable careers to a technologically mediated agriculture context, breaking up the context dimension into four structural conditions that are specific to the use of AI in Agri-FinTech, and keeps the subjective, meaning-making heart of the theory. Second, it offers operationalized propositions, and a typology of hybrid occupational roles to inform empirical studies, curriculum design, and policy. Thirdly, it incorporates the risk and critique literature (algorithmic bias, gig-ification, and gendered exclusion), which allows for the model's social implications to be considered as a governance dependent issue rather than a foregone conclusion.

1.1 Sustainable Careers Theory

The paper uses the sustainable careers theory as its only theoretical approach. According to Van der Heijden and De Vos (2015), sustainable career can be seen as a series of career experiences, which are evident in patterns of continuity over time, span across multiple social spaces, are enacted in an individual's field of action, and give meaning to the person. De Vos et al. (2020) discuss such careers on three interdependent levels: person (individual attributes, resources, and agency), context (structural, organizational, and institutional context where careers

develop), and time (accumulation of a person's career experiences over time and their long-run outcomes).

One point easily missed when using this structure in structural contexts, like De Vos et al (2020), is that sustainability is not an objective quality of a job but one that is judged by the individual based on their values and situation. Two employees in the same hybrid position (for instance, an agri-fintech agent working in the community) might have different opinions about whether a hybrid position is truly a viable career choice based on income-variability tolerance and the value they place in the job. This paper's model therefore posits the contextually preconditions that render subjectively sustainable careers more or less likely, without making the assumption that a well-specified context of its own nature becomes sustainable.

In previously, the context dimension of the theory is usually filled with one employing organization, or labor market. The paper's approach is to demonstrate how, in the context of AI in agriculture, context is not a mere product of one actor, but the result of a collective effort by various actors, including infrastructure providers, AI-model developers, FinTech firms, training institutions, and regulators, none of which can create a career pathway without the others. This multi-actor context is broken down in Section 3 into four structural conditions, but without a second theory, instead the conditions populate the context dimension.

Context conditions are important to the person dimension because a complementary construct, employability the person's ability to recognize and pursue work opportunities according to their attributes is provided (Fugate et al., 2004). Skills for employability become more about judgment, adaptability, and interpreting the results of algorithms to make local decisions as AI takes over routine measurement and calculation tasks. Later extensions focus on the career's life span and the cross-over in various life areas, influenced by globalization and the fast pace of technological change (Van der Heijden et al., 2020) which is exacerbated by digital access gaps between rural and urban populations and different generations in Agri-FinTech.

1.2 Digital Agriculture as an emerging Career Context

Digital agriculture is the use of sensors, Internet of Things, robotics, remote sensing and data analytics in farm management which are increasingly site-specific and increasingly autonomous (Klerkx et al., 2019). Unlike previous precision agriculture solutions, AI-powered tools can learn on the farm; machine-learning models can be trained with local data, to tailor to a farm's soil, climate and crop history (Khanna et al., 2024). The impact of AI on

agricultural labor can be seen in various ways: for instance, measurement and prediction instruments take some jobs from manual labor and hand over data analysis and model validation to people; automated machines replace manual jobs that require routine tasks, but add new tasks in maintenance and calibration; and recommendation systems leave it to farmers to spot check model-based recommendations against actual conditions.

Another mechanism points to the wide-spread adoption of generative AI. LLM based advisory chatbots such as Farmer. Digital Green deployed in 4 countries, with at initial evaluation more than 15,000 farmers reached, through retrieval augmented dialogue (Singh et al., 2024) is transforming agricultural extension towards a hybrid of human and AI advisory system. Yet, for LLM output to be applicable locally, it needs to be validated and curated in multiple languages, in which case, it seems like deployment of generative-AI would not replace but rather redistribute the human-intermediation work.

Most importantly, the technological context is not the same everywhere: While an increasing share of farms of over 200 hectares have access to adequate coverage of the third or fourth generation of mobile networks, a minority of very small farms (those smaller than one hectare) do not have access to such networks, especially where yield gaps and food insecurity are highest (Mehrabi et al., 2021). This divide relates to a boundary condition of the model presented below: different career orientations can emerge under the same context, depending on the nature of digital infrastructure in a region.

1.3 Agri-FinTech, Financial Inclusion and Algorithmic Risk

Agri-FinTech uses financial technology (mobile payments, digital lending, alternative credit scoring algorithms, parametrics insurance) for agricultural value chains. Due to the limited access to cash and collateral or credit history needed by smallholders, AI powered analytics enable providers to develop new, data-based loan-eligibility criteria based on mobile-usage patterns or satellite-derived yield estimates (Köster et al., 2025). Research in Indonesia proved that the Agri-FinTech platforms have enhanced the resilience of value-chains for smallholders during the COVID-19 crisis (Mahbubi et al., 2024), and a review carried out in Sub-Saharan Africa revealed that digital financial products can support smallholders in coping with production and marketing constraints when combined with investments in digital literacy skills (Mapanje et al., 2023).

The barriers to adoption are not only product availability but also trust: farmers' willingness to adopt Agri-FinTech can be traced to their relationship with trusted intermediaries, structural assurances on data

handling and perceived relative benefit (Köster et al., 2025), reflective of the focus in the financial-inclusion literature on trusted intermediation for under-served populations (Mapanje et al., 2023). Because trust-building between AI-driven platforms and farming communities needs to happen in a human way, this is directly relevant to Section 3: emergent roles (community-based digital-finance facilitators).

But the trust part of the inclusion question is only half the story: Do algorithms treat farmers fairly? Digital-footprint proxies (such as transaction histories, smartphone ownership, social-network data) are not neutral; audits of fintech lending in adjacent sectors identify the miscalibration of underwriting that can systematically misestimate risk for certain groups, even in the absence of explicit considerations of protected characteristics (Coots et al., 2025). As the models are dependent on these historical data, algorithmic underwriting risks algorithmic re-entitlement which is the first-order design consideration further developed in Section 4.4, given that these records are often scarce and thin among women, tenant farmers and smallholders.

2. Method

A conceptual research approach was taken in this paper, which combines literature review of digital agriculture, Agri-FinTech, and a career sustainability approach through narrative secondary sources review, industry resources, and case-based evidence. As is common in conceptual-paper style reviews, there was a documented although not fully systematic search-and-synthesis protocol used to guide the review, as described below, and the review generates a Person Context Time model with a clear evidence base that can be reconstructed.

Literature was identified using structured searches in Scopus, Web of Science, and Google Scholar, plus targeted searches in institutional repositories (FAO, ILO, CGIAR, IFPRI, GSMA and Center for Financial Inclusion) for practitioner and policy reports. Search strings intertwined context dimension terms with the two literatures to explore: (“digital agriculture” OR “precision farming”) AND (“artificial intelligence” OR “machine learning”); (“Agri-FinTech” OR “digital lending” OR “alternative credit scoring”) AND (“financial inclusion” OR “trust” OR “algorithmic bias”); (“sustainable careers” OR “career sustainability” OR “employability”) AND (“technology” OR “digitalization”) AND (“gig economy” OR “platform work” OR “precarity”) AND (“agriculture” OR “rural”). The window for the search covered the period of January 2000 to March 2026 and included the majority of sources that were published in 2015–2026.

Records were filtered twice. Studies were excluded from title/abstract screening if they did not have at least two of digital agriculture, Agri-FinTech/financial inclusion or career or labour-market outcomes. Full-text screening focused on peer-reviewed journal articles in agricultural economics, information systems, vocational behaviour, sociology of work and management, with institutional reports included only if they contained empirical details that could not be found elsewhere. Preprints were only kept when they described original empirical deployments that were relevant for the labour-market and governance claims raised.

This serves the aim of triangulation; if possible, every key piece of evidence regarding trust, adoption, or exclusion for Agri-FinTech is backed up by a minimum of two independent sources (such as the trust-antecedent claims are triangulated between Köster et al. (2025) and Mapanje et al. (2023); the algorithmic-bias claims are based on evidence from a fintech-lending-audit). The six propositions of the model and the model itself were developed abductively through the search of recurring patterns in the literature which included the role of the trust intermediary with respect to the adoption of Agri-FinTech, the focus on hybrid technical-financial-agronomic skills found in research on digital-transformation-skills and the documentation of algorithmic bias and gig-like precarity in adjacent platform-mediated sectors.

There are three types of scope. First, the model was developed for smallholder- and mid-scale-dominated agricultural systems found in LMICs (as the operational scope term is also used throughout, synonymous with the Global South), where the tension between the potential of digital agriculture and its uneven diffusion is most pronounced, and applicability to large-scale, highly capitalized commercial agriculture in high-income economies is highlighted for comparative research in the future. Second, the concept of “career pathway” is applied broadly and includes waged employment, self-employment and agripreneurship, and hybrid pathways of production combined with data or finance-based careers (FAO, 2021; S4YE, 2021). Third, hybrid jobs are not inherently precarious: it is an empirical question whether a specific job is a precarious, “gig” job or a sustainable career.

3. Result

3.1 A person-context-time model

To apply the sustainable careers theory in this context, it is necessary to describe each of the three aspects of the theory in the context of the AI-powered Agri-FinTech. The context dimension is further broken down into four structural conditions of this domain,

namely (C1) Digital Infrastructure, (C2) Data and AI (C3) Finance and (C4) Governance. For the person dimension, it is set as a hybrid competency set using employability, as described by Fugate et al., 2004. The time dimension is set by the imperative to constant re-skilling due to the constant changes in technology, financial products, and conditions in the agriculture sector. Tables 1, 2 and 3 summarize the model, translate the model into a typology of hybrid occupational roles, operationalize the propositions developed below respectively.

The model shown in Figure 1 represents the model described in Table 1. The context dimension is depicted as a multi-actor structure C1 (Digital infrastructure), C2

(Data and AI), C3 (Finance), and C4 (Governance) with C1 gating C2 and C3, in line with its being an infrastructural precondition (Section 1.2), and C4 as a dashed, cross-cutting moderator, reflecting Proposition 4's suggestion that governance strength conditions the degree of conversion of context maturity into sustainable, equitable careers. The person dimension- hybrid competencies through employability (Fugate et al., 2004) is fueled by the context, and the time dimension of continuous re-skilling is both positioned in front of and behind the person dimension, with the time dimension suggested by a dashed feedback arrow and the continuous re-skilling nature suggested by the recurrent nature of the arrow.

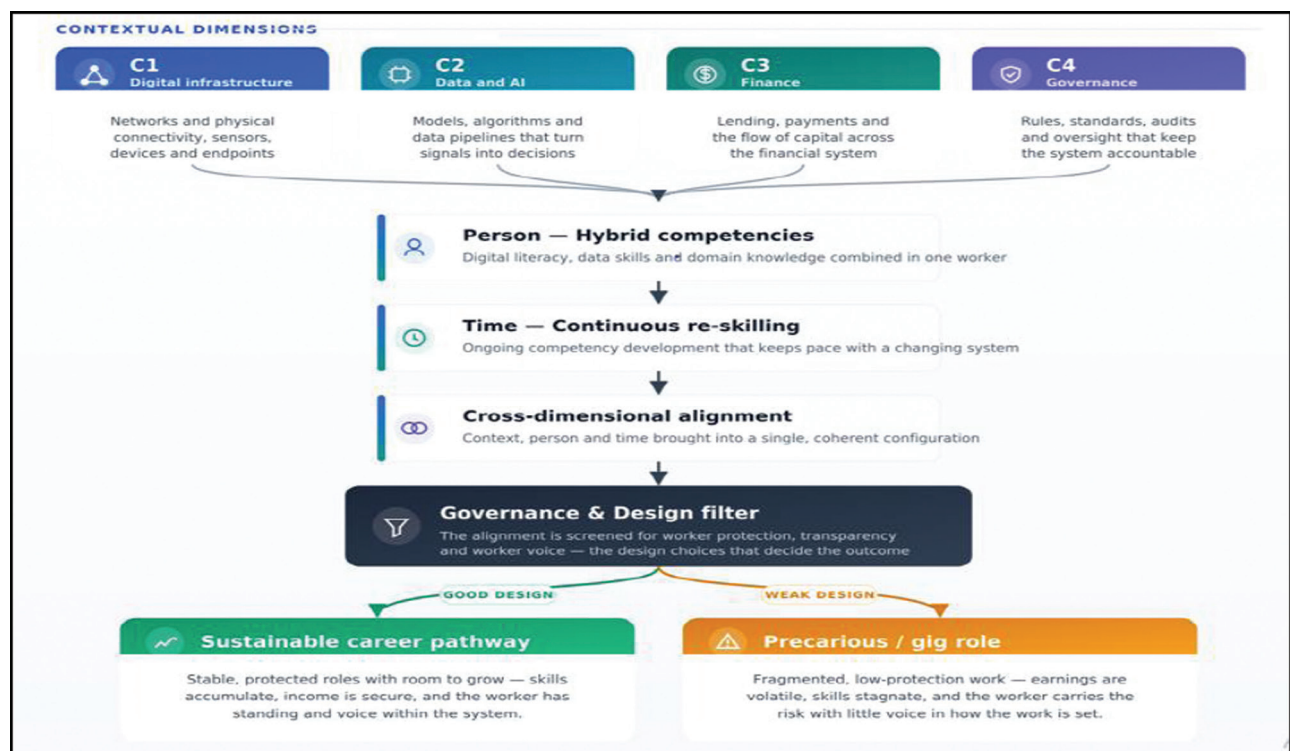


Figure 1. Person-context-Time model of AI-Driven, Agri-Fintech Career sustainability

Table 1. Person-context-Time model of AI-Driven, Agri-Fintech Career sustainability

Dimension	Component	Description	Key Mechanism
Context	C1- Digital infrastructure	Mobile/broadband connectivity, sensor networks, satellite/drone imagery, edge/cloud computing	Gating condition for C2–C3; without it, no hybrid roles can emerge locally
Context	C2-Data and AI	Algorithms, models, and data pipelines converting raw data into recommendations	Durable human-validation and local-translation roles
Context	C3-Finance	Digital lending, payments, parametric insurance, alternative credit-scoring	Trust-building intermediary roles between platforms and farmers
Context	C4-Governance	Data governance, algorithmic-bias auditing, consumer-protection regulation	Enables or constrains engagement with C2–C3; shapes equity of outcomes
Person	Hybrid competencies through employability	Digital literacy, data interpretation, entrepreneurial orientation, domain knowledge	Employability as mediating mechanism (Fugate et al., 2004)
Time	Continuous-skilling	Cumulative competency development amid shifting technology, products, and markets	Paces career sustainability across the working lifespan

The three dimensions intersect at the alignment node represented in Proposition 6, which then splits into a sustainable career pathway and a precarious, gig-ified position that is subjectively sustainable but lacks objective sustainability because of lack of employment protections or algorithmic transparency or worker voice. This visually represents the paper's central qualification an aligned, well-specified context is required but not sufficient, as in principle the same context can be structured to meet each structural requirement without the production of precarity.

3.2 The Context Dimension- Four Structural Conditions

C1-Digital Infrastructure- This condition involves mobile and broadband connectivity, sensor networks, satellite and drone imagery systems, and edge/cloud computing capacity. Because of its high level of heterogeneity (Mehrabi et al., 2021), it is also a gating condition, it is not possible for C2 (Data & AI) or C3 (Finance) to serve local functions without good connectivity, and without C2 or C3, none of the hybrid roles on which they rely can be realized.

Proposition 1 (P1): The number and diversity of AI-enabled Agri-FinTech career paths available to people in a local agricultural community is positively moderated by the density and quality of the local digital infrastructure, such that low-density, low-quality local digital infrastructure leads to limited career pathways, even with sophisticated AI or FinTech offerings.

C2 - Data and AI- This condition includes algorithms, models and data pipelines that transform raw agri- and financial data into recommendations. Local validation is also a typical requirement of the AI models used here, as farmers validate recommendations with field experience (Section 1.2), which creates a long term need for intermediary jobs like model validation technicians, local data annotators, agronomic "translators", etc., not to be completely eliminated by automation due to the role played by intermediary jobs.

Proposition 2(P2): The more local AI-driven recommendation systems such as the generative-AI advisory chatbots depend on context translation from the local to the global and/or require human validation, the more enduring the intermediary jobs involved will be against further automation, though their durability will diminish as foundation-model accuracy for a given crop-region pair increases.

C3- Finance- This condition includes digital lending platforms, payment systems, insurance products and credit-scoring algorithms, as described in Section 1.3. It creates career paths as in trust-based adoption studies (Köster et al., 2025) not only in the FinTech companies

themselves but more specifically in intermediary roles that foster farmer trust: community-based agri-fintech agents, digital-finance extension officers and cooperative-level finance facilitators.

Proposition 3(P3): Career pathways that are built around Agri-FinTech are more likely to be sustainable than are those that are built around Agri-FinTech as stand-alone digital applications, provided that the intermediary role is also defined and transparently governed to build trust, and is backed by employment-like protections, such as a base retainer, defined hours, or cooperative membership; where employment-like protections are absent, piece-rate or commission-only arrangements predict durability but do not necessarily predict subjective sustainability, as per De Vos et al. (2020), Section 3.5.

C4- Governance- This condition trumps the previous three-data governance rules, algorithmic-bias-auditing requirements and consumer protection rules. It is an enabling or constraining condition for the whole context, not a stage in itself, because, if it prevents farmers from engaging with C2 and C3 at all, or makes engagement with C2 and C3 unfair, it prevents the C2 and C3 from ever being engaged. Regardless of the level of development of C1-C3, weak governance can impede adoption or result in discriminatory outcomes.

Proposition 4 (P4): Strength and transparency of data-governance, algorithmic-bias-auditing and consumer-protection arrangements (C4) positively moderate the relationship between context maturity (C1-C3) and (a) the number of individuals that convert context participation into sustainable careers and (b) the equity of that conversion across gender and landholding status; governance effects are expected to be asymmetric, with strengthening weak governance producing larger equity gains than with strengthening already-strong governance.

3.3 Person Dimension- Hybrid competencies through employability

Sustainable engagement with this context demands a mix of digital competences, data interpretation, entrepreneurial orientation and domain-specific knowledge on agriculture, both agronomic and financial, which aligns with the research on digital-transformation-skills (Bouwman et al., 2022) but tailored to the agriculture sector. These competencies are developed by a variety of institutions including training programs, apprenticeship frameworks, and programs that support agripreneurship, and their absence will have a negative impact on career sustainability. Evidence on youth agripreneurship suggests that digital solutions are most effective when they combine aspects of finance, inputs, market access, and capacity development (S4YE, 2021).

The person dimension converts competency development to career sustainability through the capacity to continuously identify and pursue new career opportunities, which is called employability (Fugate et al., 2004). This paper, in contrast, does not consider employability as an unconnected construct side by side with institutional training investment, but rather as a mediating variable.

Proposition 5 (P5): Where (a) individual competencies in hybrids are developed, (b) institutional training and apprenticeship infrastructure are created, and (c) opportunities for continuous re-skilling exist, individual employability - which is a moderate positive function of the three dimensions - is a critical determinant of career sustainability (Fugate et al., 2004), and is a negative function when the three dimensions are not aligned on any dimension. This proposition is based on a minimum maturity level of C1-C3, and where there is no infrastructure or financial access (per P1), person-dimension investment is predicted to increase employability, but to not create the corresponding career-pathway opportunities, because there is no context in which employability is exercised.

3.4 The Time Dimension is Continuous Re-skilling

In this context, the time dimension is not defined by a moment of technology adoption but rather by the gradual evolution of hybrid competences over a working life. Later versions of sustainable careers theory also stress a lifelong career development process and the cross-over of various life domains (Van der Heijden et al., 2020): the re-skilling speed needed for continued employability is then a variable, which can be influenced by C1-C4.

3.5 An Integrative Proposition and a Boundary Condition on Precarity

Combined, P1-P5 suggest that sustainable career pathways do not result from single interventions such as rural broadband expansion or the launch of an Agri-FinTech application, but need to be developed simultaneously, across the three dimensions of career pathways theory (context, person and time).

Proposition 6 (P6): A career pathway that is structurally mature is not a prerequisite for sustainability; sustainability is achieved as a result of what is happening at the intersection, along the context (C1–C4), person and time continuum, where hybrid career pathway roles are structured with appropriate financial stability and worker voice, avoiding gig-ification, and where AI intelligence is matched with and reinforced by competency development.

As stated above, and as can be seen in the hybrid roles listed in Table 2, a number of the listed roles are very similar to gig or piece-rate employment as outlined in other sources. Accessibility of gig work through a platform also represents true flexibility as well as algorithmic control, income volatility, and the lack of typical employment rights and protections that would contribute to an understanding of sustainability in the De Vos et al. (2020) definition (Rani & Furrer, 2021; Wood et al., 2019). The community agents, who are paid by the referral of a successful loan, or the data-validation technicians who are brought in as short-term contractors, work in a structurally similar role: they are durable, and the need for their services is ongoing (P2 and P3, respectively), but not sustainable. The sustainability of a hybrid role or precarious gig depends on external to the tech governance and organizational design do

Table 2. Typology of Emergent Hybrid Career Roles

Role	Conditions	Core competencies	Evidence
Community Based Agri-FinTech Agent	C3, C4	Trust-building, basic financial literacy, local relationships	Köster et al. (2025); Mapanje et al. (2023)
Digital Credit-Scoring / Risk Officer	C2, C3, C4	Data science, algorithmic-bias auditing	Coots et al. (2025)
Model-Validation Technician / Agronomic Translator	C2	Local agronomic knowledge and data interpretation	Khanna et al. (2024)
GenAI Content Curator / Local Validator C2 Multilingual curation / quality assurance of AI advisory content Singh et al. (2024)	GenAI Content Curator / Local Validator C2 Multilingual curation / quality assurance of AI advisory content Singh et al. (2024)	GenAI Content Curator / Local Validator C2 Multilingual curation / quality assurance of AI advisory content Singh et al. (2024)	GenAI Content Curator / Local Validator C2 Multilingual curation / quality assurance of AI advisory content Singh et al. (2024)
Drone-Data Technician	C1, C2	Equipment operation, aerial-imagery interpretation	Klerkx et al. (2019)
Extension skills in combination with digital-finance literacy Extension Education Officer / Cooperative Facilitator	C3, C4	Extension skills combined with digital-finance literacy	Mapanje et al. (2023)

companies consider agents as employees or contractors; do platforms make their algorithms transparent and appeal mechanisms; do platforms have cooperative or union structures to aggregate worker voice? Therefore, P3 and P6 are specified conditionally: there must be a well-defined context that can then be linked to a gigified organizational model which meets all the structural conditions but not the subjective-sustainability condition at the heart of the theory.

While this typology is not a statement of fact, it is illustrative in a conceptual paper as it is meant to be; however, several typologies are cross referenced with documented, real-world deployments, not just speculative. Systematic occupational-classification research such as an exercise in emerging titles, or a job-posting analysis, as described in Section 4.5, is identified as a priority for confirming and refining this typology.

4. Discussion

4.1 Theoretical Contributions

This paper takes the sustainable careers theory's person–context–time framework (De Vos et al., 2020) beyond its predominantly organizational, urban, knowledge-economy context and applies it to a technologically mediated agricultural context, but does not distance itself from the theory's subject, subjective, meaning-making aspect by exclusively foregrounding the structural dimension. Prior scholarship on sustainable careers is based on the idea that career moves occur in various social places and life contexts (Van der Heijden et al., 2020), but has not yet identified the technological

and financial infrastructures linking these places in rural contexts, nor explored the potential for technologically mediated “opportunities” to be organized as precarious gig work. As the context dimension is disaggregated into four structural contexts and the mechanism between context and person-dimension outcomes is specified as employability, this paper demonstrates that context here is a layered structure brought about by multiple actors (technology developers, financial institutions, training providers, regulators), whose alignment has to be actively managed in order for career sustainability to become feasible at all. While similar accounts of prior technology-adoption and digital-innovation-ecosystems exist (e.g., Fielke et al., 2019; Wolfert et al., 2023), the present paper's contribution is that one, established theory of careers is enough to account for how that landscape gets translated into durable careers or not, without a second, competing theory.

4.2 Practical Implications

The model suggests that training institutions need to offer students courses addressing the hybrid competencies outlined in Section 3.3 digital literacy, data interpretation, entrepreneurial orientation, and domain knowledge along with continuous re-skilling mechanisms (Section 3.4) rather than single courses on digital literacy. Overall, the model suggests that investment in trust-building intermediary positions is as important as investment in digital products in the direct-to-farmer model, but may be even more important for the successful adoption and sustainable local careers of Agri-FinTech and AI-agriculture

Table 3. Operationalization of Proposition P1-P6

Proposition	Unit of Analysis	Measures	Conditions
P1.	Agricultural community / district	Mobile-broadband coverage classification; number of unique hybrid job titles	Non-linear: No hybrid positions below a minimum number; saturation above a maximum number
P2	Individual AI/advisory deployment	Proportion of AI recommendations routed through human review; retention/tenure of validation workers (3–5 yrs)	Weakens as foundation-model accuracy for a crop-region combination improves
P3	Individual in a C3 intermediary role	Role tenure; income-stability (coefficient of variation in monthly earnings); validated career-sustainability/employability self-report scales	Holds only where the role carries employment-like protections, not piece-rate/commission-only terms
P4	Regulatory jurisdiction	Composite governance-strength index (data protection, bias-audit requirements, consumer-protection capacity); gender/landholding gap in role conversion	Asymmetric (concave): greater gains to strengthen weak governance than strong governance
P5	Individual worker, training institution	Pre and post digital financial literacy assessments, density of apprenticeships, frequency of re-skilling touchpoints, employability scale (mediator)	(assumes a minimum floor of C1 – C3 maturity)
P6	Ecosystem/context as a whole	Composite alignment index across C1–C4, person, and time; worker-voice/income-stability index	Conditional on hybrid roles not being ‘gig-ified’, structuring

firms (Köster et al., 2025). However, section 3.5 notes that designing firms to run such jobs comes with a real choice between an employment-like mode which supports subjective sustainability and a piece-rate mode which could facilitate adoption to the same degree and create the same job-quality issues described in the gig-economy literature (Rani & Furrer, 2021) this is not an incidental outcome of scale, but rather a design choice. The model also makes clear that investments in infrastructure (C1) without the accompanying investment in training, as part of the person dimension (C4) (including the need for an algorithmic-bias-audit) are not enough: the model suggests that partial development, if technically possible, is not sustainable, as evidenced by the simultaneous need to invest in finance, inputs, market access, and capacity development in the context of agripreneurship investment; similar outcomes are expected for the investment in rural broadband and FinTech pilots.

4.3 Social Implications- Gender, Inclusion and youth employment

The model is especially relevant for financial inclusion, youth employment, and gender equity - rural women's access to the underlying factors that shape the model is limited long before they enter into a hybrid career position. Women in rural LMIC settings face measurable inequalities compared to men in their access to a smartphone or mobile Internet, even when mobile phones are nearly ubiquitous; a survey of smallholders in Uganda revealed that while nearly all households had a mobile phone, smartphone access was limited to about a third of respondents and inequalities stemmed from low digital literacy, time poverty, and access to a male family member's phone (Mulungu, 2025). This gap is an early filter on women's participation as C2 and C3 services are increasingly based on accessing the smartphone.

This adds to a longstanding challenge: women's weaker land rights and asset ownership in turn is also directly reflected, or used as a proxy, in alternative credit scoring models (Section 1.3). The Center for Financial Inclusion (2024) have both found that programs that focus on land tenure alone have led to less than desired outcomes of improving the day-to-day lives of tenants. This is particularly true with respect to C3 and C4, the extension of Agri-FinTech to women-credit-scoring algorithms must be audited for gender correlated bias and person-dimensional training must include explicit focus on digital-literacy and language barriers.

Concurrently, the relative lack of emphasis on land and capital ownership to the extent that they are foregrounded in the role, means that the same structure that can increase inequality in access to land and capital can offer a viable route for youth and women, as

community-based digital-finance agents or data-validation technicians, if these roles (and related training and governance processes) are not gigified, and the processes are deliberately inclusive (Section 3.5), a concern to which women in flexible, informal arrangements are singled out. Social outcomes are instead not technologically determined but are dependent on the design and governance of structural conditions in the model.

4.4 Risks and Critiques: Algorithmic Bias, Gigification, and Exclusion

The use of algorithmic bias to credit scoring is not an implementation problem, but a structural risk embedded in C3 in its current practice. Alternative data credit models can encode and amplify gender, geographic, or land-tenure-based exclusion because the distribution of these proxies for the digital footprint is uneven (Coots et al., 2025). The structural responses of the model are as follows: P4 introduces the capacity for bias-advetting into governance conditions; Table 3 envisions a measure of equity rather than just quantity of context-driven career and credit outcomes.

The gigification risk discussed in Section 3.5 suggests that the mix of hybrid roles identified here as this paper's main contribution to the labour market might just be a shift of job quality issues that are already documented among platform workers in the Global South to agriculture (Rani & Furrer, 2021; Wood et al., 2019). A reader thinking of any proliferation of hybrid roles as being a success in career sustainability is misusing the model; the claim is conditional (P3, P6) rather than unconditional. Similarly, the gender and youth entry points defined in 4.3 are not automatic, but can only happen within a certain governance context. Without conscious and intentional gender-inclusive design, current inequalities in rural access to infrastructure, land and digital literacy are likely to be passed on and even exacerbated by the market. Because of these risks, the social value of this model will not be a part of its conclusions, but rather an empirical and governance-contingent question, exercised through the measures of equity described in Table 3.

4.5 Limitations and Future Research Agenda

Like all conceptual papers, it is necessary to test this model and its propositions empirically. The literature base is triangulated, when possible, but is still deficient of the 60-100 sources that is typical of Q1 conceptual papers in this space, the next step will be a dedicated PRISMA-style systematic scoping review which will build on the search protocol outlined in Section 2.

The structure of the model gives rise to several more priorities. Proposition 1 would be tested in the first step

by comparative case studies across contexts where digital infrastructure maturity (C1) is different, which would investigate whether diversity of career-pathways changes according to the local maturity of digital infrastructure (Mehrabani et al., 2021). Second, longitudinal studies that track workers as they move into hybrid positions would enable direct measurement of the extent to which hybrid work arrangements are sustainable in the sense of De Vos et al. (2020): whether they lead to enduring, meaningful patterns or are transitional and precarious (Table 3), along with a measurement of indicators of worker voice and income stability. Third, future research should test P4 by empirically comparing governance conditions (C3), in particular regulatory environments that vary in data-protection and bias-audit regimes, with algorithmic audit studies similar to those in fintech lending, modelled after those conducted by Coots et al., 2025, but focused on agricultural credit-scoring products. Fourth, further comparative studies need to be conducted to determine if the model's predictions are confirmed, adjusted or differently weighted in the highly capitalized large-scale commercial farms of high-income countries. Fifth, the gender and youth aspects should be the subject of further empirical investigation, which builds on the evidence gathered so far on digital solutions for young agripreneurs (S4YE, 2021), training for rural digital-entrepreneurship (Bouwman et al., 2022), and gender gaps in mobile access (Mulungu, 2025). Sixth, this paper relies on an existing body of literature when building the occupational typology, so the typology should be viewed as illustrative; systematic occupational-classification research (job-posting analysis) would improve the typology.

5. Conclusion

This paper aimed to fill a gap in the literature that connects digital agriculture, financial technology and career theory, namely the digital agriculture and financial technology is transforming the way agriculture is organised and financed, but there is limited theory to guide sustainable career pathways for people working in this sector. This paper established a person–context-time model based on the theory of sustainable careers (De Vos et al., 2020; Van der Heijden & De Vos, 2015), which specifies that the technological and financial environment for AI-driven agriculture (AI context) forms a multi-actor context of digital infrastructure, data and AI intelligence, financial intermediation, and governance and trust, in interaction with individual hybrid competencies and continuous re-skilling, to determine the sustainability of a career.

The model's core theoretical proposition, stated in six propositions, is that the emergence of sustainable career pathways with this domain is an emergent phenomenon,

the result of aligning across person, context, and time dimensions of a single established theory, not the result of any single technological, financial, or educational intervention, and that this alignment is achieved through governance choices that either lead to genuine sustainability or a well-aligned but gigified pathway alternative (Section 3.5). In this re-framing of career sustainability in the digital agriculture, it becomes clear that complementary capabilities will need to be developed at the infrastructure provider, algorithmic-bias auditor, AI developer, FinTech, training provider and regulator levels for careers to remain sustainable and equitable over time in the rural context, if they are to be sustainable at scale. The model provides a testable application of theory of sustainable careers to a new arena for scholars, as well as a set of falsifiable propositions for practitioners and policy makers, who can use it as a diagnostic tool to understand the structural condition that currently prevents the conversion of digital agriculture investments into durable rural livelihoods and as a risk checklist (algorithmic bias, gigification, gendered exclusion - Section 4.4) to assess whether the conversion is taking place equitably. The governance-aware design of this model seeks to create sustainable and inclusive careers, not only efficient infrastructure and precarious work, and this will be critical for AI-driven Agri-FinTech as it spreads to the Global South and beyond.

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Declaration of Conflicting Interests

The authors declare no conflict of interest.

Declaration of Generative AI and AI-assisted Technologies in the Writing Process

During the preparation of this manuscript, the authors have not used generative AI or AI-assisted technologies. The authors independently developed the conceptual framework and scholarly arguments and remain fully responsible for the accuracy, originality, and integrity of the manuscript.

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