World Development 196 (2025) 107192

Contents lists available at ScienceDirect

World Development

journal homepage: www.elsevier.com/locate/worlddev

Regular Research Article

Membership in farmers' organizations and intention to innovate: A mixed random utility and behavioral approach

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ARTICLE INFO

Keywords:
Africa
Behavioral factors
Innovation adoption
Farmers' organizations
Risk attitude
Trust

ABSTRACT

Despite a growing body of literature on the adoption of agricultural innovations, their uptake by smallholder farmers in developing countries is often slow. The processes underpinning farmers' decision-making in these countries are yet to be fully understood, and the existing literature remains contradictory regarding the factors explaining adoption. Conflicting conclusions emerge from studies on different countries, which may result from specific social, cultural, and institutional environments. We develop a theoretical model that combines random utility and behavioral approaches to assess how membership in farmers' organizations affects the intention to innovate. Using a two-step framework, we assume that membership in such organizations acts as a mediator variable between background factors and the intention to innovate. Three distal behavioral factors – openness to new ways of production, attitude toward risk, and trust in organizations promoting innovations – are considered additional intermediate drivers. We test our framework using primary survey data from five African countries, covering a total of 4,529 farmers and more than twenty farmers' organizations. We find that generic organizational membership has limited mediating power and a marginally positive impact on the intention to innovate, which becomes non-significant when accounting for the behavioral attitudes of individual farmers. These attitudes do work as mediator variables between the background factors classically included in random utility models (i.e., farm, household, and farmer's characteristics) and the intention to innovate. In turn, membership in some specific organizations proves to be a significant predictor of the intention to innovate, although the direction is not univocal. A specific institutional approach is thus needed to evaluate which characteristics of a farmers' organization impact its members' intention to innovate. We provide some hypotheses based on local knowledge.

1. Introduction

Despite a growing body of literature on the adoption of agricultural innovations, their uptake by smallholder farmers in Africa remains limited and uneven (Kaliba et al., 2018; Meijer et al., 2015). Furthermore, the processes underpinning farmers' decision-making in

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https://doi.org/10.1016/j.worlddev.2025.107192
Accepted 14 September 2025
Available online 25 September 2025
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developing countries are yet to be fully understood, as the literature remains contradictory regarding the factors explaining adoption (Adnan et al., 2017).

Most of the extant research has been conducted in specific national or regional contexts. Nevertheless, assessing the external validity of recognized factors across countries and cultures is necessary (Dessart et al., 2019). Indeed, conflicting conclusions frequently emerge from studies in different countries and may result from different social, cultural, and institutional environments. It is thus crucial to identify the interactions among these factors and farmers' intention to innovate (Feder et al., 1985).

One of the factors frequently discussed when dealing with agricultural innovation is the role of membership in farmers' organizations.[1] Many authors include it among the drivers of adoption. The specific causal mechanism linking organization membership to innovation is interpreted in different ways and may include: (i) a spillover effect (Manda et al., 2020), where "[a] production practice used by the majority of members is likely to be adopted by other members" (Adnan et al., 2017); (ii) the credit and information provision guaranteed or facilitated by organizations (Manda et al., 2020), which are trusted more than other sources (Nwankwo et al., 2009); (iii) the pooling of resources to develop economies of scale (Kolade & Harpham, 2014); (iv) the role of extension officers, donors, and non-governmental organizations, which reach organization members more easily than isolated individuals (Blekking et al., 2021; Chagwiza et al., 2016; Okafor & Okafor, 2017); (v) the role of social capital within a network (e.g., a cooperative) in promoting economic transactions (Sutherland & Burton, 2011).

Literature reviews focused on specific typologies of farming innovations are a good starting point to assess whether membership in farmers' organizations really fosters innovation. Prokopy et al. (2008) reviewed 25 studies on the adoption of management practices in the USA, finding that participation in organizations was positively correlated with adoption in seven studies, negatively correlated in one, and not correlated in eight. Knowler and Bradshaw (2007) reviewed 23 studies about conservation agriculture around the world, finding that participation in organizations was positively correlated with adoption in two studies and not correlated in one.

Many empirical papers have assessed the relationship between participation in farmers' organizations and the adoption of innovation in Africa. Some focus on this relationship as the main objective of the study, while others include organization membership among many potential drivers. Among the papers that specifically focus on organization membership, Manda et al. (2020) concluded that it increases the speed of adoption of improved maize varieties in Zambia; Kolade and Harpham (2014) found cooperative membership to have a higher impact than other socioeconomic factors such as land access, gender, and educational status on farmers' uptake of technological innovations in southwest Nigeria; Okafor and Okafor (2017) demonstrated that cooperative members adopt more agricultural technologies than non-members in Nigeria; and Chagwiza et al. (2016) showed that cooperatives facilitate technological transformations among dairy smallholders in Ethiopia.

Many other papers include organization membership among the variables potentially explaining innovation without it being the focus. Some found a positive correlation, others identified no significant relationship. Cases where a positive correlation has been found include, among others, the adoption of new rice varieties in Sierra Leone (Mansaray et al., 2019); soil and water conservation practices (Nkegbe & Shankar, 2014); maize production technologies in Ghana (Abawiera Wongnaa et al., 2018); biosecurity measures against avian influenza outbreaks among poultry farmers in Nigeria (Oladipo et al., 2020); sustainable soil management practices among fluted pumpkin producers in Nigeria (Olowa et al., 2019); and crop technology packages in Ethiopia (Tefera et al., 2020). In turn, authors did not identify any significant correlation between membership in farmers' organizations and the adoption of aquaculture technologies by smallholder fish farmers in Kenya (Obiero et al., 2019); improved maize varieties (Takam-fongang et al., 2019); technology maize packages in Cameroon (Mabah Tene et al., 2013); and improved maize varieties in Ethiopia (Zeng et al., 2018). In the case of cage tilapia farming in Ghana, Mantey et al. (2020) observed that membership has no correlation with adoption but is negatively correlated with disadoption.

Thus, empirical studies show that membership in organizations is not always a driver of adoption. On the one hand, despite their many potential benefits, organizations may suffer from several problems, including low managerial capacity, free riding, corruption, or mismatches between individual and collective interests (Chagwiza et al., 2016), and this can affect their capacity to foster innovation. First, the attitude and motivation of leaders matter (Périlleux & Szafarz, 2015). Furthermore, farmers' organizations can have very different objectives and can serve different needs of their members, including production, purchasing, marketing, socialization, and information-exchange services (Adnan et al., 2017). Chagwiza et al. (2016) distinguish between "marketing" cooperatives, and "livelihood" cooperatives (specialized in the provision of public goods). For this reason, the effects of membership are mixed and context-specific. This could also be due to governance characteristics, for example, more or less centralized structures (Peng et al., 2018), and to the quality of social interactions (Bourdieu, 1986; Sutherland & Burton, 2011).

On the other hand, membership in organizations is not independent of the characteristics of the farmers. Most of the factors driving membership, according to the literature, coincide with those normally associated with the adoption of new technologies, and include age, gender, education, household size, land ownership, access to off-farm income, and contacts with extension agents (Manda et al., 2020). For Chagwiza et al. (2016), the probability of joining a cooperative is higher among older (more risk-averse), more educated, and larger farmers. This finding is confirmed by Blekking et al. (2021), who concluded that the poorest farmers are often excluded from cooperatives in Zambia. In a different study, Yahaya et al. (2019) found that membership in cooperatives and adoption of rice intensification technology are both influenced by other variables such as the age, gender, and educational level of the respondents.

Most of the above papers adopt methodologies derived from the random utility approach to test the impact of background factors (including membership in organizations) on innovation adoption. However, in the recent years, these approaches have been enriched by including behavioral drivers and personal attitudes.

Based on the above considerations, the objective of this paper is to assess how membership in farmers' organizations affects intention to innovate in a framework that takes into account the personal attitudes of the individual farmers. This will shed light on the mixed results obtained so far in the literature on the role of farmers' organizations. Our theoretical background integrates random utility and behavioral models, including cultural (on a geographical basis), social (i.e., membership in farmers' organizations), and behavioral factors, i.e., attitudes (Bourdieu, 1986; Burton, 2012). Using a two-step framework, we assume that background and cultural (geographical) factors influence farmers' membership in organizations, which in turn affects their intention to innovate. Behavioral factors are assumed to work as additional mediator variables that are interrelated with membership. The role of membership in specific organizations is also discussed. To achieve our objective, we use primary survey data collected in five African countries, involving 4,529 farmers and more than twenty farmers' organizations.

We find that generic membership has limited mediating power and a

[1] In this paper we use "organizations" as a generic term since most of the literature does not differentiate clearly between different institutional settings, like "associations" and "cooperatives." However, the distinction between institutional settings will become explicit in the empirical chapters, where we focus on actual organizations from our case study areas.

marginally positive impact on the intention to innovate, which becomes non-significant when accounting for individual behavioral attitudes such as openness to new ways of production, willingness to take risks, and trust. These factors do mediate between background characteristics (i.e., location, farm, household, and farmer's characteristics) and the intention to innovate. In turn, membership in selected organizations proves to be a significant predictor of the intention to innovate, although the direction is not unequivocal. This result calls for institutional approaches to evaluate which characteristics of a farmers' organization impact the intention to innovate of its members.

The remainder of the paper is organized as follows: the next section presents a literature review on the main approaches used to investigate innovation adoption. Section 3 illustrates the materials and methods, including hypothesis development and the data collection procedure, followed by a description of the empirical approach used in the analysis, in Section 4. Section 5 presents the results, Section 6 discusses them, while Section 7 concludes and offers key reflections for researchers and policymakers.

2. Theoretical models of innovation adoption

Most studies on the adoption of agricultural technologies are grounded in the random utility framework (Adnan et al., 2017), which posits that adoption decisions are influenced by factors affecting farmers' expected utility, such as resource limitations and various constraints (Métouolé Méda et al., 2018). These studies usually analyze actual adoption, rather than the intention to adopt (Adnan et al., 2017). Within this framework, a large set of factors may influence adoption: Knowler and Bradshaw (2007) list 142 variables that are statistically significant in at least one of the 31 studies on adoption of conservation agriculture around the world, membership in farmers' organizations being just one of them. These factors have been grouped in different ways by different scholars. Meijer et al. (2015) distinguish between (a) characteristics of the farmer, (b) characteristics of the external environment, and (c) characteristics of the innovation. Ainembabazi and Mugisha (2014), on the other hand, consider the following classification: (a) resource endowments (e.g., land, labor, livestock, and farm equipment), (b) market access (e.g., credit and input and output markets), (c) risk and uncertainty, (d) topographic factors (e.g., slope, soil type, and location of the farm), and (e) intellectual capital accumulators (e.g., education, experience, and extension). Edwards-Jones (2007) categorizes factors as (a) farmer characteristics, (b) household characteristics, (c) farm structure, (d) social milieu, and (e) characteristics of the policy (in their paper, policy—rather than technology—was considered).

The characteristics of the innovation itself can be particularly relevant for farmers' final decision and should not be omitted from studies analyzing adoption. Rogers (1995), for example, identifies five characteristics: relative advantage, compatibility, complexity, trialability, and observability. The well-established OECD classification from the Oslo Manual (OECD/Eurostat, 2018) considers four types of innovation: product innovation, process innovation, marketing innovation, and organizational innovation. Furthermore, farming technologies can be categorized as technologies involving long-term investments versus short-term input use (Zeng et al., 2018), or as labor-saving versus land-saving technologies (Vemireddy & Choudhary, 2021).

In farming studies, interest in socio-psychological methods, sometimes known as the behavioral approach (Burton, 2004), has been sparked by discontent with random utility models. Indeed, the variables used within that approach often result in non-significant coefficients, and it is not possible to identify generalized and consistent patterns across studies (Adnan et al., 2017; Borges et al., 2014; Daxini et al., 2019).

Knowler and Bradshaw (2007) conclude that the focus should shift to the particular conditions of individual locales. They also stress that differences in results can be explained by differences in statistical analysis methods (Knowler & Bradshaw, 2007). Nevertheless, attempts to summarize findings to date have been made. For instance, based on the review of 25 years of literature on best management practices in the USA, Prokopy et al. (2008) conclude that the variables most often (but not always) positively correlated with adoption are education level, capital, income, farm size, access to information, and social network access.

Behavioral factors include a wide range of socio-psychological mechanisms, such as cognitive, emotional, personal, and social processes (Dessart et al., 2019). Several theories and models stemming from sociological, psychological, and economic disciplines build on those elements. Socio-psychological approaches normally used to explain the intention to adopt rather than actual adoption are, among others, the Theory of Planned Behavior (TPB) (Ajzen, 1991), the Reasoned Action Approach (RAA), the Technology Acceptance Model (TAM) (Davis, 1989), and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). The constructs adopted in these theoretical frameworks include attitude toward technology, subjective norms, and perceived behavioral control in the case of the TPB; and perceived usefulness and perceived ease of use in the TAM. These constructs, and the survey instruments used to assess them, are generally technology-specific; in other words, the questions are tailored to understanding farmers' attitudes towards specific innovations rather than to generic situations.

Quite frequently, empirical studies adopt econometric methods that mix assumptions and tools derived from both the random utility and behavioral approaches. Burton (2004) argues that, by incorporating within the behavioral dimension other "aspects of the farm such as farm size, family structure, land quality, and so on, this general approach offers a far broader and arguably more realistic perspective of farmers' decision-making environments" (p. 363). Adnan et al. (2017) suggest that linking economic factors and thinking processes[2] can open "a window for building an integrative theoretical framework bridging the gaps between theories" (p. 45). Similarly, Meijer et al. (2015) combine "extrinsic" (i.e., characteristics of adopters and the environment) and "intrinsic" (i.e., attitudes) factors but warn that "there is little understanding of how perceptions and attitudes are shaped by the various extrinsic factors." Van Hulst and Posthumus (2016) highlight that it is essential to theorize how (and not only if) a factor has an influence on adoption.

In an attempt to build a framework that bridges different behavioral approaches, Dessart et al. (2019), drawing on Flay et al. (2009), distinguish between distal behavioral factors, i.e., "higher-order, general macro principles, relatively remote from specific decision-making situations" (e.g., personality, motivations, values, beliefs, general preferences, and objectives), and proximal behavioral factors, i.e., "micro variables directly or almost directly related to the focus of the decision-making" (e.g., perceptions of the relative benefits, costs, and risks associated with a particular technology) (p. 421). In the following, to facilitate the reading of our modeling strategy, which attempts to link elements from various approaches, we will refer to this classification.

[2] The actual process of thinking whether to adopt, with all the bias and behavioral drivers that it entails.

3. Methods and data

3.1. The theoretical model

In this paper, we do not assume that all intrinsic and extrinsic factors directly influence the intention to adopt, as is often implied in single-equation models used in much of the empirical literature. Instead, following Adnan et al. (2017) and Meijer et al. (2015), we adopt a mediated framework in which background (extrinsic) factors shape farmers' individual beliefs and attitudes (intrinsic factors), which in turn influence their intention to adopt innovations (see Fig. 1). While these authors draw on the Theory of Planned Behavior (TPB) and emphasize the role of proximal behavioral factors closely tied to specific technologies, our approach diverges by focusing on more distal behavioral constructs. These broader psychological dimensions, as suggested by Dessart et al. (2019), may be applicable across a range of innovation types and contexts.

We select three distal behavioral factors (hereafter simply "behavioral factors") that we name "openness to new ways of production," "attitude toward risk," and "trust toward organizations promoting innovations."[3] Alongside membership in farmers' organizations (which refers to the farmer's social networks rather than individual characteristics), behavioral factors are assumed to mediate (i.e., explain at least part of the relationship) between background (extrinsic) factors and intention to innovate. In other words, as suggested by the literature, participation in farmers' groups is not exogenous, but affected by the characteristics of the farm, the household, the environment, and the cultural framework (Chagwiza et al., 2016; Manda et al., 2020).

The choice of the three mediating behavioral factors was based on the literature as well as theoretical assumptions. Openness to new ways of production is generally associated with specific characteristics of the innovation on one hand, and of the potential adopter on the other hand. For Rogers (1995), the innovativeness of an individual is defined by the moment of innovation adoption, distinguishing people into innovators, early adopters, early majority, late majority, and laggards. Macours (2019) reviews how different characteristics and benefits of innovations (e.g., yield-increasing, cost-reducing, risk-reducing, quality-enhancing) can affect adoption. However, here we are interested in a more general attitude toward innovation as a mediating variable, as assessed by Škodová Parmová and Novotná (2022). Thus, "openness to new ways of production" can be considered a generalized version of the "attitude toward using technology" commonly used in the TPB and UTAUT approaches.

Risk preferences are frequently associated with the process of technology adoption (Liu & Huang, 2013), and the intention to innovate (Juma et al., 2010), mainly in relation to the availability of insufficient information (Zeweld et al., 2019). In the economic literature (e.g., expected utility theory), risks are frequently assumed to be well-defined and quantifiable; in this paper, however, our focus is not on specific decisions under risk (which would be a "proximal" behavioral factor) but on a more general attitude of the farmer, assessed through a self-elucidation approach (Weber & Milliman, 1997; Weber et al., 2002; Zeweld et al., 2019). The literature suggests that people who are risk-averse will be reluctant to invest in technology (Juma et al., 2010). Interpretation of the risks is subjective, and in developing countries, farmers' risk attitudes can be influenced by several factors, including education, experience, group membership, social influence, household size, and economic conditions (Feder et al., 1985). For instance, poor Kenyan farmers are generally more risk-averse (Juma et al., 2010). Other empirical studies, in turn, have found no correlation between risk attitude and age, gender, education, household size, or income (Grisley & Kellog, 1987; Haile, 2007; Mosley & Verschoor, 2007). In the field of agricultural technology, Le Cotty et al. (2018) found no statistically significant link between risk aversion (measured through hypothetical experiments) and fertilizer use in Burkina Faso. On the contrary, Liu (2013) found that in China, more risk-averse farmers adopt genetically modified cotton later than others, and Liu and Huang (2013) found that risk aversion is positively correlated with farmers' resistance to decrease the use of pesticides in new resistant cotton varieties.

In the rural sector, networks involving government support agencies, research institutes, and NGOs are critical to successful and sustainable development (McKitterick et al., 2019); thus, scholars highlight the necessity of improving the knowledge about the nature and role of trust in these networks (Ezezika & Oh, 2012; Vasa et al., 2014; Zawojska, 2010). Many studies have been conducted on the socio-economic drivers of trust toward governments, but few have been carried out for the farming sector. For example, Zawojska (2010) finds that farmers' characteristics do not relate to trust, except for age. Most studies, by contrast, focus on how trust is formed and lost, and on the relevance of subjective factors, such as faith in loyalty, honesty, capability, local embeddedness, and empathy (McKitterick et al., 2019; Vasa et al., 2014). Trust is considered to be correlated with strong social relations in rural communities. Empirical literature has focused on the role of extension services in Iran (Kavakebi et al., 2023), China (Fan et al., 2022), Poland (Zawojska, 2010), and the Organization of Eastern Caribbean States (Ganpat & Narine, 2015). Arbuckle et al. (2015) examined the relationship between farmers' trust toward environmental or agricultural interest groups as sources of climate information, and their climate change beliefs. Lv and Li (2023) measured how different sources of information affect the adoption of sustainable environmental practices. Dilleen et al. (2023) discuss how trust in social media and vendors impacts the adoption of smart farming technology.

The overall structure of the theoretical framework adopted in this paper, based on the above considerations, is shown in Fig. 1. It includes two levels. The first level is given by Relations 1–4, which link background (extrinsic) factors to membership in farmers' organizations and to the three behavioral factors described above. The second level is represented by Relation 5, which links the behavioral factors and membership (i.e., the dependent variables of Relations 1–4) to the intention to innovate. The background factors in the first step of the model include some of the variables frequently used in random utility models: farmer characteristics (age, gender and education); household characteristics (number of adult members, migration of any of the household members, extent to which remittances contribute to the household's welfare, share of income spent on purchased food, extent to which the household's food needs have been met)[4]; farm characteristics (total land size); and institutional characteristics (possession of a mobile phone as a proxy for access to information, access to formal loans, and informal credit). Finally, location characteristics are synthesized by geographical dummies for the areas covered by our sample.

[3] These behavioral factors were measured using a 5-point Likert scale and the following question: "How much do you agree with the following statements?"

1) I like to try new ways of producing on my farm.
2) I prefer to avoid taking risks when it comes to managing my farm interests.
3) Most organizations promoting innovations in agriculture can be trusted.
The scores assigned to statement 2 have been reversed in this paper to facilitate interpretation of the results.

[4] The last two variables were chosen as proxies of income since it was difficult to establish comparable cross-country income levels and because incomes tend to be underreported or misreported if asking directly.

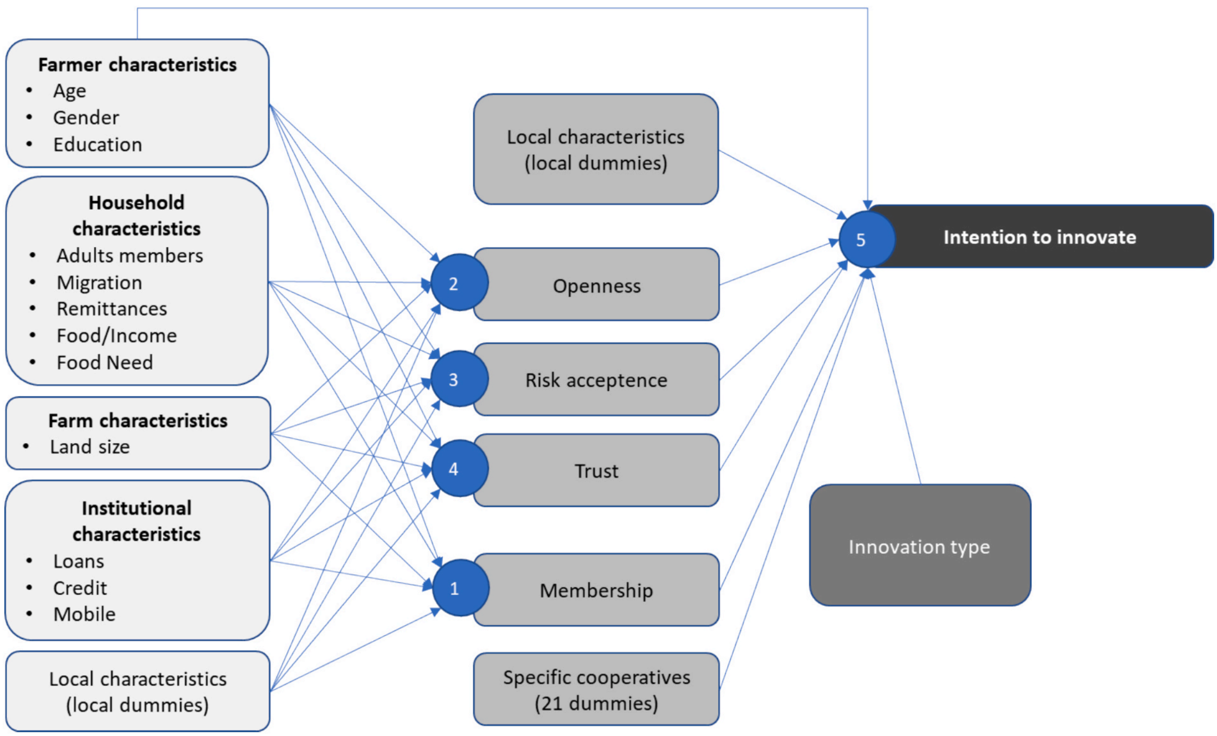

Fig. 1. The overall structure of the theoretical framework.

In our paper, the intention to innovate is evaluated separately for five different innovations through an equal number of survey questions[5]:

1) A new technology that can help overcome a limitation faced by the farmer (farmers were previously asked which limitations they face).
2) A new irrigation system that can increase yields.
3) A new crop with a higher selling price.
4) A new crop with a higher nutritional content at parity of selling price.
5) An agreement between farmers that allows them to sell their crop production jointly in exchange for a higher unit price.

Innovation 1 is unspecified and tailored to each farmer's needs. Innovation 2 can be considered a process innovation, involving land-saving technology and long-term investment. Innovation 3 is a product innovation, involving land-saving technology and short-term input use. Innovation 4 is similar to innovation 3, but instead of being market-oriented, it is oriented to subsistence and health. Innovation 5 is an organizational innovation, involving investment in social capital.

Relation 5 includes a further set of explanatory variables, namely membership in specific organizations. During data collection, many associations and cooperatives were identified empirically; however, only a subset of them was selected to be included in the model via a set of dummy variables. The selection procedure is explained in Section 3.2. The choice to include dummy variables for specific organizations in addition to generic membership was motivated by the results of previous literature, which have returned mixed conclusions on the role of organizations, pointing to the need to consider the nature and characteristics of these organizations.

In our theoretical framework, the influence of background factors on the intention to innovate passes through membership in organizations and behavioral factors. In other words, it is not the size of the farm, or the education of the farmer that affects the intention to innovate directly: these variables act indirectly, through their effect on behavioral factors, and by influencing farmers' decision to join an organization. For example, an educated farmer with a large farm could be more trusting toward organizations promoting innovation and more willing to take risks and, therefore, more inclined to accept innovations. However, other unobserved behavioral factors (e.g., moral and environmental concerns; injunctive and descriptive norms; signaling motives; etc.) may affect the final decision too. For this reason, we expect that background factors still play a role, not fully absorbed by our mediating factors, in the intention to adopt innovation.

Based on previous empirical research in Africa (Adnan et al., 2017; Chagwiza et al., 2016; Makate et al., 2019; Manda et al., 2020; Mansaray et al., 2019; Métouolé Méda et al., 2018; Zeng et al., 2018), the expected direction of the effects is indicated in Tables 1 and 2. Table 1 refers to Relations 1, 2, 3, and 4, i.e., the effects of background factors on behavioral factors and membership in farmers' organizations. Ex-ante assumptions are limited in the case of Relations 3 and 4, since the literature does not provide enough evidence on the direction of the

[5] The five questions used are as follows. All of them were assessed using a 5-point scale.

1) You are given the option to change your production activity by adopting a new technology (e.g., a new fertilizer, a new equipment/tool) that allows you to overcome a limitation you are facing: to what extent would you be interested in adopting this technological innovation? (NB: this question is asked immediately after the farmers are asked which are the limitations they are facing).

2) Imagine you are growing an irrigated crop and that a new irrigation system raising yields has been adopted in the area: to what extent would you consider introducing this technology in your farm?

3) You are given the option to change your production by introducing a new crop (e.g., an orphan crop, an improved vegetable line, or a novel local variety) with a higher nutritional content at parity of selling price and costs: to what extent would you be interested in adopting this new crop?

4) You are given the option to change your production by introducing a new crop (e.g., an orphan crop, an improved vegetable line, or a novel local variety) with a higher selling price at parity of costs: to what extent would you be interested in adopting this new crop?

5) Imagine you can sell your crop production jointly with the other farmers' crop production to sell them at a slightly higher unit price for the whole group, but you must align the variety you grow as well as the seeding and harvesting time with the group: would you sell your production jointly?

Table 1
Expected effect of background factors on membership in farmers' organizations and behavioral factors.

Variable	Variable description and measurement	Mean (st. dev.) or % observations	Membership	Openness (2)	Risk acceptance (3)	Trust (4)
Farmer characteristics						
Age	Age of household head in years	46.1 (14.6)	+	0	0	0
Female	Binary value = 1 if household head is female; 0 otherwise	Yes: 33.3 %	0	0	0	0
Education	Educational level of the household head, from 1 = illiterate to 5 = more than secondary school	3.0 (1.1)	+	+	+	0
Household characteristics						
Adult members	Number of adult members in the farmer's household (aged 14 or older)	3.9 (2.2)	0	+	0	0
Migration	Binary value = 1 if any of the household members has migrated; 0 otherwise	Yes: 33.0 %	0	0	0	0
Remittance contribution	Extent to which remittances contribute to the household's welfare: bounded integer (from 0 = not at all, to 5 = a lot)	0.5 (1.3)	0	+	0	0
Food/ Income	Share of the income spent on purchased food: bounded integer [from 1 = A very limited part (less than 25 %), to 5 = Almost all (from 75 % to 100 %)]	2.7 (1.4)	0	0	0	0
Food need	Extent to which the household's food needs have been met: bounded integer (from 1 = Yes, more than enough, to 5 = No, I experience serious food shortages)	2.9 (1.2)	0	0	0	0
Farm characteristics						
Size	Land size: hectares (in logarithmic form in the models)	3.1 ha (6.1)	+	+	+	0
Institutional characteristics						
Loan	Access to formal loans = 1 if yes; 0 otherwise	Yes: 15.5 %	+	+	+	0
Credit	Access to informal credit = 1 if yes; 0 otherwise	Yes: 29.8 %	+	+	+	0
Mobile	Possession of a mobile phone = 1 if yes; 0 otherwise	Yes: 94.6 %	+	+	+	0

Table 2
Expected effect of membership and behavioral factors on intention to innovate.

Variable	Variable description and measurement	Mean (st. dev.) or% observations	Expected effect on intention to innovate
Membership	Farmer's membership in local farmers' organization = 1 if yes; 0 otherwise	Yes: 39.9 %	+
Openness	Extent to which the farmer agrees to: "I like to try new ways of producing on my farm": Bounded Integer (from 1 to 5)	4.5 (1.1)	+
Risk acceptance	Extent to which the farmer agrees to: "I prefer to avoid taking risks when it comes to managing my farm interests." Bounded Integer (from 1 to 5; the scale is reversed in the analysis, so that higher values indicate higher risk acceptance)	2.7 (1.6)	+
Trust	Extent to which the farmer agrees to: "Most organizations promoting innovations in can be trusted." Bounded Integer (from 1 to 5)	4.0 (1.3)	+

effect. Table 2 refers to Relation 5, i.e., the effect of membership and behavioral factors on the intention to innovate. Accordingly, we derive the following research hypotheses, which will be tested empirically using data from five African countries:

- **H1**: Intention to innovate is positively related to membership in farmers' organizations.
- **H2a**: Intention to innovate is positively related to openness to new ways of production.
- **H2b**: Intention to innovate is positively related to risk-taking attitude.
- **H2c**: Intention to innovate is positively related to trust toward organizations promoting innovations.

4. Research cases

The data used in this article were collected via a cross-country survey administered within an international project focused on the promotion of local, more sustainable, and more diversified food products and production methods in Africa.[6] Firm- or farm-level surveys represent a necessary tool to gather information on behaviors, economic outcomes, and innovation decisions in cases where secondary data are not available; cross-country approaches, in particular, provide rich information and heterogeneous data that help control for other effects (Mazzanti et al., 2016). However, econometric analysis using survey data, particularly cross-sectional data, should tackle several problems, such as endogeneity due to omitted variables, simultaneity, and measurement errors, as well as sample selection bias (Cainelli et al., 2020). While our cross-country approach, as well as our sampling procedure, should have mitigated some of these shortcomings, we acknowledge this as a limitation of our study that warrants further research.

Data were collected in ten rural areas from five African countries (see Table 3): Ait Ouallal Bittit/Ait Yazem and Dir Beni Mellal in Morocco, Mukurweini and Kitui in Kenya, Kilombero and Mvomero in Tanzania, Chebika and Fernana in Tunisia, and Kamuli and Nakaseke in Uganda. These areas and their geographical boundaries were purposively selected by project partners based on the local agri-food productions and their suitability for the demonstration of the technological innovations and innovative practices developed within the project. Consequently, they are very different in terms of geographical size as well as environmental, institutional, economic, and agronomic characteristics. In these areas, project partners established so-called "Food Hubs," i.e., "communities of local operators [primarily smallholder farmers] making joint research and development decisions and enabling the adoption

[6] Horizon 2020 FoodLAND "FOOD and Local, Agricultural, and Nutritional Diversity" (2020-2025).

Table 3
List of areas and farmers' organizations chosen for the empirical model.

Country	Area	Interviewed	Members of associations	% members on sample	Farmers' Organizations	Number of members in the sample
Morocco	Beni Mellal	400	140	35 %	ZITOUNE Coop.	33
					COLEZA Coop.	18
	Ait Ouallal Bittit	500	115	23 %	KHARICHFA Association	12
Kenya	Kitui	482	252	52 %	Nehema self-help group	20
	Mukurweini	505	400	79 %	Rugi farmer cooperative society	67
					New Gikaru farmer cooperative society	112
					Rumukia farmers' cooperative society	42
					Ruthaka farmers' cooperative society	68
					Wakulima cooperative society	72
Tanzania	Kilombero	407	72	18 %	Kidatu Sugarcane Growers Association (KSGA)	22
	Mvomero	504	31	6 %	–	
Tunisia	Chebika	431	134	31 %	GDA Karma	23
					GDA Jefna	19
					GDA Ayaycha	17
	Fernana	500	114	23 %	SMSA	26
					GDA Hrayer Gloub Thiren	44
					URAP	32
Uganda	Kamuli	400	301	75 %	Busiba cooperative society	22
					Kamuli Nankulyaku Maize cooperative	22
					Edikokolima Saving and Credit Association	20
	Nakaseke	400	250	63 %	Namasinda kwekulakulanya group	20
					Nakaseke vegetable producers and seed multiplication association	19
TOTAL		**4,529**	**1,809**	**40 %**		**730**

of innovations" (Carloni et al., 2025). In most areas, annual crops dominate, except for Dir Beni Mellal and Chebika, where olive trees are the main agricultural resources.

Before implementing any other project activities, in all the Food Hubs, we administered a survey on farm and household characteristics and farmer behaviors to establish a baseline for the successful dissemination of innovations. In this article, we use data from this survey. To limit sample selection bias at the collection stage, small-scale crop farmers from each area were recruited through stratified random sampling, with strata based on age, gender, and farm size (all binary), and without filtering criteria related to innovation adoption, interest, or other variables that would reduce the comparability of respondent subsamples (Mazzanti et al., 2016). Equally, the target response rate (overall and by stratum) was set ex ante. In the Food Hubs where several villages were involved, we used two-stage sampling, first selecting a subset of villages and then a subset of farmers therein. Where one gender (usually females) accounted for less than one third of the reference farming population, farmers from that gender were oversampled to shed light on gender-related issues, in accordance with the funder's requirements.

The questionnaire was standardized in all the countries and regions and comprised 36 questions (some involving the completion of tables) on farmers' habits and conditions, trust, (stated) propensity to innovate, risk perception, experiences, and demographic characteristics, as well as contextual factors (Kuhfuss & Piras, 2025). The questionnaire, drafted in English in collaboration between local and international project partners, was translated into local languages, back-translated for consistency checks, and pilot-tested with students and then farmers. Potential participants were invited to a central locality, where they were administered the questionnaire and delivered training relevant to the activities planned locally. Travel was either organized by the project, or travel costs were reimbursed, and refreshments were provided.

Data collection took place between March and November 2021, depending on local climatic conditions and the agricultural calendar. Tunisia was the first country to start, with the Fernana Food Hub, and the last to finish with the Chebika Food Hub. Morocco and Tanzania conducted fieldwork between May and June, Kenya in July and September, and Uganda between May and August. The total sample includes 4,529 smallholder farmers, distributed as specified in Table 3. Data were collected using pen and paper in Kenya, Tunisia, and Uganda, and tablets in Morocco and Tanzania, then entered into pre-prepared Excel sheets (or uploaded in the same format).[7] Data cleaning was centralized to ensure homogeneity. All the missing values and outliers, defined as $< Q1 - 3*IQR$ or $> Q3 + 3*IQR$, were flagged to local partners and cross-checked with farmers. The final datasets were published in an open-access repository.[8]

In all the Food Hubs, it is possible to find forms of organization among farmers, motivated by different objectives and managed under different institutional frameworks, such as cooperatives or associations (listed in Table 3). In total, 1,809 farmers belonged to at least one group, which represents 40 % of the total. The area with the highest membership rate is Mukurweini (Kenya), with 79 % of the farmers being members of at least one group; the area with the lowest membership rate is Mvomero (Tanzania), with 6 %.

Among the 450 cooperatives and associations named by the interviewees overall, we chose 21 to be included in the econometric model as dummies (Relation 5). In total, 730 farmers are members of one of these 21 organizations, i.e., 40 % of those who are members of at least one association. Twenty organizations were selected for being those with the largest number of members in our sample (from 17 members, the least represented, to 112). Using this approach, all the ten areas are represented by at least one group, except for Ait Ouallal Bittit/Ait Yazem (Morocco) and Mvomero (Tanzania). For Ait Ouallal Bittit/Ait Yazem, we decided to include the largest group in the area, i.e., the Kharichfa Association, with twelve members in the sample. On the contrary, no group was selected for Mvomero, where the associative system seems to be poorly developed, and there are no groups with more than four members in the sample. The names of the associations or cooperatives chosen for the analysis, and their relative incidence on the sample from the local area, are found in Table 3, while Table A1 in the Appendix provides a more detailed overview of their characteristics. These organizations may differ significantly in terms of objectives and institutional

[7] Since the data collection method is collinear with the country, it is not possible to disentangle the country and tablet effects. Nevertheless, the tablet version did not include any constraints that could have biased the responses.

[8] See Data availability statement for the DOI.

forms. However, most of them are private or third-sector organizations registered under the national laws regulating cooperatives. The main exception is found in Tunisia. Here, the survey includes one "*Société mutuelle de services agricoles*" (SMSA), roughly corresponding to a cooperative of services aimed at pooling equipment while strengthening farmers' bargaining power, and four "*Groupements de développement Agricole*" (GDAs, French acronym for Agricultural Development Groups), which are public-interest organizations, composed of owners and users, mandated by the state to manage natural resources, in particular water. GDAs, contrary to SMSAs, are not authorized to engage in commercial activities. Another remarkable distinction is the Edikokolima Saving and Credit Association which, under Ugandan law, is a self-help group dealing with microfinance (i.e., mobilizing and managing savings).

5. Empirical approach

To test our assumptions, we adopted two econometric approaches: (1) separate estimation of the five Relations in Fig. 1; (2) simultaneous estimation with generalized Structural Equation Models (generalized SEM; Rabe-Hesketh et al., 2004). For the first approach, we developed two datasets: one with one observation per farmer (4,529 in total) to estimate Relations 1, 2, 3, and 4; and one with five observations per farmer (22,645, i.e., one for each innovation)[9] for Relation 5.

For the simultaneous estimation, we used a single dataset with one observation per farmer and treated the intention to adopt innovations as a latent construct inferred from the variables measuring intention to adopt the specific innovations. We assume that the latent variable is a common cause of the five intentions to adopt specific innovations; therefore, our model is a so-called "reflective SEM," which differs from the "formative SEMs," whereby the latent variable is instead a composite construct summarizing the common variation of the observed indicators (Edwards and Bagozzi, 2000). Besides the possibility of using latent variables, SEM has several advantages. First, it allows us to address endogeneity (and thus correlation of the errors) through simultaneous estimation. While correlation between exogenous observed variables is assumed, correlation between endogenous variables (in our case, the membership in organizations, and the three behavioral factors) is not; for this reason, we include dependencies between these variables in the form of correlation between standard errors, thus obtaining a path analysis model (Acock, 2013).[10] More precisely, since all the exogenous variables are assumed to influence all the endogenous variables, we have a multilevel, multivariate regression model where membership and behavioral factors work as mediators between background factors and intention to adopt. Second, the SEM approach allows us to avoid the "artificial" reduction of the standard errors caused by the five-fold multiplication of the sample size for Relation 5. Third, the mediation nature of the model allows estimation of indirect and total effects of the background factors (Baron & Kenny, 1986). By comparing the two approaches and discussing them jointly, we increase the robustness of our findings.

Before running the separate or simultaneous estimations, we implemented a logarithmic transformation of the land size to overcome the issue of skewness, and we checked all models for collinearity by calculating the variance inflation factor. No issues were detected in this regard. We also tested whether the fact of receiving loans or credit, the share of income spent on food, and the level of food security were endogenous (in addition to the membership and the behavioral factors, which are so by construction) using the Durbin and Wu-Hausman tests after instrumental variable estimates, but the tests did not confirm endogeneity; therefore, OLS estimation was deemed preferable.[11]

One of the model types most used in the literature on innovation adoption is logistic regression (Zeweld et al., 2019). This is an appropriate method when the dependent variable is binary or ordered categorical, as in our case. Therefore, for the first econometric approach (separate equations), we estimated one logit model (Relation 1) and four ordered logit models (Relations 2, 3, 4, and 5). For the second approach (SEM), we estimated linear models to ensure that our overall model is non-recursive, and obtained the latent dependent variable (intention to innovate) endogenously.[12]

The empirical form of Relations 2, 3, and 4 for farmer i is the following:

$$y_i^* = \boldsymbol{X}_i^{\mathrm{T}}\beta_X + \boldsymbol{W}_i^{\mathrm{T}}\beta_Y + \boldsymbol{Z}_i^{\mathrm{T}}\beta_Z + \varepsilon_i \tag{1}$$

where $\boldsymbol{X_i}$ is a vector of farmer and household characteristics, $\boldsymbol{W_i}$ is a vector of farm economic characteristics, $\boldsymbol{Z_i}$ is a vector of local characteristics (location dummies), β's are the model coefficients, and ε_i is the error term. In the estimation with separate equations, y_i^* is an unobserved latent variable discretized by means of the Likert scale, while the observed ordered categorical variables, which do not appear directly in the empirical equation, are n_i for openness to new production methods, r_i for risk-taking, and t_i for trust. The ordered logit estimates also include cutoff points for y_i^* to assume the discretized 1-to-5 values, while in Relation 1, y_i^* is replaced by $logit(\mathrm{E}[m_i|\boldsymbol{X_i}, \boldsymbol{W_i}, \boldsymbol{Z_i}])$, where m_i is a dummy for cooperative membership. In the SEM linear estimation, y_i^* is replaced by n_i, r_i, t_i, and m_i, respectively.

In the estimation with separate equations, Relation 5 assumes the empirical form below:

$$y_{ik}^* = \beta_k + \beta_m m_i + \boldsymbol{\beta_A} + \beta_N n_i + \beta_R r_i + \beta_T t_i + \boldsymbol{X}_i^{\mathrm{T}}\beta_X + \boldsymbol{Y}_i^{\mathrm{T}}\beta_Y + \boldsymbol{Z}_i^{\mathrm{T}}\beta_Z + \varepsilon \tag{2}$$

where k are the innovations, β_k are innovation-fixed effects, $\boldsymbol{\beta_A}$ is a vector of organization-fixed effects (each farmer can belong to more than one organization), and y_i^* is, again, an unobserved latent variable discretized by means of the Likert scale: the observed variable is the intention to innovate p_{ik}.

Instead, in the SEM estimate, Relation 5 assumes the following linear form:

$$P_i = \beta_m m_i + \boldsymbol{\beta_A} + \beta_N n_i + \beta_R r_i + \beta_T t_i + \boldsymbol{X}_i^{\mathrm{T}}\beta_X + \boldsymbol{Y}_i^{\mathrm{T}}\beta_Y + \boldsymbol{Z}_i^{\mathrm{T}}\beta_Z + \varepsilon \tag{3}$$

[9] In this approach, "Intention" to innovate is treated as a single dependent variable assuming five potentially different values for each farmer (one for each innovation typology), and four dummies are included as additional explanatory variables to assess how each innovation typology impacts Intention (with the fifth innovation representing a baseline).

[10] Two other options would have been to include the behavioral factors as mediators between the background factors and membership, or between the latter and intention. However, our cross-sectional data do not allow us to determine the direction of causality, and the literature is not conclusive in this regard. Therefore, we opted for including dependencies between these variables rather than a more sequentially oriented approach.

[11] Before selecting the two estimation approaches described, we trialed instrumental variable (IV) estimation of Relations 1, 2, 3, and 4, using setbacks (income loss, job loss, farm cost increase, and food shortages) as instruments. More common IVs—such as plot distance, rainfall patterns, local population data, etc.—were not available at granular level for the locations surveyed. However, the endogeneity tests were inconclusive, and the available instruments had insufficient explanatory power. The loss in efficiency when using an IV estimator can be significant; therefore, unless IV estimation is clearly warranted, OLS should be preferred. These considerations led us to abandon the IV approach.

[12] Estimating logit and ordered logit models with generalized SEM results in recursive models, whereby the estimates of endogenous variables cannot be used in other equations; therefore, the estimates of Relations 1, 2, 3, and 4 would coincide with the separate ones, while Relation 5 would only differ because of the latent variable approach. The use of linear models is also necessary to allow for correlation of standard errors in the endogenous variables. Preliminary SEM estimates using logit and ordered logit models did not differ significantly from the current SEM, as shown by the comparison between the separate estimates and the SEM results.

where P_i is the latent intention to innovate, and innovation-fixed effects are excluded from the right-hand side.

To appreciate the importance of controlling for individual behavioral factors when assessing the impact of organization membership on intention to innovate, and thus show the relevance of our initial hypotheses, we re-estimated Relation 5 of the separate models as well as of the whole SEM after excluding the behavioral factors. Without behavioral factors, the SEM only includes Relations 1 and 5. The estimation results are reported in the Appendix alongside the coefficients of the models with behavioral factors.[13]

For robustness, because the membership in specific organizations entails membership in organizations in general, we tested whether the coefficients for m_i, and for membership in each organization $\beta_{A_1}, \cdots, \beta_{A_n}$ in turn, are jointly significantly different from zero. Also, because we assumed that $\boldsymbol{X}_i$ and $\boldsymbol{Y}_i$ impact p_{ik} (or P_i, depending on the estimation approach) both directly, and indirectly through n_i, r_i, t_i and m_i (mediator variables), we also calculated the indirect effects of these variables on p_{ik} and P_i (i.e., the effects mediated by the mediator variables) and the total effects (i.e., the sum of direct and indirect effects), and whether these effects differed significantly from zero.

All the estimates were implemented using Stata 15 (Stata Corp, 2017) and the *gsem* command for the generalized SEMs (Stata Corp, 2023).

6. Results

Descriptive statistics are reported in Tables 1 and 2 above. The results of the estimations, illustrated in Tables 4–7, show that there are limited differences in the results obtained with the two approaches, i.e., the separate equations (Table 4) and the generalized SEM (Table 5). Almost all the variables that are statistically significant with one approach are also significant (and with the same sign) with the other.

Many of the hypotheses made about membership in farmers' organizations (Relation 1, Tables 4 and 5) are supported by our data. In fact, there is a positive (and statistically significant at the 5 % level) relationship between membership, on the one hand, and age,[14] education, land size, and access to formal loans and informal credit, on the other hand. Additionally, female farmers are significantly more likely to be members. The extent to which the household's food needs have remained unmet has, on the contrary, a negative sign—i.e., farmers who experience food insecurity are less likely to be members.

Regarding "Openness to new ways of production" (Relation 2, Tables 4 and 5), we find a positive association with age,[15] education, number of adult household members, land size, share of income spent on purchased food, and (only in the separate estimate) the extent to which the household's food needs have remained unmet. This suggests that poorer and more food insecure farmers are more open to new ways of production, possibly as a way to overcome their current challenges. Conversely, a negative association is found with the presence of emigrated household members, suggesting that the shortage of farm labor may reduce openness to innovation.

Risk acceptance (Relation 3, Tables 4 and 5) is positively associated with access to informal credit and the extent to which the household's food needs have remained unmet. Unexpectedly, a negative relationship is detected with access to formal loans.

Finally, trust in organizations (Relation 4, Tables 4 and 5) is positively associated with age,[16] number of adult household members, and access to formal loans, which indeed requires trust in banking institutions.

Regarding Equation 5 (Table 6), the information about the five innovations proposed is treated differently depending on the approach. In the separate ordered logit model, each innovation is represented by a dummy variable, which yields a specific effect on the intention to adopt or not. In the SEM, the five innovations are considered as five observations, driven by an "Intention" latent variable. Despite this difference, the results obtained with the two approaches are identical in terms of the effects of the four mediating variables.

Generic membership in farmers' organizations is not significantly related to the intention to adopt, meaning that our **H1** is **not verified**. Nevertheless, the coefficient is positive and close to significance (i.e., the probability that the coefficient differs from zero is 10.6 % in the separate model and 11.5 % in the SEM). Additionally, if we had omitted the behavioral factors, the coefficient would have been positive and

Table 4
Estimates of relations 1, 2, 3 and 4 using ordered logistic regression.

Variables	Membership (1)	Openness (2)	Risk acceptance (3)	Trust (4)
Farmer characteristics				
Age	0.065 (0.015) ***	0.040 (0.013) ***	−0.019 (0.011) *	0.047 (0.011) ***
Age squared	−0.000 (0.000) ***	−0.001 (0.000) ***	0.000 (0.000) **	−0.000 (0.000) ***
Female	0.215 (0.088) ***	−0.108 (0.081)	0.091 (0.067)	0.064 (0.066)
Education	0.141 (0.038) ***	0.078 (0.036) **	−0.021 (0.030)	−0.011 (0.030)
Household characteristics				
Adult members	0.008 (0.018)	0.053 (0.018) ***	0.005 (0.014)	0.044 (0.014) ***
Migration	0.120 (0.102)	−0.269 (0.098) ***	−0.047 (0.083)	−0.138 (0.081) *
Remittance contribution	0.039 (0.129)	0.145 (0.124)	0.013 (0.102)	0.025 (0.102)
Food/Income	0.031 (0.030)	0.080 (0.272) ***	0.020 (0.023)	0.028 (0.023)
Food need	−0.157 (0.033) ***	0.111 (0.031) ***	0.178 (0.026) ***	−0.018 (0.026)
Farm characteristics				
Size log	0.336 (0.066) ***	0.181 (0.063) ***	0.038 (0.052)	−0.046 (0.052)
Institutional characteristics				
Loan	0.868 (0.102) ***	0.150 (0.106)	−0.196 (0.083) **	0.285 (0.083) ***
Credit	0.270 (0.081) ***	−0.007 (0.078)	0.186 (0.063) ***	−0.094 (0.063)
Mobile	1.039 (0.204) ***	−0.153 (0.153)	0.096 (0.131)	0.036 (0.130)
Prob > chi2	0.000	0.000	0.000	0.000
Pseudo R2	0.247	0.048	0.099	0.022
Log-likelihood	−2,293.361	−3,926.82	−5,990.691	−5,902.05
Sample size	4,529	4,529	4,529	4,529
BIC	4,780.34	8,072.51	12,200.26	12,022.98
AIC	4,632.72	7,905.63	12,033.38	11,856.10

*10% level; **5% level; ***1% level.

[13] Although the reduced form of the SEM is estimated as a whole, only Relation 5 differs from the model that includes the behavioral factors. The same is true for the separate estimates. Therefore, in the Appendix we only report Relation 5.

[14] But negative for Age squared, suggesting that the probability of being a member is inverted U-shaped, i.e., it increases up to a certain point and decreases for older farmers, *ceteris paribus*.

[15] But negative for Age squared, suggesting that the openness to new ways of production increases up to a certain point and then decreases for older farmers, *ceteris paribus*.

[16] But negatively for Age squared, suggesting that the relationship is inverted U-shaped.

Table 5

Estimates of relations 1, 2, 3 and 4 using SEM.

Variables	Membership (1)	Openness (2)	Risk acceptance (3)	Trust (4)
Farmer characteristics				
Age	0.010 (0.002) ***	0.016 (0.006) ***	−0.011 (0.008)	0.028 (0.007) ***
Age squared	0.000 (0.000) **	0.000 (0.000) ***	0.000 (0.000) *	0.000 (0.000) ***
Female	0.036 (0.014) **	−0.018 (0.036)	0.071 (0.050)	0.049 (0.043)
Education	0.023 (0.006) ***	0.051 (0.016) ***	−0.005 (0.022)	−0.002 (0.019)
Household characteristics				
Adult members	0.002 (0.003)	0.027 (0.008) ***	0.006 (0.010)	0.030 (0.009) ***
Migration	0.026 (0.018)	−0.125 (0.045) ***	−0.085 (0.062)	−0.053 (0.054)
Remittance contribution	−0.002 (0.022)	0.084 (0.056)	0.129 (0.078) *	−0.020 (0.068)
Food/Income	0.006 (0.005)	0.030 (0.012) **	0.010 (0.017)	0.016 (0.015)
Food need	−0.027 (0.006) ***	0.016 (0.014)	0.117 (0.020) ***	−0.025 (0.017)
Farm characteristics				
Size log	0.061 (0.012) ***	0.076 (0.029) ***	0.037 (0.040)	−0.037 (0.035)
Institutional characteristics				
Loan	0.167 (0.018) ***	0.068 (0.044)	−0.136 (0.061) **	0.175 (0.053) ***
Credit	0.045 (0.014) ***	−0.020 (0.034)	0.129 (0.048) ***	−0.037 (0.041)
Mobile	0.128 (0.028) ***	−0.095 (0.071)	0.051 (0.098)	0.023 (0.085)
Covariance				
Membership	–	0.003 (0.006)	−0.027 (0.009) ***	0.031 (0.008) ***
Openness	0.003 (0.006)	–	0.195 (0.022) ***	0.378 (0.020) ***
Risk acceptance	−0.027 (0.009) ***	0.195 (0.022) ***	–	0.062 (0.026) **
Trust	0.031 (0.008) ***	0.378 (0.020) ***	0.062 (0.026) **	–
Constant term	−0.302 (0.075) ***	3.446 (0.187) ***	3.484 (0.258) ***	3.186 (0.225) ***

*10% level; **5% level; ***1% level; Sample size: 4,529. Log-likelihood (full SEM): −56,617.35. BIC: 114,615.30. AIC: 113,562.70.

Table 6

Estimates of relation 5 using ordered logistic regression and SEM, including indirect and total effects.

Variables	Ordered logit	SEM: Direct effect	SEM: Indirect effect	SEM: Total effect
Behaviors and membership				
Membership	0.091 (0.057)	0.037 (0.023)		
Openness	0.390 (0.024) ***	0.190 (0.011) ***		
Risk acceptance	0.092 (0.016) ***	0.038 (0.006) ***		
Trust	0.192 (0.017) ***	0.077 (0.007) ***		
Innovations				
Irrigation system	0.069 (0.040) *			
Joint sale	−0.706 (0.038) ***			
Nutritive crop	−0.859 (0.037) ***			
Profitable crop	−0.162 (0.038) ***			
Control variables				
Age	0.034 (0.008) ***	0.014 (0.003) ***	0.005 (0.002) ***	0.019 (0.004) ***
Age squared	0.000 (0.000) ***	0.000 (0.000) ***	−0.000 (0.000) ***	−0.000 (0.000) ***
Female	−0.037 (0.052)	−0.001 (0.020)	0.004 (0.009)	0.003 (0.021)
Education	−0.002 (0.021)	0.004 (0.009)	0.010 (0.004) **	0.014 (0.010)
Adult members	0.005 (0.010)	0.004 (0.004)	0.008 (0.002) ***	0.011 (0.005) **
Migration	−0.016 (0.062)	−0.009 (0.024)	−0.030 (0.011) ***	−0.039 (0.026)
Remittance contribution	0.101 (0.082)	0.038 (0.030)	0.019 (0.014)	0.057 (0.033) *
Food/Income	−0.043 (0.017) **	−0.018 (0.007) ***	0.007 (0.003) **	−0.010 (0.007)
Food need	0.099 (0.020) ***	0.040 (0.008) ***	0.005 (0.004)	0.045 (0.009) ***
Farm size (log of hectares)	0.054 (0.036)	0.032 (0.016) **	0.015 (0.007) **	0.048 (0.017) ***
Loan	0.063 (0.065)	0.012 (0.024)	0.027 (0.012) **	0.039 (0.026)
Credit	0.059 (0.046)	0.031 (0.019) *	−0.000 (0.008)	0.031 (0.020)
Mobile	0.239 (0.090) ***	0.105 (0.038) ***	−0.010 (0.018)	0.095 (0.042) **
Prob > chi2	0.000			
Pseudo R2	0.089			
Log-likelihood	−22,840.191			
Sample size	22,645			
BIC	46,231.91			
AIC	45,790.38			

*10% level; **5% level; ***1% level.

significant in the separately estimated model (Table A4), but not in the SEM (Table A5), highlighting the importance of accounting for individual behavioral characteristics. We will focus in more detail on membership in the next subsection.

In turn, openness to new ways of production (**H2a**), risk acceptance (**H2b**), and trust (**H2c**) are all positively and significantly associated (at the 1 % level) with the intention to innovate, both in the separate ordered logit model and in the SEM. Openness yields the largest effect, followed by trust, and, finally, risk acceptance. Therefore, our **H2a**, **H2b**, and **H2c** are all **verified**.

In the ordered logit model (separate estimates), where the baseline is the intention to adopt "An unspecified new technology that can overcome a limitation faced by the farmer," our results indicate a comparatively higher intention to adopt "A hypothetical irrigation system that can raise yields." In contrast, the intentions to adopt "A new crop with a higher nutritional content," "A new crop with a higher selling price," and "An agreement among farmers that allows to sell crop produce jointly" are all lower compared to the baseline. As explained above, in the SEM, the relationship between the single innovations and the intention to adopt is not measured within the structural model. Instead, all five innovations are assumed to be the observed realizations of the latent variable "Intention," as shown in the SEM measurement model (Table A7 in the Appendix). The latent variable presents the strongest association with the intention to adopt a nutritious crop,

Table 7
Membership in organizations and intention to innovate: specific effects (only the coefficient estimated for the dummy) and total effect (joint significance of dummy and general membership in farmers' organizations).

Country	Area	Organization	Specific effect in separate models	Total effect in separate models	Specific effect in SEM	Total effect in SEM
Morocco	Beni Mellal	ZITOUNE Coop.				
		COLEZA Coop.				
	Ait Ouallal Bittit	KHARICHFA Coop.	++	+++	+++	+++
Kenya	Kitui	Nehema self-help group				
	Mukurweini	Rugi farmer cooperative society		+	++	+++
		New Gikaru farmer cooperative society				
		Rumukia farmers' cooperative society				
		Ruthaka farmers' cooperative society				
		Wakulima cooperative society		+		
Tanzania	Kilombero	Kidatu Sugarcane Growers Association				
	Mvomero	–				
Tunisia	Chebika	GDA Karma				+
		GDA Jefna	−−−	−−−	−−−	−−−
		GDA Ayaycha		+		+
	Fernana	SMSA				
		GDA Hrayer Gloub Thiren	−	−		
		URAP				
Uganda	Kamuli	Busiba cooperative society				
		Kamuli Nankulyaku Maize cooperative	+++	+++		
		Edikokolima Saving and Credit Assoc.	+++	+++		
	Nakaseke	Namasinda kwekulakulanya group				
		Nakaseke vegetable producers and seed multiplication association				

+; ++; +++: positive effects at 10%, 5% and 1%. −; −−; −−−: negative effects at 10%, 5% and 1%. Empty cells indicate no significant effect.

followed by the joint sale of products, a more profitable crop and, at some distance, a new irrigation system – all positive and significant relationships. While these results seem to contradict those of the separate models, they actually confirm them, and are a consequence of the reflective nature of our SEM, whereby the latent construct influences the single intentions rather than being a combination of them. For instance, while the benefits for the farmer of adopting a highly nutritious crop are less visible, and confounding factors such as profit maximization are thus unlikely to drive intention, other innovations such as a more profitable crop might be appealing also to less innovative farmers, reducing the relative share of variance explained by the latent construct. The relative "ranking" of the innovations is preserved when we omit the behavioral factors, net of some scale effects (Table A4 for the separate models, and A7 for the SEM).

Finally, most of the geographic dummies (reported in the Appendix, Tables A2 and A3 for Relations 1–4, and Table A6 for Relation 5) also generate significant coefficients, suggesting that location (with its specific cultural and socio-economic characteristics) matters, but the direction of the relationship is variable.

6.1. Relationship between membership and behavioral factors

In the SEM, we included dependencies between membership and behavioral factors in the form of correlations between standard errors. The results in this regard are reported at the bottom of Table 5. First, openness to new ways of production, risk acceptance, and trust are all significantly and positively correlated with each other, the strongest relationship being between openness and trust (0.378), and the weakest between trust and risk acceptance (0.062). As expected, membership is positively correlated with trust in the organizations promoting innovation, but negatively correlated with risk acceptance, suggesting that farmers may join organizations to share and therefore reduce risk. In turn, there is no significant correlation between openness and membership, suggesting that these factors act separately. Nevertheless, these figures are based on generic membership, while the members of specific organizations may differ from those of others. For this reason, in Table 8 below, we report the results of statistical tests comparing behavioral factors between the members of specific organizations and those of other organizations in the same Food Hub, while the results of the tests on background factors are reported in Tables A10 and A11 in the Appendix. While we are unable to identify clearcut patterns, trust seems to differ significantly for various specific organizations. The characteristics of specific organizations are presented in more detail in Subsection 5.2 below and discussed qualitatively in Subsection 6.1.

6.2. Results for specific cooperatives and associations

Even when controlling for generic membership, being a member of some specific associations and cooperatives, included in Relation 5, is still significantly related with the intention to innovate. As previously explained, the coefficient for generic membership in farmers' organizations in Relation 5 is just above the 10 % level of significance. However, this generic coefficient, which could be interpreted as referring to membership *on average*, does not consider the specific effect of being a member of one of the 21 farmers' groups included in our model. This latter set of coefficients represents, instead, the effect of being a member of that specific organization *beyond* basic membership (which is common to all organizations). To evaluate the total effect of generic membership and the specific effect of membership in one organization, we implemented joint tests on the significance of pairs of coefficients. The results of this test are shown in Table 7, while the coefficients are reported (for the estimates with and without behavioral factors) in the Appendix (Table A8 for the separate estimate, and Table A9 for the SEM). With limited exceptions, the direction and significance of the coefficients for specific organizations are coherent across the models, with and without behavioral factors, and regardless of whether they are

Table 8
Difference in behavioral factors between the members of specific cooperatives and the members of other cooperatives in the same Food Hub.

Food Hub	Organization	Openness		Risk acceptance		Trust	
		Diff.	*p*-value	Diff.	*p*-value	Diff.	*p*-value
Dir Beni Mellal	ZITOUNE Coop.	−0.34	0.275	**−0.61**	**0.034**	−0.29	0.265
	COLEZA Coop.	0.12	0.873	−0.55	0.130	−0.04	0.700
Ait Ouallal Bittit	KHARICHFA Association	0.00	0.341	0.62	0.219	**0.88**	**0.014**
Kitui	Nehema self-help group	**0.42**	**0.009**	**−0.83**	**0.007**	**0.43**	**0.079**
Mukurweini	Rugi farmer cooperative society	0.00	0.482	0.05	0.933	0.03	0.839
	New Gikaru farmer cooperative society	−0.11	0.658	−0.13	0.468	0.07	0.706
	Rumukia farmers' cooperative society	0.14	0.780	0.18	0.541	−0.22	0.324
	Ruthaka farmers' cooperative society	−0.11	0.383	0.01	0.640	**−0.41**	**0.009**
	Wakulima cooperative society	0.03	0.731	0.13	0.479	**0.37**	**0.030**
Kilombero	Kidatu Sugarcane Growers Association	−0.28	0.598	−0.06	0.908	0.16	0.500
Mvomero	–						
Chebika	GDA Karma	0.02	0.677	0.15	0.654	−0.35	0.147
	GDA Jefna	**−0.75**	**0.006**	−0.41	0.188	−0.20	0.216
	GDA Ayaycha	**1.11**	**0.001**	0.51	0.201	**1.04**	**0.000**
Fernana	SMSA	0.31	0.380	**0.63**	**0.065**	−0.08	0.609
	GDA Hrayer Gloub Thiren	0.20	0.616	0.16	0.299	**0.68**	**0.001**
	URAP	−0.16	0.908	−0.17	0.558	**−0.53**	**0.019**
Kamuli	Busiba cooperative society	**−0.11**	**0.055**	−0.36	0.414	−0.12	0.706
	Kamuli Nankulyaku Maize cooperative	0.09	0.265	−0.31	0.460	0.17	0.414
	Edikokolima Saving and Credit Assoc.	0.09	0.290	0.33	0.608	**0.20**	**0.047**
Nakaseke	Namasinda kwekulakulanya group	**−0.45**	**0.000**	0.41	0.309	**−0.68**	**0.007**
	Nakaseke vegetable producers and seed multiplication association	−0.14	0.347	0.25	0.530	**0.44**	**0.069**

Diff.: Difference in the mean between the members of the cooperative specified, and the members of other cooperatives in the same Food Hub (including those not listed). *p*-value: *p*-value of a Wilcoxon rank-sum test.

tested separately or jointly with generic membership, suggesting that the individual effects are robust. Nevertheless, the direction is not univocal across organizations, thus providing some nuances to our **H1** on generic membership. Namely, two organizations (GDA Jefna and GDA Hrayer Gloub Thiren) are negatively associated with intention, while six positively.

Following the above considerations, we tested if the members of the organizations positively or negatively related to the intention to innovate differ from those of other organizations in the same Food Hubs in terms of background factors (see Tables A10 and A11), and behavioral factors (Table 8). While we could not identify clearcut patterns in terms of background factors, behavioral factors show some interesting elements. Although the difference is not always statistically significant, the average "value" of behavioral factors is greater than for the other organizations in the same Food Hub for all the organizations positively related to intention to innovate (while being negative in GDA Jefna). Trust is the factor that presents a statistically significant difference more frequently (four out of six times).

6.3. Effect of background factors

The models for Relation 5 (Table 6) illustrate the relationship between background factors (the same included in Relations 1–4) and intention, to assess if there is still a significant residual association, or if the effect of the latter has been completely endogenized by the behavioral factors and the memberships in farmers' organizations. Or, adopting a different point of view, to assess how far the behavioral factors and the membership in organizations operate as mediator variables between background factors and intention to innovate.

The estimates indicate that some background factors are still significantly associated with the intention to innovate. In particular, age, the extent to which the household's food needs have remained unmet, and possession of a mobile phone, are all positively (directly) and significantly related to intention in both models, while the share of income spent on food (a proxy of poverty) is negatively related. In the SEM model, the farm size and access to informal credit too, are positively associated with intention. The last two columns of Table 6, based on the SEM, report the indirect effects, as mediated by behavioral factors and membership in organizations, and the total effects, which are the sum of the latter and the direct effects.[17] In most cases, the indirect effects are at least as significant as the direct effects, and for a few variables (i.e., education, number of adult members, migration, access to formal loans), the total effect is mainly captured by the mediating variables, supporting our choice to include them as mediators in the theoretical model. We should also point out that except for the expenditure on food and age squared, whose indirect and direct effects go in opposite directions, yielding a non-significant total effect in the first case, when significant, the direct and indirect effects always go in the same direction (negative or positive). The negative coefficient for age squared suggests an inverted U-shaped relationship between age and intention to innovate. Noteworthy, if we were to exclude the behavioral factors and thus Relations 2, 3, and 4 from the model (Table A5 in the Appendix), none of the indirect effects would be significant, while the direct effects would become significant in many instances. Therefore, individual behavioral factors, rather than generic membership in organizations, mediate between background factors and intention to innovate.

7. Discussion

This research used a mixed theoretical framework, where the relationship between background factors and the intention to adopt innovation is mediated by a set of elements, among which is membership in farmers' organizations, which is the result of a farmer's decision (leading to increased social capital). This approach allows us to consider the separate effect of cultural (on a geographical base), social (i.e., membership in farmers' organizations), and personal (i.e., behavioral) factors (Bourdieu, 1986; Burton, 2012). Several assumptions embedded in this framework are confirmed by the results, even if our main hypothesis (**H1**), which assumed a positive relationship between membership and intention to adopt innovation, remains controversial and cannot be statistically confirmed when generic membership (i.e., regardless of the characteristics of specific organizations) is considered. This result needs to be discussed in parallel with the role of the three behavioral factors and of membership in specific organizations.

[17] The indirect effect sums up the indirect effects through all the mediator variables (three behavioral factors and membership).

The mediating attitudes included in our model are clearly positively related to the intention to innovate. This confirms our assumptions based on the existing literature, in particular: **H2a**) "openness to new ways of production" can represent a generalized version of the "attitude toward using technology" used in the TPB (Ajzen, 1991) and UTAUT (Venkatesh et al., 2003) approaches; **H2b**) people who are risk averse are reluctant to invest in technology (Juma et al., 2010); and **H2c**) trust in institutions is a significant driver of intention to innovate (Fan et al., 2022; Kavakebi et al., 2023; Zawojska, 2010).

However, the effect of personal attitudes is difficult to disentangle from the effect of membership in farmers' organizations. The personal decision to join an organization, which in turn allows one to increase one's own social capital, is positively associated with trust in organizations promoting innovations, but negatively associated with risk acceptance. In future research, it will be important to focus on this aspect and, if possible, define the causal direction of these relationships by means of panel data. Farmers could join cooperatives because they trust these organizations, are personally less willing to accept individual risk, and thus want to share it with organization members; or, conversely, being part of an organization (i.e., counting on a larger social capital) could cause farmers to become more trustful of institutions but less willing to take individual risks. Concerning background factors, many of them are significantly associated with membership in farmers' organizations. The results confirm what emerged in the comprehensive literature review by Manda et al. (2020) that age, education, land size, access to liquidity (i.e., formal loans and informal credit), and social networks (i.e., mobile phone ownership) are associated with membership in organizations. On the contrary, we found that female-headed households are more likely to be members of cooperatives than their male counterparts, which is the opposite of what was found by Manda et al. (2020). Naturally, this aspect is strongly linked to specific cultural and institutional factors on a geographical basis. The household size turned out not to be significantly associated with membership.

Some of the above-mentioned variables are significantly associated with "openness to new ways of production," confirming most of the expected results from Manda et al. (2020). On the contrary, it is much more difficult to find variables clearly associated with "attitude toward risk" and "trust in organizations promoting innovations."

Finally, the results indicate that the intention to adopt is, unsurprisingly, related to the type of innovation. Organizational innovations that require investment in social capital (such as collective marketing efforts), along with those lacking immediate monetary benefits, like the adoption of nutritionally enhanced crop varieties with no price premium, are less likely to be embraced. In contrast, process innovations such as the installation of irrigation systems (typically long-term, land-saving investments) are more likely to be accepted. However, it is important to note that these findings pertain to intention, which may not always translate into actual adoption due to various constraints. These differences may be further shaped by the structure and functioning of input and output markets, an area that warrants further investigation (Kuhl, 2018). Interestingly, farmers who express a strong intention to adopt one type of innovation also tend to show a similar disposition toward others, suggesting a general openness to change or innovation readiness.

7.1. The role of specific organizations

Membership in specific farmers' organizations can be positively or negatively associated with the intention to adopt. The direction of the significant coefficients is summarized in Table 7, while a more detailed overview is provided in Tables A8 and A9 in the Appendix. The explanation for these performances must be searched both in the characteristics of the members of the organizations and in the organizations themselves. In the first case, we are assuming that social capital (i.e., the strength and value of the network) builds on the characteristics of individuals and can thus be considered endogenous. In the second case, it builds on some exogenous or unpredictable drivers (e.g., the role of a competent or charismatic leader) that go beyond the "average" cultural and institutional environment of a geographic area (roughly embedded in the geographical dummy).

Overall, in our survey, it is not possible to identify homogeneous patterns in terms of background characteristics (e.g., age, education, etc.) of the members, which would allow us to better understand why the membership in specific organizations is positively or negatively related to intention to innovate. In the absence of clear patterns related to the characteristics of members, we may assume that the factors that make a good organization (at least for promoting innovation) are mainly embedded in the organization itself. They can be linked to elements such as among others, the institutional structure, the objectives of the group, and the role of its leadership.

Identifying these organizational characteristics is beyond the scope of this paper and would require more systematic data about single organizations. However, some considerations could be drawn based on the knowledge of local experts, and on informal conversations with members and managers of the organizations included in our sample, especially concerning the difference between organizations within the same country.

In Morocco, the three organizations included in the model have the same institutional structure: they are all cooperatives. Furthermore, they have similar objectives and engage in similar activities such as the pooling of resources and the storage and marketing of agricultural products. Thus, the reason for the positive effect associated with the Kharichfa Cooperative cannot be found in institutional differences but might be due to specific characteristics of the group or leadership. Based on local experts' opinion, the leadership of this cooperative seems to have a great (positive) influence on the openness of its members and on their intention to accept technological innovations. The president of this cooperative is a retired agricultural advisor, and his deputy is a member of the local administration. The members of the cooperative trust their decisions and the direction taken. Other important aspects that explain the good functioning of the Kharichfa Cooperative, and consequently, the trust in the innovations proposed by it, are the homogeneity of members and their common involvement in activities connected with irrigation and water saving.

In Kenya too, particularly in the Mukurweini area, the cooperatives included in our model have a similar structure and implement similar activities. This region is particularly suitable for coffee production, and cooperative participation is very common among farmers. All five cooperatives selected for this area deal with coffee production, collection, and marketing, and own coffee factories. Thus, also in this case, organization-specific effects on the propensity to innovate of their members might be linked to the intrinsic characteristics of each cooperative. Wakulima Cooperative, and especially Rugi Farmers' Society, are the two cooperatives yielding positive effects, while others do not generate any significant effect. According to the opinion of experts in the field, the members of these two cooperatives are pooling resources for investing in high quality coffee crops and high value-added technologies.

The Tunisian organizations included in our study are mostly characterized by the GDA (Agricultural Development Groups) form. Two GDAs (Jefna and Hrayer Gloub Thiren) are the only organizations in the entire sample whose membership is negatively associated with intention to innovate. This could indicate that these GDAs are having performance problems and, consequently, their members are discouraged from innovating and investing. However, membership in two other GDAs (Ayaycha and Karma) yields a positive effect; thus, the effects seem to be again the result of incidental situations inside the groups. In fact, many GDAs in Tunisia are still facing a wide range of financial, technical, and organizational constraints (Farolfi et al., 2022; Mahdhi et al., 2021).

Contrary to the previous countries, the Ugandan organizations included in our sample encompass cooperatives and associations with different legal forms; thus, multiple factors could affect their role in fostering intention to innovate. Two organizations yielded positive and significant effects. The first is Kamuli Nankulyaku Maize Cooperative, which processes and sells maize flour to big buyers outside the district. In 2022, this cooperative acquired technological support in the form of a free solar-powered irrigation system from the Ministry of Agriculture, Animal Industry, and Fisheries. It also deals with savings and loans as one of its major activities. The fact that this cooperative is engaged in various business initiatives and is interested in large investments suggests high organizational willingness to innovate, which may act as a driver of its members' intention regardless of their individual behavioral characteristics (which do not seem to differ from the members of other organizations; see Table 8). The second organization is Edikokolima Saving and Credit Association, involved in maize shelling with their own machinery. This group does not share any association profit with members, but uses this money either to loan members, or to make investments. The chairperson declared to these authors that they have not yet reached the stability level at which they could share profits; they want to buy more assets and have more money available for loans. This approach could be a strong sign (and possibly a cause) of the higher intention to innovate shown by its members.

Finally, our sample includes a single individual organization from Tanzania, whose membership does not yield any significant coefficient.

8. Conclusion

This study is based on a cross-country survey conducted in ten regions of five African countries, involving 4,529 smallholder farmers. An approach that links random utility and behavioral models has been used to assess if four variables work as mediators between the background factors normally adopted in random utility models (i.e., socio-demographic and economic characteristics of the farmers, households, and farms), and the intention to adopt innovations. The four mediating variables include membership in different types of farmers' organizations, which represents (or should represent) a relevant source of social capital, as well as three behavioral (personal) factors related to risk-taking, trust, and openness to innovation. Joining a farmers' organization was considered an intermediate decision that, like distal behavioral factors, is associated with background factors and is, in turn, related to the intention to innovate. Cultural, institutional, and environmental aspects were also considered in the analysis by controlling for the ten geographical areas.

While the studies adopting the standard random utility model provide insights into *how* background factors affect intention to innovate, this study aspired to provide insights into *why* background factors affect intention to innovate. In other words, we posited that factors such as land size and age do not directly affect innovation propensity, but rather affect individual attitudes such as trust, openness to innovation, and risk-taking, as well as social capital through organization membership. However, as always happens with cross-sectional models, the causality (direction) of these relationships cannot be tested and, consequently, cannot be assured. Causal relationships in this framework are based on underlying assumptions, partially justified by related literature and logical inference.

Our findings suggest that local conditions consistently influence behavioral factors, membership in farmers' organizations, and the intention to adopt innovations. This underscores the importance of conducting cross-country studies using standardized methodologies—such as the one employed in this research—to assess whether the classical variables commonly used in innovation adoption studies exert similar effects across different contexts (Crudeli et al., 2022). However, the drivers of some behavioral factors (namely, openness to new ways of production) could be identified more easily than others (namely, attitude toward risk, and trust in organizations). Furthermore, the latter factors showed correlation with membership in organizations, highlighting the necessity of further studies to verify the causal relationship between cultural drivers, social capital, and individual behavioral characteristics (Bourdieu, 1986; Burton, 2012).

The main goal of this paper was to advance understanding of whether and how membership in farmers' organizations affects intention to innovate. The extant literature provided mixed results, which could be due to differences in the methodologies used. We adopted the same methodology—including the data collection tool and theoretical framework—across five countries and more than twenty farmers' organizations. The results (unsurprisingly) suggest that the effect of membership varies across organizations, and that a more specific institutional approach is necessary to evaluate which characteristics of an organization affect its members' intention to innovate. If the effectiveness of farmers' organizations is primarily driven by external drivers—as we could not identify consistent background characteristics among the members of virtuous organizations—then endogenous interventions, including the training of leaders (whose role remains essential for the performance of organizations), could affect members' attitudes and intention to innovate. In other words, organizations would be a source of empowerment for individuals. Farmers' organizations can also provide market-based solutions to structural value chain problems (Kuhl, 2018), including access to information, and input and output markets (see, for instance, the relevance of credit for the performance of the Ugandan Edikokolima Saving and Credit Association). Simultaneous adoption of social, organizational, marketing (e.g., joint sale of production, credit access), and technological innovations (e.g., irrigation systems, new crop varieties) is key for local development; let's think of a value chain needing constant and uniform supply of new, higher-value crops (Kuhl, 2018), and thus requiring organization among farmers.

Our study presents some limitations. First, the cross-sectional nature of the dataset does not allow us to determine the direction of causality. In the future, longitudinal studies could allow a better understanding of whether, for instance, joining a cooperative increases the intention to adopt innovations, or vice versa. Second, we measure behavioral factors through Likert-scale statements rather than revealing them through incentivized experiments or by observing and recording actual behaviors. Third, we only focus on intention rather than actual adoption, which is subject to social desirability bias, i.e., the farmers might overstate their intention to adopt to please the interviewers (or in the hope of receiving funding), since there are no direct consequences for their welfare. Intention will not necessarily result in adoption, although we expect the bias to go in the same direction for all farmers. Fourth, our analysis is mainly focused on technological aspects, while market drivers could provide new insights into the complex relationships between attitudes and choices.

In the future, background factors, membership in farmers' organizations, and behavioral traits could be linked with actual adoption measured through randomized controlled trials to verify if intention aligns with the latter. Additionally, we could reveal behavioral traits such as attitude to risk and trust using incentivized experiments—this has been already done in the same project, but only in a subset of locations, and for a significantly smaller sample size. Finally, future projects could adopt a longitudinal approach by contacting the same farmers at different points in time, thus overcoming some of the data limitations we faced.

CRediT authorship contribution statement

Luca Mulazzani: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Simone Piras:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation. **Claudia Giordano:** Writing – review & editing, Writing – original draft, Methodology, Funding acquisition. **Atsede Ghidey Alemayehu:** Writing – review & editing, Methodology. **Carla Barlagne:** Methodology, Funding acquisition. **Ali Chebil:** Writing – review & editing, Methodology, Investigation, Data curation. **Chokri Thabet:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation. **Faten Khamassi:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition, Data curation. **Johnny Mugisha:** Writing – review & editing, Project administration, Methodology, Investigation, Funding acquisition. **Josephine Kisakye:** Writing – review & editing, Methodology, Investigation, Data curation. **Evans Ligare Chimoita:** Writing – review & editing, Methodology, Investigation, Data curation. **Sophia Ngala:** Writing – review & editing, Investigation, Data curation. **Dismas Lyegendili Mwaseba:** Writing – review & editing, Methodology, Investigation, Data curation. **Noureddine Mokhtari:** Writing – review & editing, Software, Project administration, Methodology, Investigation, Funding acquisition, Data curation. **Marco Setti:** Writing – review & editing, Resources, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research is part of the project FoodLAND (Food and Local, Agricultural, and Nutritional Diversity), which has received funding from the European Union's Horizon 2020 Research and Innovation Programme under grant agreement No. 862802. The views and opinions expressed are the sole responsibility of the authors, and do not necessarily reflect the views of the European Commission. We thank all the FoodLAND partners for the fruitful discussions during the past few years. For implementing the fieldwork, we are sincerely grateful to the teams of University of Nairobi (Kenya), École Nationale d'Agriculture de Meknès (Morocco), Sokoine University of Agriculture (Tanzania), Institut Supérieur Agronomique de Chott-Mariem and Institut National Agronomique de Tunisie (Tunisia), Makerere University and National Agricultural Research Organisation (Uganda). A final thank goes to the enumerators who supported data collection in the field, and to all the smallholder farmers for taking part in the survey.

Appendix A. Supplementary information

Supplementary data to this article can be found online at https://doi.org/10.1016/j.worlddev.2025.107192.

Data availability

The data used in this article are available at this DOI (embargoed until 28 February 2026): https://doi.org/10.5281/zenodo.14284426. The Stata code used for the analysis is provided as online Supplementary information.

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