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Consequences of increased farm resilience on food security in Tajikistan

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Abstract

Unprecedented climate change, socio-economic shocks, and political conflict exacerbate food insecurity. Worsened conditions and increased vulnerability now give prominence to improving farm resilience to withstand shocks. This article aims to analyse the effect of farm resilience on food security outcomes in Tajikistan. Using panel data collected in 12 districts in the Khatlon Province of Tajikistan from 2015 to 2023, the study has the following. (a) measure farm resilience determinants (pillars) through adaptive capacity, transformation capacity, and robustness; (b) estimate the relationship between resilience pillars and food security outcomes; (c) cluster farm households based on the level of resilience pillars; and (d) estimate the effect of farm resilience on food security outcomes. The study first measures farm resilience pillars using Principal Component Analysis (PCA). Next, Latent Profile Analysis (LPA) is used to classify farm households into three resilience categories: “Low Resilience”, “Medium Resilience”, and “High Resilience”. The estimation strategy involves making causal claims using LPA and Propensity Score Matching (PSM) techniques. Our results suggest a positive relationship between farm resilience and food security outcomes. Our findings also confirm that “High Resilience” and “Medium Resilience” profiles experience better dietary diversity, higher fruit and vegetable consumption, or decreased household hunger, compared to the “Low Resilience” profile. Such a positive relationship underlines the importance of strengthening farm resilience. Further development agendas for Tajikistan should consider resilience thinking, especially in shock-prone zones. Objectives: (a) measure farm resilience determinants (pillars) through adaptive capacity, transformation capacity, and robustness; (b) estimate the relationship between resilience pillars and food security outcomes; (c) cluster farm households based on the level of resilience pillars; and (d) estimate the effect of farm resilience on food security outcomes. The study first measures farm resilience pillars using Principal Component Analysis (PCA). Next, Latent Profile Analysis (LPA) is used to classify farm households into three resilience categories: “Low Resilience”, “Medium Resilience”, and “High Resilience”. The estimation strategy involves making causal claims using LPA and Propensity Score Matching (PSM) techniques. Our results suggest a positive relationship between farm resilience and food security outcomes. Our findings also confirm that “High Resilience” and “Medium Resilience” profiles experience better dietary diversity, higher fruit and vegetable consumption, or decreased household hunger, compared to the “Low Resilience” profile. Such a positive relationship underlines the importance of strengthening farm resilience. Further development agendas for Tajikistan should consider resilience thinking, especially in shock-prone zones.

Keywords Farm resilience · Food security · Hunger · Latent profile · Central asia

1 Introduction

Farm households in developing countries are prone to shocks and stresses. In Central Asian countries (Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan and Uzbekistan), the

intensity of climate-related shocks has increased in recent years. Extreme climate change events pose significant threats to agriculture and food security in the region (Reyer et al., 2017). Farming systems are among the most vulnerable to environmental shocks, which exacerbate both the

physical environment and socio-economic conditions on farms. In this context, the farm's operational, socio-economic, and agro-ecological differences determine the overall implications of climate change (Habtemariam et al., 2017). Adaptation and mitigation strategies for climate change are critically needed in Central Asia (Liu et al., 2020), particularly to enhance climate resilience in the agricultural sector (Zong et al., 2022).

Mainstreaming resilience thinking in the context of food security discussions is already at the centre of the research arena and political agenda (Fan et al., 2014; Pelletier et al., 2016). In the meantime, resilience as a multifaceted concept has already become a cornerstone of the development agenda (Béné, Newsham et al., 2014). For example, socio-ecological resilience is a powerful tool in the development agenda (Béné et al., 2014; Scown et al., 2023) that helps to individualize coping mechanisms at individual or household levels (Ferguson & Wollersheim, 2023). Another prevailing strategy is that food insecurity resilience should mitigate the impact of climate change on food security, as suggested by the level of household resilience (Sundayet et al., 2023). Farm resilience as a coping mechanism for climate change has gained prominence in the current unprecedented climate variability (Altieriet et al., 2015; Beitneset et al., 2022; Jamil et al., 2021).

Meanwhile, a notable gap in the literature so far is the lack of understanding regarding the interplay between farm resilience and food security outcomes, particularly among farmers in Central Asia. It is essential to distinguish the farm resilience framework from the broader concepts of general and specific resilience. Meuwissen et al. (2019) offered a framework to assess farm resilience, distinguishing specific resilience and general resilience. The framework outlines *five essential steps* to determine whether farm resilience is generic or specific (Sect. 1 and Table S1 in Supplementary Material). The manuscript further operationalises *farm resilience to food insecurity in the presence of climate shocks*. This paper examines a relationship between farm resilience and food security in Khatlon province of Tajikistan. Although findings from other studies have already confirmed the role of agriculture in nutritional outcomes in the region (Takeshima et al., 2018, 2020), the present study aims to address the gap in relation to food insecurity and farm resilience in Tajikistan. Egamberdiev et al. (2024) confirmed the importance of household resilience in addressing food insecurity in Tajikistan; however, a study examining the effects of farm resilience on food security outcomes is needed.

Another major limitation is that the present methodologies to quantify resilience are inconsistent (Ansah et al., 2019), particularly in defining resilience levels or thresholds. Therefore, this study contributes to the literature by quantifying farm resilience with different determinants of resilience capacity. Many current approaches to measuring resilience capacity are based on average-level scores obtained from observed variables; however, this approach is often embedded in the problem of heterogeneity. The study also clusters farm resilience capacity into homogeneous profiles using latent class modelling. Development science has already recognized the importance of a latent class approach that may deal with the problem of heterogeneity and multidimensionality (Kim, 2023; Lanza & Cooper, 2016; Scotto Rosato & Baer, 2012). Finally, the present paper aims to contribute to the literature by introducing a novel methodological approach to detect causal references between resilience and food security outcomes.

Tajikistan, geographically located in Central Asia, is a low-income and landlocked country (IFAD, 2024). The country is highly vulnerable to socioeconomic and environmental shocks because it is the most remittance-dependent in the world (Ganget et al., 2018; WB, 2024). For example, many rural households in Tajikistan experienced instantaneous pressure on food consumption due to the COVID-19 pandemic, particularly in remittance-dependent families (Zhaot et al., 2024). More than nine million people in Tajikistan face food insecurity challenges (WFP, 2024), and the spillover effects of the war in Ukraine had a detrimental impact on food and nutrition security (WB, 2022). It is evinced by some facts that Tajikistan did not achieve food sufficiency, although there was a growth in domestic food production (Qiqi Li & Liu, 2021). In addition, chronic energy insecurity is also deleterious to food security and nutritional status (Qi et al., 2020), requiring an integrated approach to water-energy-food security realization in Tajikistan (Hao et al., 2022). Agricultural reforms aim to improve livelihoods; however, a weak adaptation mechanism has remained a significant challenge. A pertinent question is how Tajik farm households can improve food security with limited resources, particularly land and water (Kawabata et al., 2020). Adaptation measures are a priority in the National Strategy for Adaptation to Climate Change of the Republic of Tajikistan- 2030 (Babuet et al., 2024). A continued policy response to strengthen farmers' adaptability and robustness is indispensable to enhancing farm resilience to climate change in the region. Given the constraints and conditions in Tajikistan, a policy agenda focused on improving food security and enhancing resilience to climate change is

at the forefront, paving the way for promoting farm resilience capacity (Akramov et al., 2021).

In this manuscript, we first measured farm resilience capacity to food insecurity through adaptive capacity, transformation capacity, and robustness. Meuwissen et al. (2019) confirmed that capacity-based measurements are predominantly used to quantify farm resilience. We used Principal Component Analysis (PCA) to measure farm resilience pillars in the estimation. We also applied Latent Profile Analysis (LPA) to obtain homogeneous profiles clustering adaptive capacity, transformation capacity, and robustness in dealing with the problem of heterogeneity. Finally, we established a relationship between farm resilience and food security outcomes. The objective of the relationship between resilience pillars and food security outcomes was fulfilled by applying the Multiple Indicator Multiple Cause (MIMIC) model. We also modelled a causal inference analysis by integrating latent analysis with propensity score modelling for the effect of farm resilience on food security outcomes.

2 Farm resilience and food security

2.1 Farm resilience capacity

Theoretical concepts of resilience generally define household resilience as a latent, index variable and capacity (Constaset al., 2014; d'Errico et al., 2016). Despite some variations in theory, the measurement of farm resilience has underpinnings that operationalise resilience in the farming system. A review study analysing resilience conceptualisation in farming systems defines resilience as a capability or process grounded in the prominent practices (capacity, practice, and resource) and the perturbations (shocks, exposure, and sensitivity) (van der Lee et al., 2022). The capacity-based approach to conceptualizing farm resilience distinguishes three types of capacity: adaptive capacity, transformability, and robustness (Meuwissen et al., 2019; Slijper et al., 2020, 2022). According to the authors, *robustness* defines the capacity to withstand shocks and stresses in farming operations. Therefore, robust farmers are expected to cope with shocks and stresses without changing the farm structure. *Adaptive capacity* refers to the ability to adapt to a changing environment without altering the farming system. It represents how effectively farmers adjust their functioning to a dynamic or changing environment with a minimal system of change. *Transformation capacity* explains the ability to change the farming system in response to shocks and stresses. It represents the condition in which the farm system undergoes a complete

transformation into another system during shock scenarios. When the current system becomes untenable, transforming the system into a completely new state becomes a viable option for farm households (Meuwissen et al., 2019). Similar studies measuring farm resilience through robustness, adaptability, and transformation have confirmed that the outcome can be either increasing persistence in the face of change, making adjustments to the dynamic environment, or completely transforming the farm (Jones & d'Errico, 2019; Slijper et al., 2020). Therefore, farm resilience embodies complex dynamic systems interconnected through various adaptive pathways. Further studies are available in Table S2 in the Online Supplementary Material. Measuring farm resilience, particularly in terms of its capacity, relies on properties that explicitly address socio-economic, environmental, and cultural resources. Such a complex pattern of resilience requires rigorous methods to measure farm adaptability, robustness, and transformability in order to assess overall farm resilience. In addition, findings by d'Errico et al. (2018) reaffirmed the importance of critical thresholds for resilience. The concept should include critical thresholds that may have a reciprocal relationship with well-being and other related factors in the estimation.

2.2 Farm resilience capacity and food security

In this manuscript, we aim for a pragmatic application of the resilience concept to establish a causal relationship between farm resilience capacity and food security. For example, findings by Pelletier et al. (2016) largely corroborated the discussions on resilience-enhancing agricultural practices for food security development. The authors paid considerable attention to rural capacity to shocks as one of the ways to achieve food and nutrition security. The relationship between resilience as a household capacity and food security outcomes is accentuated by different authors (Ansah et al., 2023; Beyene et al., 2023; d'Errico & Pietrelli, 2017; d'Errico et al. 2023; Kalumanga et al., 2022; Lascano Galarza, 2020; Melketo et al., 2021; Mossie et al., 2024; Suh et al., 2023; Sunday et al., 2023; Temesgen Gelata et al., 2024), particularly at different livelihood systems (Adoet al., 2019; Atara et al., 2020; Watete & Kogi-Makau, 2021). Similarly, another study reviewing the conceptualization of resilience towards food insecurity confirmed that most studies measure resilience capacity through robustness, transformability, and adaptive capacity (Meyer, 2020).

A further seminal paper analysing the conceptualization of food insecurity resilience explicitly explains that resilience capacity may change food and nutritional outcomes;

however, a two-way causality in the relationship between resilience capacity and food security is one of the main challenges in empirical studies (Ansah et al., 2019). In the meantime, the study analysing the conceptualization of food insecurity resilience in the context of COVID-19 and shocks provided a plausible explanation for the importance of resilience (Béné, 2020).

As for Central Asian countries, findings confirmed that household resilience capacity is likely to have a positive effect on dietary diversity and food expenditure in the presence of endogenous and exogenous shocks (Egamberdiev et al., 2023; Egamberdiev et al., 2024). In this case, Curity in Tajikistan (Takeshima et al., 2024). This relationship can be strengthened with more agricultural training that may build or strengthen resilience in technical efficiency (Takeshima et al., 2024). Findings by Scott, Chi, and Glenna (2024) also confirmed the importance of resilience that may pronouncedly improve food security conditions in Central Asian agropastoral communities. In addition to resilience in croplands (Jiang et al., 2024), the role of social capital may interweave resilience with food security outcomes in Central Asian rural areas (Egamberdiev, 2024). From another aspect, climate change and regional insecurity have already changed the belief of the immanence of food insecurity resilience in crises.

3 Data and methodology

3.1 Data

The analyses make use of household survey panel data collected from 2,000 households interviewed in 2015 and 2023, representative for the population in 12 districts in the South-west of Tajikistan (Fig. 1). These twelve districts formed the USAID's main operational area since 2012. In 2015, the survey aimed to interview households previously interviewed in the 2012 FEEDBACK PBS (Lambrecht et al., 2024). Further details on the dataset can be obtained from the study by Lambrecht et al. (2023). The sample design of the 2012 FEEDBACK PBS relied on a two-stage cluster sample designed to represent the population in these twelve districts. Standard enumeration areas (based on the 2010 Census), stratified by district and urban or rural location, were selected with probability proportional to size. In each selected enumeration area, 20 households were selected randomly from a full household list. Sampling weights were calculated to take into account the sample design features. The households from the 2012 sample that could not be interviewed in 2015 were randomly replaced by another

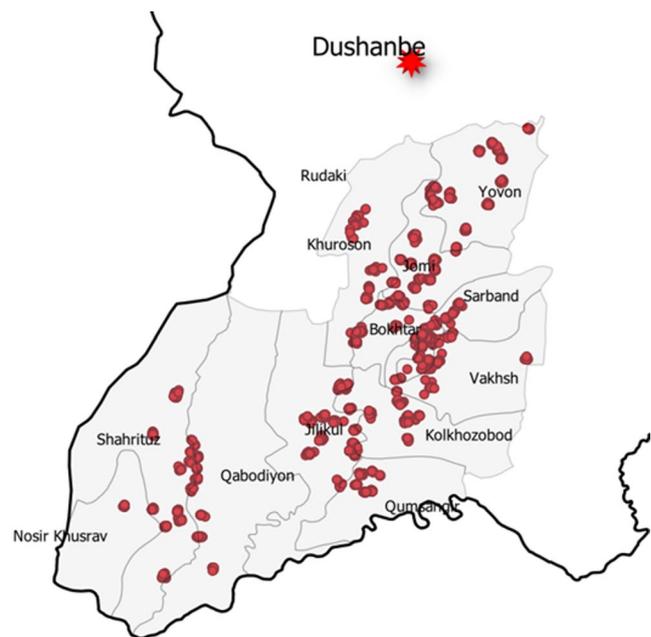


Fig. 1 Household survey locations in Khatlon Province, Tajikistan. Source: Authors' own compilation

household in the same enumeration area. In 2023, enumerators sought to reinterview the households also interviewed in 2015. Among the 2,000 households interviewed in 2015, 402 households were not available for interview and were replaced by the nearest neighbour. The 2012 sample could not be used as a basis for the interviews, as identifying information of the households originally interviewed in 2012 was not available to the survey team. Given minor differences in questionnaire design of the 2015 and 2023 datasets that might affect our measures of resilience pillars, we used the data as pooled cross-sectional survey data and we did not rely on the panel data structure for the analyses in this study.

3.2 Key indicators

The manuscript focuses on three outcome variables: dietary diversity, fruit and vegetable consumption, and household hunger score. We used the *Simpson Index* to measure dietary diversity, representing the proportion of food groups consumed. The proxy is widely applied to analyse the relationship between household resilience capacity and food security (d'Errico & Smith, 2019). According to FAO (2016), food security outcome through the category-based Simpson index is frequently used to measure dietary diversity in resilience modelling. Although Simpson based dietary diversity explains diet quality through the diversity measures ranging from 0 to 1, it does not fully capture adequacy and dietary patterns in food security. Therefore, the manuscript used *the*

adequacy of fruit and vegetable consumption as a reflection of adequacy in dietary quality. According to WHO (2002), fruit and vegetable consumption is recognized as low if individual intake is less than 400 g per day. Food security is also proxied by *the household hunger score*. One of the primary reasons for applying a hunger score is that it is validated and comparable across cultures and regional settings (Deitchler et al., 2011). This method represents a household food deprivation scale and is referred to as a perception-based approach (Ballard et al., 2011). The measurement is based on a score ranging from 0 to 6, with a score of 6 indicating severe hunger in the household.

The measurement of resilience is mostly based on two types of indicators: (i) pre-defined and observed indicators and (ii) perception or perceived resilience variables (Spiegel et al., 2021). The farm resilience capacity pillars in this manuscript use pre-defined and observed indicators based on the data availability, context specification, and a literature review. Tables S3-S5 in the Supplementary Material provide detailed statistics of the selected variables. Adaptive Capacity, as a pillar, comprises constructed Tropical Livestock Unit (TLU), crop diversity index (Simpson index), agricultural assets, total agricultural land in ha, cultivated land in ha, extension agricultural service (binary), and availability of greenhouse (binary). The articles presented salient facts that the integration of crop-livestock agriculture can enhance household resilience to climate change shocks (Gil et al., 2022). In this case, households may retain interdependent portions of livestock and crops by utilising farm resources through inputs from one system to another (e.g., waste from crop production as an input to livestock production) (Mishra et al., 2024). A series of studies confirmed that crop diversity pervasively improves household resilience through improved agricultural production and yield (Matsushita et al., 2016; Njeru, 2013), elucidating a pathway towards better food security outcomes (Ibrahim et al., 2024; Keegan et al., 2024). In this case, there is a clear and unequivocal need to have plots and cultivated lands available in farm operations (Li et al., 2016; Yin et al., 2024). In this case, the measurement of the capacity uses both total and cultivated land because not all farmers effectively use total land for cultivation purposes (Husenov et al., 2020). In addition to this, there is a potential environmental impact that may affect the land availability for cultivation. Agricultural extension service is also important to underpin farm resilience (Hunt et al., 2011; Knook et al., 2024). In the light of weather-related crop losses, cultivating greenhouse crops nurtures better production and food security (Goddek et al., 2023).

The Transformation Capacity pillar includes nonfarm investment over the last 12 months (binary), the ratio of nonfarm investment in the past 10 years, the ratio of nonfarm investment in the past 12 months, the Safety Net Index (income diversity for non-agricultural income sources), and nonfarm income sources. In this case, fostering the transition into a new development direction might be important when shocks intensify in farm operations (Meuwissen et al., 2019). Safety nets related to nonfarm income activities are also efficacious when farms mitigate the adverse effects of shocks and stresses (Abay et al., 2022). This is particularly true in the context of Tajikistan, where rural households may activate coping mechanisms through safety nets (Egamberdiev et al., 2024).

The Robustness pillar comprises the income shock ratio, loss in TLU (binary and reversed), loss in agricultural assets (binary and reversed), harvest loss due to the shock (binary and reversed), and crop affected due to the shock (binary and reversed). Fewer available income sources are likely to be the precursor to a remarkable failure in farm operations. Farmers may cope with shocks and stresses by maintaining a diversification strategy strengthened with market opportunities, financial capital, technologies, and alternative income sources (Tacconi et al., 2022). In addition, farmers are likely to strengthen their resilience with diversified income sources because they are less vulnerable to shocks (Ersado, 2005). Therefore, the income shock ratio explains how households can balance between income diversification and shock exposure. Robustness also includes reversed variables for the loss in TLU, agricultural assets, and harvest, as it represents the ability to maintain farm functioning in the face of shocks or stresses (Dardonville et al., 2021).

The manuscript includes different confounders. Table S6 provides summary statistics for the included variables. The confounders include head female (binary), higher education (binary), older adults (binary), and migration over the last decade (binary). There are also continuous variables: household size, the number of shocks experienced over the last 12 months and 10 years. The regional heterogeneity is controlled through 12 binary regional variables in the Khatlon province.

3.3 Measuring farm resilience pillars

To measure adaptive capacity, transformation capacity, and robustness, we applied Principal Component Analysis (PCA) to reduce the dimensionality of a dataset (Alinovi et al., 2010). To obtain or predict a final component score, we used the scoring method proposed by Bartlett (1937):

$$\Gamma^{-1} \wedge \Psi^{-1} x \quad (1)$$

where

$$\Gamma = \wedge \Psi^{-1} \wedge \quad (2)$$

We applied *min-max scaling* approach because there is no natural scale in the factor estimation.

$$X^* = \frac{(X - X_{min})}{(X - X_{max})} \quad (3)$$

Our decision was based on the *Kaiser-Meyer-Olkin (KMO)* statistic for sampling adequacy, which should be a minimum of 0.5 (Field, 2024). For the robustness, we also had the *Bartlett Test of Sphericity* to check the orthogonal condition. The test should provide a statistically significant result to obtain orthogonal variables (Acock, 2013). In addition, we included the *Determinant of R-Matrix* for multicollinearity, and the threshold is greater than 0.00001 (Field, 2024). We also decided to use the *Kaiser criterion*, including factors with an Eigenvalue greater than 1 (Acock, 2013). In order to maximize the dispersion in the obtained factors, we applied the *Varimax Rotation* method (Kaiser, 1958). The decision is also based on further validity analysing *Communality* for the convergence validity or to check whether applied measurement correctly measures intended farm resilience pillars. Table S7 includes the factorability mentioned above in the analysis.

3.4 Latent profile analysis

A latent class study, identifying homogenous subgroups in a sample, is a widely applied statistical analysis to deal with the problem of unobserved heterogeneity (Vermunt, 2002). The method allows for obtaining the fitted latent classes based on *latent class membership (posterior probability membership)* and *item-response probabilities* for each item response to the set of observed variables. In this case, latent class membership probabilities explain the class distribution by the estimated proportion of each individual in the separated class (Lanza et al., 2003). It represents a condition that a particular item becomes a member of a certain latent profile. If L is a categorical latent variable with $c = 1, \dots, C$ latent classes in Eq. 4, γ_c is the prevalence of latent class c :

$$\sum_{c=1}^C \gamma_c = 1 \quad (4)$$

The equation represents that latent classes are mutually exclusive and exhaustive. Therefore, each observation can be a member of only one class.

Item-response probabilities describe the class-based probability of a particular response on a particular observed variable to the given class membership (Lanza & Cooper, 2016). The item-response probabilities, providing the basis for labelling the latent categorical variable, are crucially important in measuring the latent variable. As for Eq. 5, it indicates that ρ is the item-response probability of response r_j for observed j variable. Therefore, $\rho_{j, r_j | c}$ is the item-response probability because a condition on the class membership is equal to 1.

$$\sum_{r_j=1}^{R_j} \rho_{j, r_j | c} = 1 \quad (5)$$

We further used the item-response probabilities to label the obtained classes. Taking $P(L = c | \mathbf{Y} = \mathbf{y})$ as the probability of individual's response pattern \mathbf{y} in the class c , it is referred to the posterior probability of membership (Lanza et al., 2003).

$$P(L = c | \mathbf{Y} = \mathbf{y}) = \frac{P(\mathbf{Y} = \mathbf{y} | L = c) P(L = c)}{P(\mathbf{Y} = \mathbf{y})} \quad (6)$$

Equation 6 represents each respondent's probability of membership to be in one of the latent classes. Therefore, homogeneity and latent class separation indicate that the posterior probabilities should be higher in one latent class while they are smaller in other remaining classes. In other words, the posterior probabilities tend to be identical in poor class separation or homogeneity identification. Empirically, few item-response probabilities tend to be exactly 0 or 1; accordingly, the posterior probability of membership is $P(L = c | \mathbf{Y} = \mathbf{y}) > 0$ with response pattern \mathbf{y} for each class c . Therefore, the conclusion is that the item-response probabilities conditioned on c should be around 0 or 1 for making the latent class homogeneous. Otherwise, the item-response probability condition on c tends to be far from 0 to 1. We applied AIC and BIC criteria to obtain the best model fit (Tein et al., 2013). For robustness, we applied an entropy-based criterion for the best fit in obtaining latent models (Larose et al., 2016). Table S8 provides model fit statistics for the profile selection.

The capacity-based measurement of latent analysis might be characterized by the level of high skewness of certain capacities or determinants. Therefore, the assumptions of

normally distributed resilience capacities might provide biased results. In this case, latent class modelling is relevant in describing population heterogeneity based on the set of observable variables (Lanza et al., 2003). As for the development research, latent analysis in the cross-sectional study of multidimensional constructs gives an impetus to identify and describe complex multidimensional phenomena (Lanza & Cooper, 2016). In resilience studies, the conclusions are based on the observed mean relations of the resilience pillars. However, a major limitation of this approach (e.g., SEM or factor analysis) is its disregard for the patterns of relationships in data, as it is based on the correlation or the variance-covariance matrix (Bergman & Magnusson, 1997). Although the concept of homogeneity in latent modelling is analogous to factor saturation or the absolute value of factor loadings (coefficients), a prominent advantage of latent analysis is the estimation of latent class or profile membership while accounting for measurement error (Lanza et al., 2003). The authors also noted that the estimation strategy of latent profiles is based on the assumptions that the underlying structure is discrete, mutually exclusive, and exhaustive. Compared to other clustering approaches that use the obtained distance or density in the observed variables, latent modelling, as a model-based approach, computes the estimates with classification errors (Leite et al., 2021). This condition is important for classifying farm resilience into latent profiles that are inferred from observed variables. Exhibiting similar patterns of characteristics, distinct from identifying a factor structure for the linear relations among the variables, is directly pertinent to latent profile modelling (Lanza et al., 2003).

The present study aims to identify homogeneous subgroups of farm resilience with varying resilience pillars before claiming causal inferences between farm resilience and food security outcomes. The manuscript used the three-step approach for exploring the relationship between latent and auxiliary variables (Asparouhov & Muthén, 2014; Bakk et al., 2013; Bolck et al., 2004). Including auxiliary information in the form of covariates or outcomes with the three-step method in the mixture model provides a robust modelling approach (Nylund-Gibson et al., 2014). In this approach, the first step is used to estimate the latent class model by indicator variables without any covariates. The latent classes are obtained as a nominal variable in the second step using the item-response probabilities. In the final stage, the latent class variable is regressed with distal variables.

4 Estimation strategy

4.1 Multiple indicator multiple causes (MIMIC) for the relationship

We applied a Multiple Indicator Multiple Cause (MIMIC) model for the relationship between farm resilience and food security outcomes. Multiple indicators define the underlying latent variable while the multiple causes affect it (Section S2 in the Online Supplementary Material). d'Errico and Smith (2019) recommends using the MIMIC approach for simply combining factor analysis (for the food security indicators) and regression analysis (for the association between capacity indicators and resilient latent variable). In this respect, the MIMIC approach has two measurement components: formative and reflective models (Edwards & Bagozzi, 2000). A formative model assumes that observed variables are treated as causes of the latent variable. A reflective model assumes that a latent variable is treated as the cause of observed variables. Although formative and reflective models or MIMIC are applied to causal conclusions, they rarely provide causal inferences (Edwards & Bagozzi, 2000). Equation 4 shows that three pillars influence farm resilience capacity.

$$= [\beta_1, \beta_2, \beta_3] \times \begin{bmatrix} \text{Farm Resilience Capacity} \\ \text{Adaptive Capacity} \\ \text{Transformation Capacity} \\ \text{Robustness} \end{bmatrix} + [\varepsilon_R] \quad (7)$$

As for the reflective part, latent variable or Farm Resilience Capacity (FRM) reflects its pillars in Eq. 7.

$$= [\Lambda_1, \Lambda_2, \Lambda_3] \times \begin{bmatrix} \text{Dietary Diversity} \\ \text{Adeq. Fruit and Vegetable Con.} \\ \text{Household Hunger} \end{bmatrix} + [\varepsilon_{DD}, \varepsilon_{HHS}, \varepsilon_{FVC}] \quad (8)$$

4.2 Propensity score estimation in latent analysis

Randomization enables the estimation of the average treatment effect (ATE) by randomizing participants into treatment and control groups because randomized groups are adjusted to possible confounders (Greenland et al., 1999). Under the identifiability conditions, causal inferential analysis can be applied to estimate ATEs in the observational data by using the Propensity Score Matching (PSM) techniques (Imbens, 2000). This technique explicitly provides an alternative for the causal inference in observational data. In other words, there

are myriad ways that observed confounders adjust the treatment effect through the regression models. For example, the prediction of the probability of receiving the treatment can be adjusted for the observed confounders through PSM; therefore, the method allows for obtaining a single propensity score.

For the estimation of propensity score, $\hat{\pi}_h$ denotes the propensity score for h household. Detailed discussions for the causal inferences in latent analysis are provided in Section S3 in the Online Supplementary Material. Since the propensity scores are applied to estimate the effect of treatment by adjusting for the covariates. Taking an exposure T , membership in the exposed or $T = 1$ against not exposed or $T = 0$ profile is predicted by the potential confounders. Therefore, households in the exposed group are represented by $\hat{\pi}_h = P(T = 1|x_h)$; otherwise, it is denoted by $\hat{\pi}_h = P(T = 0|x_h)$ to be in the not exposed group. The inverse propensity score weights are obtained from $1/\hat{\pi}_h$. The calculation of the propensity scores for the exposure group $P(T = 1|x_h)$ is based on the following equation:

$$P(T = 1|x_h) = \frac{\exp(\beta_0 + \beta_1 x_{h1} + \dots + \beta_p x_{hp})}{1 + \exp(\beta_0 + \beta_1 x_{h1} + \dots + \beta_p x_{hp})} \quad (9)$$

where p is a set of potential confounders that might affect the membership in the exposed group. As for the membership in the not exposed, it is derived from $P(T = 0|x_h) = 1 - P(T = 1|x_h)$. For the multinomial exposure or n_T , the estimation of the propensity score with the multinomial regression is derived from the logistic regression. *The probability of membership* in the profile to which the household belongs is still conditional on the potential confounders:

$$\hat{\pi}_h = P((T = T_h | x_h)) = \sum_{t=1}^{n_T} p(T = t | x_h) I \{T_h\} \quad (10)$$

where it is equal to 1 if $T_h = t$ or otherwise it is equal to 0. In this case, the estimation of the propensity scores for the exposure group, a multinomial logistic regression is applied:

$$P(T = t|x_h) = \frac{\exp(\beta_{0t} + \beta_{1t} x_{h1} + \dots + \beta_{pt} x_{hp})}{\sum_{t=1}^{n_T} \exp(\beta_{0t} + \beta_{1t} x_{h1} + \dots + \beta_{pt} x_{hp})} \quad (11)$$

In our context, the presence of latent exposure group requires to apply *the posterior probability of a membership* of class t with x_h covariates and u_h item-response indicators or variables. Therefore, a proposed propensity score for multinomial latent exposure group is obtained from the following equation:

$$\hat{\pi}_h = \sum_{t=1}^{n_T} p(T = t|x_h) P(T = t|x_h, u_h) \quad (12)$$

where $P(T = t|x_h, u_h)$ represents the posterior probabilities.

The equation indicates that the propensity score for latent class exposure is the sum of the probabilities of membership and posterior probabilities of membership in the exposure group. As for the presence of latent exposure, the association between latent class membership (resilience profiles) and potential confounders in the Eq. 12 is based on the three-step approach.

For PSM, we used Regression Adjustment (AR), a common approach for the treatment effect analysis from observational data. As a double robust estimation, we applied Inverse Probability Weighted Regression Adjustment (IPWRA) and Augmented Inverse Probability Weighted (AIPW) (Bang & Robins, 2005; Imbens & Wooldridge, 2009; Linden et al., 2016). We also used the Ordinary Least Squares (OLS) and Logistic Regression (Logit) models to compare the results. After conducting the propensity score measurement, the overlap in the propensity scores from the treatment and control should exist (Garrido et al., 2014). The Kernel density distribution of the estimated probabilities for the profiles in Fig.S3 in the Online Supplementary Material indicates that none of the plots is near 0 or 1. The overlap assumption implies that estimators provide “double robust” results. The model balancing the covariates before analyzing the treatment effect is of particular importance (Rubin, 2008). In this case, we used a test for balance proposed by Imai and Ratkovic (2014), implying that the treatment model is balanced with the given covariates in the null hypothesis. The overidentification test for covariate balance indicated balanced covariates.

5 Results

5.1 MIMIC findings for resilience and food security relationship

The results in Fig. 2 are relied on measuring an underlying latent Farm Resilience Capacity (FRC) with multiples indicators (three food security outcomes) and multiples causes (three capacities). Food security indicators are household dietary diversity (DD), adequacy of fruit and vegetable consumption (AFV), and household hunger score (HHS). The observable variables or causes in the title of the model are the pillars used to construct latent FRC: Adaptive Capacity (AC), Transformation Capacity (TC), and Robustness (R). The sign and significance levels indicate that the adaptive (AC) and transformation (TC) pillars are statistically significant at the 1% level. The relationship between robustness (R) and farm resilience (FRC) is positive and significant at 10%. As expected, Farm Resilience Capacity (FRC)

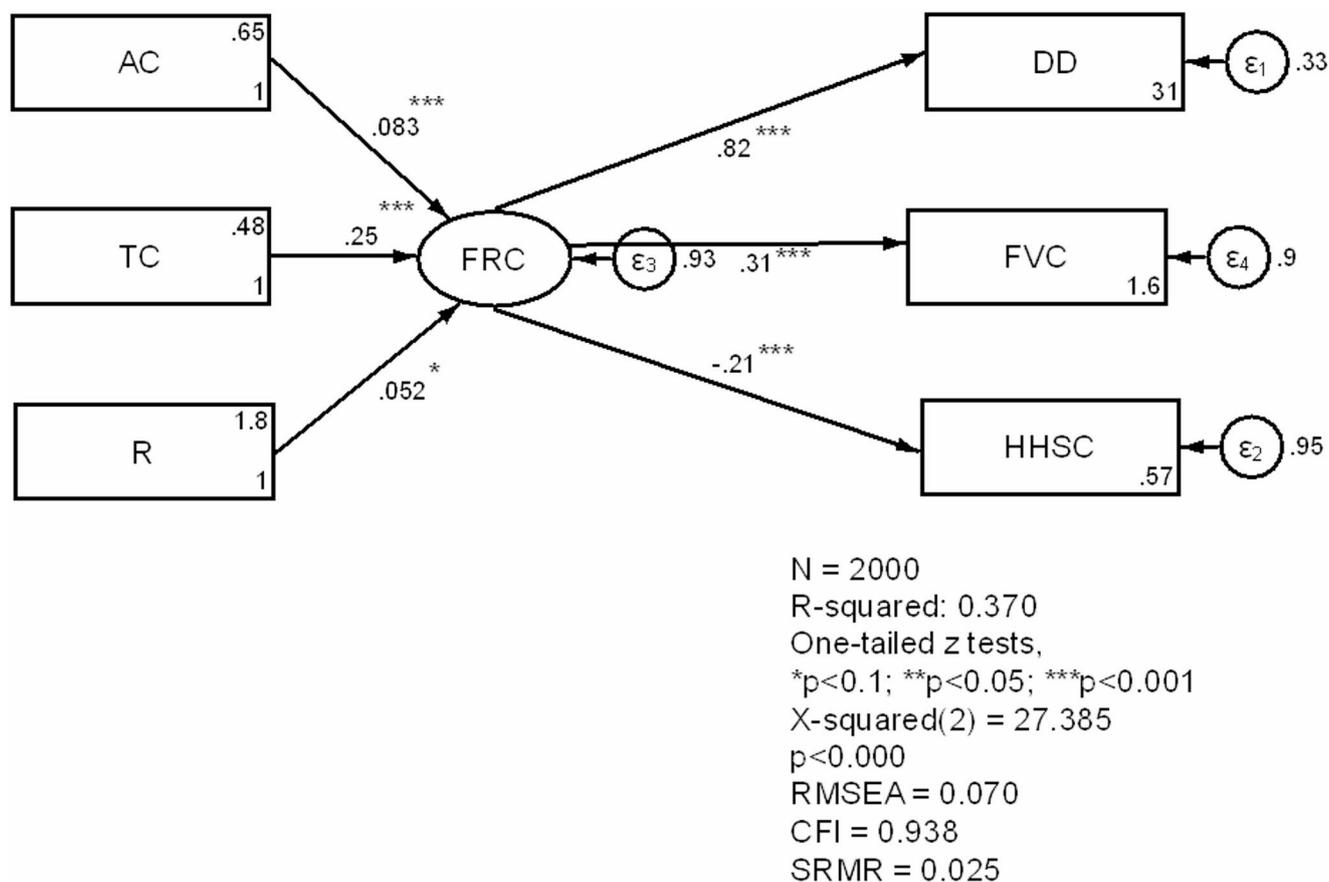


Fig. 2 Multiple Indicator Multiple Cause Model. Note: AC-Adaptive Capacity, TC-Transformation Capacity, R-Robustness, FRC-Farm Resilience Capacity; DD-Dietary Diversity; FVC-Adequacy of Fruit and Vegetable Consumption, and HHS-Household Hunger Score

improves household food security conditions. It increases both dietary diversity (0.083 units for the Simpson index) and adequacy of fruit and vegetable consumption (0.31 g per person daily) while it decreases household hunger (HHS) (0.21 scores for the hunger). This relationship aligns with findings confirming a positive association between resilience and food security outcomes in Tajikistan (Egamberdiev et al., 2024).

Our approach to constructing a transition capacity comes from the livelihood diversification perspective, which is essential for food insecurity resilience. PCA analysis in Transformation or TC shows that two components were retained, characterizing households transiting into non-farm activities (Figure S4). Compared to other pillars, the TC pillar shows the strongest association with farm resilience (FRC). In this mechanism, a review study analysing the relationship between livelihood diversification and food security context confirmed the particular importance of non-farm or off-farm activities (Kassegn & Endris, 2021). As for the current situation in Tajikistan, a study by Mirzabaevet

al. (2023) showed the pervasiveness of land degradation in Central Asia, which has negative consequences for farming profits. Such findings suggest that income diversification through nonfarm activities contributes to farm resilience capacity, especially for households experiencing the negative consequences of climate change. In addition, outmigration in Central Asia complicates the situation (Visser et al., 2019); some households may diversify their livelihood through outmigration.

As for AC, the extent of the relationship is the second strongest among the pillars (Fig. 2). Within the component analysis, we retained three components defining specific household characteristics (Figure S5). According to the illustration in the supplementary material, Factor-3 has higher loadings on TLU, crop diversity, and extension service. Therefore, this factor group is interpreted as the highest level of farm diversification through crop and livestock production. Many prominent findings confirm a positive relationship between crop diversity and food security (Rajendran et al., 2017; Zsögön et al., 2022). This is particularly important

for nutritional improvement in Tajikistan (Takeshima et al., 2018), and this is especially true for self-produced crops in Tajik households (Takeshima et al., 2022).

Factor-3 also indicates the integration between crop and livestock systems at farm scales. For example, findings by Sekaran et al. (2021) confirmed that an integrated crop-livestock system may enhance food security outcomes. A similar finding is manifestly true in the context of the climate change scenario (Rufino et al., 2013). Agricultural extension services also positively function in building farm resilience (Hunt et al., 2011), in which gender equality and innovation are substantive matters (Muhammad et al., 2016). In this case, the extension services for improving agricultural productivity and dietary diversity are primarily mentioned in the government policy of Tajikistan (Buisson & Balasubramanya, 2019). Compared to other factors, retention, Factor-2 mostly describes another diversified farm operation due to the highest loadings on TLU, agricultural assets and greenhouse farming. This cluster mainly characterizes greenhouse farming and livestock production. The findings confirm that food security crops are mainly produced in greenhouses by small-scale farmers in Central Asia (Maredia et al., 2015). Resilience at the farm scale is also intertwined with livestock diversification (Bullock et al., 2017). The last factor group (Factor-1) mainly describes farmers producing a limited number of crops. As highlighted in the graph, these types of farmers are heavily dependent on agricultural assets and land. For example, findings by Zakirova et al. (2023) confirmed that farmers in Khatlon province in

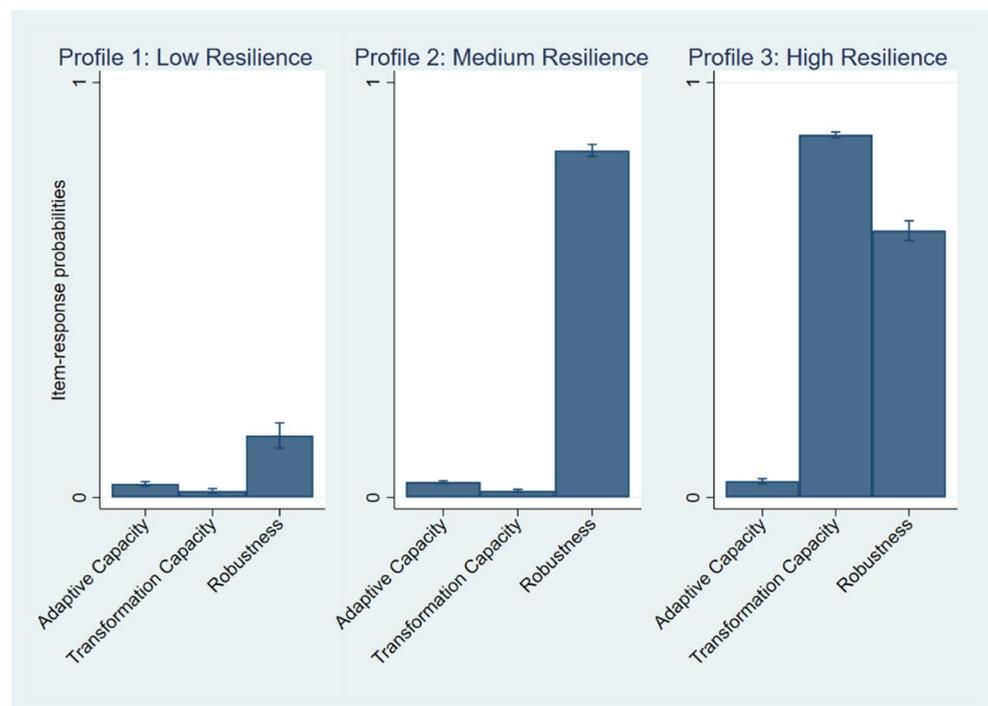
Tajikistan are limited with resources and dependent on cotton cultivation. Although the government of Tajikistan has initiated many road maps and policy incentives to diversify crop production, cotton still remains the primary crop in farm production (Hofman, 2021).

After a rotation in the Robustness pillar, the extent of the relationship between R and FRC is positive (Fig. 2). Factor-1 represents farm households that are robust to the changes (decline) in livestock and agricultural assets (Figure S6). For example, findings concluded that higher farm or agricultural resilience is embedded in alternative or mixed agricultural systems in which crops and livestock are produced in the farm (Gil et al., 2017; Sekaran et al., 2021). As for Factor-2, the loadings indicate that this factor is robust to harvest losses and crops affected due to the shock. In order to maintain a desired level of crop production for resilience, Urruty et al. (2016) accentuated the importance of robustness. The last Factor-3 shows that the shock ratio and crop-affected indicators have the highest loadings. This indicates that farm households with a higher shock ratio are able to maintain the quality of crop and agricultural production.

5.2 Latent profiles of farm resilience

Figure 3 illustrates a three-profile model for farm households: Low Resilience, Medium Resilience, and High Resilience. According to the characteristics of the model, each profile is homogeneous based on the item-response probabilities. The profiles represent unobserved farm

Fig. 3 Item-response probabilities of latent profiles



resilience groups that share comparable patterns in Adaptive Capacity (AC), Transformative Capacity (TC), and Robustness (R). While the item-response probabilities of AC are mostly consistent across the three profiles, they are distinct based on TC and R patterns. This illustration confirms that each profile is homogenous with distinct probabilities, primarily due to the variations in the TC and R pillars. The profile separation is based on the model fit indices recommended by Lanza et al. (2003). According to the model fit criteria in Table S8, we selected a three-profile model. The model selection was based on the values of AIC and BIC. In addition to the parsimony in the mode, we checked model accuracy by using Entropy, which should be a minimum of 0.60 (Weller et al., 2020). According to the model fit criteria and Entropy, we used a three-class model solution.

The pattern in the “Low Resilience” profile shows that farm households in this profile experience the lowest probabilities of three resilience pillars: 0.032 for AC, 0.015 for TC, and 0.149 for R. We label Profile 1 as a “Low Resilience” of farm household. Although the level of AC and TC are noticeably low, farm households may have a certain level of robustness climate change or socio-economic shocks and stresses. As for the profile membership, this profile represents 23% of the sample (Figure S7 in the Online Supplementary Material).

The following latent profile appears with the item-response probabilities, indicating the second lowest level of AC at 0.036. Similar to the first profile, it has a 0.015 probability for TC. The item response probability of R represents 0.835, indicating that households experiencing lower levels of AC and TC are likely to have a more than medium level of R. This finding aligns with the conclusions of by Egamberdiev et al. (2023), confirming a trade-off between resilience

pillars in the case of Central Asian Kyrgyzstan. We label this profile as a “Medium Resilience” in farm households. A higher level of resilience in this profile is mostly due to the farm household’s increased robustness. This finding suggests that farms are resilient to climate shocks and stresses due to their high level of robustness. Parameter estimates indicate that Profile 2 represents 61% of the total sample (Figure S7 in the Online Supplementary Material). This indicates that more than half of the sample is characterized as medium farm resilient households.

Households in the third profile have the highest item-response probabilities for TC, with a coefficient of 0.873. The profile also has the second highest R, making up the coefficient of 0.642. Although the AC pillar accounts for only 0.038, this is the highest among all the profiles. This profile is high resilient profile representing farm households experiencing the highest levels of R and TC across the profiles. Therefore, we name this profile a “High Resilience” for farm household. The last profile representing the highest item-response probabilities of farm resilience pillars makes up 17% of the sample.

5.3 Farm resilience effect on food security

In Table 1, we consider different pairwise comparisons for the effect of resilience on food security outcomes. Generally, more resilient farm households are likely to experience a higher dietary diversity level or a lower household hunger score. In particular, “Medium Resilience” farm households have a 0.005 higher index score compared to those labelled as “Low Resilience” profiles. The average dietary diversity increases by approximately 0.020 index score when households experience high resilience or are classified as “High Resilience” compared to households characterised as “Low Resilience”. As for percentage change, the improvement in

Table 1 Farm resilience effect on food security

	Dietary diversity		Adequacy of fruit and vegetable consumption		Household hunger score	
	Medium resilient profile	High resilient profile	Medium resilient profile	High resilient profile	Medium resilient profile	High resilient profile
IPWRA	0.005** (0.002)	0.018*** (0.002)	12.822* (7.771)	28.494*** (10.519)	-0.334*** (0.083)	-0.511*** (0.093)
AIPW	0.005*** (0.002)	0.018*** (0.002)	12.021 (7.930)	22.585** (10.665)	-0.324*** (0.079)	-0.495*** (0.089)
RA	0.005** (0.002)	0.018*** (0.002)	18.256** (8.181)	32.253*** (11.025)	-0.371*** (0.083)	-0.553*** (0.092)
Change (%)	0.500** (0.002)	0.202 (0.002)	6.798** (0.032)	12.011*** (0.043)	-39.975*** (0.060)	-59.671*** (0.063)
OLS	0.004*** (0.001)	0.017*** (0.002)	12.168 (8.528)	27.073** (10.851)		
Logit					-0.424*** (0.131)	-0.618*** (0.176)

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. A base class for farm resilience is “Low Resilience” Profile. Standard errors in parentheses. The excluded regional dummy is Yovon

dietary diversity for those “Medium Resilience” and “High Resilience” households represent approximately 1% and 2%, respectively. A similar situation is true for the outcomes of vegetable and fruit consumption although the results across RA, AIPW, and IPWRA are not very consistent. According to the findings from IPWRA, medium resilient farm households are likely to consume approximately 13 g more fruits and vegetables per person compared to those experiencing a low level of resilience (IPWRA). If the farm household experiences high resilience (High Resilient profile), this different tends to be even twice more. A percentage change is also relatively high representing above 6% and 12% in “Medium Resilient” and “High Resilient” farm households, respectively. In this case, a study from the region confirmed that resilience in rural households positively affects dietary diversity in Tajikistan (Egamberdiev et al., 2024).

Regarding the relationship between household resilience and hunger score, the magnitude of the effect of resilience is even stronger compared to the relationships found in the outcome of dietary diversity. To be more precise, moving from a lower resilient (Low Resilience profile) to a medium level of farm resilience (Medium Resilience profile) decreases the hunger score by around 0.334. The finding implies that the average percentage change represents close to 40% of the change in the hunger score. Similarly, those households characterized as “High Resilience” experience even more decreased hunger level by 0.511 score compared to those labelled as “Low Resilience”. In other words, the average hunger score falls by an estimated 60% when households experience a high resilience level relative to when households have a low resilience level. This finding is supported by Anderson et al. (2018), who concluded that agricultural productivity is likely to reduce household hunger. Another finding from the region confirmed that agricultural productivity is linked to improvements in nutritional outcomes (Takeshima et al., 2020).

5.4 Robustness analysis

We used the multinomial endogenous treatment effects (METE) model as a robustness analysis. The main advantage is that METE helps correct self-selection bias and unobserved confounders (Deb & Trivedi, 2006). A particular significance of this model is that the parameters of the model are still identified by using identical regressors in both outcome and treatment models. Although finding instruments is overwhelmingly challenging, we included three instruments for robust identification. To represent the condition of the soil, we included a binary soil quality variable. As for the exclusion restriction, soil quality is indispensable to achieve yield stability, which is important for food security outcomes (Qiao et al., 2022). Another

instrumental variable is agricultural cooperatives and associations, which are unequivocal in their contribution to improving the capacity to withstand shocks (Ergene & Ergene, 2025). The existence of such cooperation or association may create social capital that contributes to resilience capacity towards food insecurity (Egamberdiev, 2024). The last variable represents a binary land certificate indicating a legal document or ownership right of the plot. In this case, Calo et al. (2021) elucidate the relationship between ownership and resilience. A statistical analysis of the selected variables is available in Table S9 in the Supplementary. In general, the included instrumental variables are likely to affect food security conditions only by improving or building farm resilience. Our first-stage analysis suggests that the instrumental variables are statistically significant (except for the relationship between cooperation and association at a medium resilience level), indicating that better soil quality, more cooperation, and associations in the community, as well as land rights entitlement, are likely to improve farm resilience (Table S10 in the Supplementary Material). The magnitude of the relationship is notably stronger between IVs and the “High Resilience” Profile. Further analysis of the controlling variables shows a positive correlation between household size and resilience. However, there is a negative relationship between the head of the household and household resilience. Fuller and Lain (2020) found that female-headed households have a lower level of resilience compared to male-headed households. This finding further indicates that the resilience concept is not gender-neutral. A negative relationship between shocks experienced over the last 12 months and resilience suggests that less resilient farm households are more sensitive to shocks. However, a positive relationship between shock experienced over the last decade and resilience is also observed. This relationship is significant for the “High Resilience” profile, as it highlights the higher vulnerability of low resilience levels in farm households. This finding is consistent with empirical evidence from Tajikistan confirming a positive relationship between shocks and household resilience (Egamberdiev et al., 2024). The positive relationship between shocks and farm resilience might be due to exposure experience and coping mechanisms that increase resilience in the long term. Also, the authors claimed that assets or safety nets in Tajikistan are efficient response strategies, strengthening resilience when shocks intensify. Since resilience is a dynamic process (d’Errico et al., 2016), farm households experiencing shock may strengthen resilience pillars or response mechanisms.

Table 2 shows that our findings with LPA-PSM modeling remain robust across the findings obtained from the METE model (the second stage results are available in Table S11 in the Supplementary Material). The findings

Table 2 Farm resilience effect on food security

	Dietary diversity	Adequacy of fruit and vegetable consumption	Household hunger score
Medium Resilience	0.004 (0.003)	-0.639 (6.857)	-0.282 (0.266)
High Resilience	0.018*** (0.003)	19.240** (8.707)	-0.987*** (0.260)
Observation	1998	1998	1998

*** $\rho < 0.01$, ** $\rho < 0.05$, * $\rho < 0.1$. A base class for farm resilience is “Low Resilience” Profile. Standard errors in parentheses. The excluded regional dummy is Yovon

for the controlling variables indicate that education and household size are positively associated with food security outcomes. However, household size is negatively associated with the adequacy of fruit and vegetable consumption. This finding is consistent with the conclusion that fruit and vegetable consumption decreases noticeably as the number of household members increases in Central Asian Kyrgyzstan (Egamberdiev et al., 2023). However, there is a negative relationship between female-headed households and food security. This negative relationship might be due to household social structures or gender-specific differences in ownership (Mason et al., 2015). Although shocks increase household hunger, a positive association exists between long-term shocks and both dietary diversity and fruit and vegetable consumption. Since both types of shock increase household hunger, a positive relationship between them may be due to the long-term impact on food security outcomes (Matz et al., 2015). In other words, households experiencing shocks in the long term may trigger stronger resilience or experience post-shock recovery in food security outcomes. Moreover, households may activate short-term coping strategies (Budiawati et al., 2024; Ochieng & Grote, 2025) or use resilience capacity to mitigate the shock effects on food security in the long term (Sunday et al., 2023). This pattern is also observed in Tajikistan (Egamberdiev et al., 2024).

6 Conclusion

The findings of this manuscript confirmed a strong causal relationship between farm resilience and food security outcomes. The study provides empirical evidence that farm resilience may be a viable pathway to achieving food security. Within the framework aimed at improving food security, farm resilience is built by strengthening adaptive capacity, transformation ability and robustness. Béné et al. (2012) argued that strengthening resilience should not be an end but linked with positive outcomes. From this perspective, the findings in

this manuscript confirmed a positive effect of farm resilience on food security outcomes. To be more precise, our first finding was to construct specific farm resilience by defining it through indispensable characteristics. Incorporating general resilience without specifying it may not yield the expected results, as resilience should be specified in relation to systems, shocks, functions, capacities, and attributes.

Our findings from both MIMIC and LPA-PSM models confirmed that farm resilience improves household food security conditions. The findings concluded that all adaptation (AC), robustness (R), and transformability (T) strengthen household food security conditions by improving dietary diversity and reducing household hunger levels. By strengthening the pillars, the household food security condition becomes more resistant to climate change shocks and stresses. The LPA-PSM approach enabled a comparison of farms that capture different levels of resilience capacity across the defined profiles. A classification found that both transformation capacity and robustness are particularly important to change farm resilience. It implies that farm households mostly prefer transformability rather than adaptive capacity, highlighting changes in the functions, structure, or even identity of farm operations in the presence of intense shocks. Similarly, van der Lee et al. (2022) concluded that absorption and adaptation to shocks may be less desirable making farm resilience to transform in response to shocks and stresses. In this case, farmers may experience transformation if there are fundamental changes in the farm functioning (Nicholas-Davies et al., 2021); therefore, unsustainable functions may not be preferable (e.g., farmers may not be able to achieve the desired level of private goods) (Meuwissen et al., 2019). As for farmers exposed to severe shocks affecting the functioning of farm operations in the Khatlon region, they may support small and incremental changes. In this context, the enhancement of farm transformation might be at the expense of robustness because the findings from latent analysis confirmed that robustness is lower in the “High Resilience” profile. Therefore, the consideration of transformation in strengthening farm resilience may allow trade-offs across resilience pillars. Although Béné et al. (2012) confirmed a high possibility of trade-offs relationships between resilience pillars or determinants, this conclusion should be analysed in terms of food security outcomes to make farm resilience food security-specific (*resilience to what*). The differentiation in food security outcomes should be explained by either trade-offs or synergies between or across resilience pillars. Therefore, we further analyzed the relationship between resilience (low, medium, and high farm resilience) and food security outcomes through causal inferential analysis. The analysis confirmed that achieving a higher level of farm resilience

(e.g., moving from low resilience to high resilience condition) promises to achieve better food security outcomes.

6.1 Policy implications

Future development agendas for the Khatlon zone in Tajikistan should focus on strengthening or improving farm resilience. Enhancing farm resilience should align with the objectives defined in the Tajikistan Country Strategic Plan (2023–2026), which aims to strengthen resilience and adaptive capacities. To achieve this, mainstreaming resilience thinking in the policy agenda necessitates more holistic and integrated approaches in the marginalized areas of the region (Zakirova et al., 2023). An intervention to build resilience should adopt capacity-focused approach. This means that farm resilience capacity should be strengthened by considering their trade-off and synergetic relationship.

Moreover, a shift towards resilient agriculture should be expanded by recognizing local settings and farm experience. Interventions should aim to build or strengthen farm resilience by integrating the traditional knowledge and experience of local contexts. Local knowledge may contribute to building resilience when it is effectively combined with scientific knowledge and practices. In this regard, the role of the agricultural extension service is vital to strengthening farm adaptability. We also emphasize the significance of connecting formal and informal institutions for agricultural extension services. Additionally, the role of social capital and informal networking in enhancing household adaptability is of particular importance. Following the findings on the positive effect of social capital on household resilience towards food security in climate-affected zones of Central Asia (Egamberdiev, 2024), institutional support is necessary for strengthening both official and unofficial networking.

For the interventions on strengthening farm resilience, the question of *resilience for whom* should be at the center of the interventions. It requires careful mediation and negotiation among those who build and are affected by farm resilience enhancement programs. For example, women left behind in Tajik regions due to high levels of migration should participate in supporting resilience building strategies. From this perspective, the government should promote gender-related indicators in enhancing farm resilience. The formulation and monitoring of gendered policies in resilience-building activities have been reflected in the National Strategy for the Activation of Women in Tajikistan (2021–2030) (FAO, 2022). Therefore, potential impediments to the gendered-resilience approach can be removed through empowering women, particularly dependent women.

The study area of the Khatlon region has favourable conditions, allowing intercropping, better harvesting, and livestock development. The region has experienced extensive

growth in crop cultivation and livestock development; however, farmers still face limited capacity due to a shortage of agricultural assets, machinery, and agricultural finance (Khakimov & Ashurov, 2025). Sustaining agricultural and horticultural development in the region requires continued efforts to promote the expansion of resources for agricultural and livestock investment. A further support is related to increased crop and livestock diversification, extension services, greenhouse production, and other activities at the farm scale. Although we support the integration of crop and livestock production, the specialized and concentrated crop and livestock farming operations may cause increased contaminants and pollution. Therefore, our strong motive is to enhance an integrated crop-livestock system by supporting sustainable agriculture.

A policy agenda promoting adaptability and robustness without facilitating the transition to non-farm activities may exacerbate food insecurity if farmers lack viable options to adapt to a changing environment. In this context, shifting to non-farm activities could be essential for addressing climate change impacts. However, one of the primary challenges might be the lack of familiarity with adapting to a new system of livelihood. Therefore, robust institutional interventions and inclusive financial support will likely be crucial in aiding such transitions. Moreover, it is of importance to have multiple resilience lenses because the distinction between robust and transformative farm resilience depends on system characteristics, functions of resilience, other integrated capacities, and the types of shocks or stresses.

6.2 Future research

Further research examining the relationship between farm resilience and food security outcomes may employ other food security determinants. As Vaitla et al. (2020) found, resilience capacity is sensitive to the types of food security indicators. In this case, both quality and quantity dimensions of food security should be integrated into resilience modeling. For example, consumption score, micronutrient intake, child nutritional outcomes, and anthropometric measures can be integrated. Since Central Asia has been experiencing unprecedented climate change and environmental degradation, the measurement should integrate socio-ecological resilience indicators that may invigorate resilience capacity measurement for both household and community levels. Further resilience studies are expected to consider the combination of agency and power in resilience-building activities. For example, empirical analysis of the role of gender equality or women's empowerment in resilience-building activities helps to make the concept of resilience not simply a technical but a social phenomenon. In the presence of male outmigration, future studies should certainly consider

farm resilience in the context of the feminization of agriculture (Mukhamedova & Wegerich, 2018) or intrahousehold equality (Takeshima et al., 2022). From this perspective, women's access to livestock in Tajikistan is likely to increase the dietary diversity of children (Egamberdiev et al., 2025; Klassen et al., 2019). In addition, strategies towards strengthening or building resilience capacity should embody livelihood diversification strategies. In this case, findings by Manlosa, Hanspach, Schultner, Dorresteijn, and Fischer (2019) found the diversification approach as a primary pathway to food security. Another focal point to analyse farm resilience and food security is further research recommendations to understand the role of AI-based technologies (e.g., climate-smart agriculture) for agricultural or farm resilience (Usigbe et al., 2024). Since our findings confirmed both negative and positive relationships between shocks and resilience, capturing shocks at different spatial and temporal scales is particularly important. In addition, early warning systems at the local level may provide more insights into making resilience shock-specific. Further studies should also consider a mediation analysis to explain how farm resilience mitigates the adverse shock effects on food security outcomes. Correspondingly, coping mechanisms may also moderate or mediate the relationship.

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Declarations

Conflict of interest The authors declare that they have no conflict of interests and/or competing interests.

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