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Farmer Typologies and Quality of Life
: A Cluster Analysis of Farmers in Nakhon Si Thammarat, Thailand

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Abstract

This study aimed to identify farmer typologies based on demographic, socioeconomic, agricultural, family, and digital characteristics using the K-prototypes clustering algorithm, compare multidimensional quality of life (QoL) among the identified farmer typologies, and characterize the identified typologies and discuss their implications for targeted rural development and QoL improvement strategies. A cross-sectional study was conducted among 311 farmers randomly selected from 1,395 farming households in Na San Subdistrict, Phra Phrom District, Nakhon Si Thammarat Province, Thailand. Farmer typologies were identified using the K-prototypes clustering algorithm based on demographic, socioeconomic, agricultural, household, and digital characteristics. The optimal clustering solution was determined using the average silhouette coefficient, Davies–Bouldin index, cluster interpretability, and bootstrap stability analysis. Differences in QoL among the identified typologies were examined using one-way analysis of variance (ANOVA), followed by Tukey's honestly significant difference (HSD) post hoc test. Three distinct farmer typologies were identified: Traditional Farmers with Limited Digital Inclusion (32.48%), Intermediate Farmers with Moderate Digital Inclusion (41.80%), and Digitally Connected Progressive Farmers (25.72%). Significant differences in QoL were observed across all domains and the overall QoL score (all $p < .001$), with Digitally Connected Progressive Farmers consistently reporting the highest QoL and Traditional Farmers with Limited Digital Inclusion reporting the lowest. These findings indicate that farmer typologies characterized by multidimensional demographic, socioeconomic, agricultural, household, and digital characteristics are associated with variations in QoL. The study extends current knowledge by demonstrating the value of multidimensional farmer typologies for understanding heterogeneity among farmers and providing evidence to inform typology-based strategies that support digital inclusion and promote inclusive rural development. Because this study employed a cross-sectional design, the observed associations should not be interpreted as evidence of causal relationships.

Keywords: Cluster analysis, Farmer typology, Digital inclusion, Quality of life

Introduction

Agriculture remains fundamental to rural livelihoods and sustainable development worldwide. However, contemporary farming communities are increasingly challenged by climate change, economic uncertainty, and widening socioeconomic and digital inequalities that shape farmers' opportunities to sustain their livelihoods and improve their well-being. In addition, fluctuating commodity prices, rising production costs, labor shortages, and rapid digital transformation continue to place considerable pressure on farming households. Collectively, these challenges affect not only agricultural productivity but also farmers' quality of life (QoL), making improved rural well-being a key priority for sustainable agricultural and community development (Brennan *et al.*, 2023).

In rural development research, QoL is increasingly regarded as an important outcome reflecting improvements in people's everyday lives beyond productivity or income. QoL is a



multidimensional concept encompassing physical health, psychological well-being, social relationships, environmental conditions, work participation, and economic welfare (Veenhoven, 2024). Previous studies have shown that farmers' QoL is associated with educational attainment, household income, farming experience, farm characteristics, family support, and access to digital technologies (Niu *et al.*, 2023; Minh *et al.*, 2024). These characteristics are closely interconnected and interact to create substantial heterogeneity among farming households, suggesting that farmers should not be treated as a homogeneous population.

Farmer typologies have increasingly been used to classify farming households according to shared demographic, socioeconomic, and agricultural characteristics. Typology-based approaches can identify groups of farmers with similar characteristics who may require different forms of policy support, thereby facilitating more targeted agricultural and rural development strategies (Iles *et al.*, 2021; Suárez *et al.*, 2021). However, existing farmer typologies have primarily emphasized production systems, farm structure, or socioeconomic characteristics, with limited consideration of digital inclusion as an integral component of farmer classification.

Digital inclusion has emerged as an increasingly important determinant of agricultural development and farmers' well-being. Universal access to technology is not limited to just accessibility; it also includes individuals' ability to access, use, and benefit from digital resources in ways that enhance social engagement, economic opportunity, and overall well-being. In agricultural settings, access to the internet, smartphones, and other digital technologies enables farmers to obtain agricultural information, communicate with extension services, improve farm management, and respond more effectively to environmental and market changes (Khanna, 2021; Qin *et al.*, 2022). Although previous studies have examined digital inclusion and QoL separately or incorporated digital variables within conventional regression models, few have integrated demographic, socioeconomic, agricultural, household, and digital characteristics to identify farmer typologies before comparing multidimensional QoL. Consequently, important differences among farmer subgroups may remain overlooked.

Thailand is one of Southeast Asia's leading agricultural countries, where agriculture remains a major source of employment and household income. Na San Subdistrict, Phra Phrom District, Nakhon Si Thammarat Province, is an agricultural community in which rubber and oil palm cultivation constitute important agricultural activities. According to the local development plan, the subdistrict covers 29,687 rai, of which 7,343.73 rai are used for agriculture, including approximately 3,840.5 rai of rubber plantations and 745 rai of oil palm plantations, alongside rice and other crops (Na San Subdistrict Municipality, 2025a). This agricultural diversity provides a relevant context for examining variation in farm size, farming experience, and household income. In addition, differences in household conditions, internet accessibility, digital training participation, and digital device ownership provide an appropriate context for examining digital inclusion alongside demographic, socioeconomic, agricultural, and household characteristics. These characteristics are closely related to the multidimensional QoL examined in this study and make Na San Subdistrict a contextually relevant setting for identifying heterogeneous farmer profiles and



comparing their QoL. Previous studies have primarily applied variable-centered approaches, including multiple regression, logistic regression, and structural equation modeling, to examine farmers' QoL (Zhou *et al.*, 2025). While these methods identify factors associated with QoL, they provide limited insight into distinct farmer subgroups that may require different policy interventions.

To address this gap, person-centered approaches such as cluster analysis focus on identifying relatively homogeneous subgroups based on multiple characteristics rather than estimating average relationships among variables. Cluster analysis can accommodate both continuous and categorical variables through appropriate algorithms and has been increasingly applied to classify individuals with similar characteristics (Dou Zhou *et al.*, 2026; Liu & Wang, 2025). However, its application in agricultural QoL research remains limited. Few studies have simultaneously integrated demographic, socioeconomic, agricultural, household, and digital characteristics to construct farmer typologies and compare multidimensional QoL across the resulting groups. Consequently, little is known about how these characteristics jointly differentiate farmer typologies and multidimensional QoL, particularly in rural agricultural communities in Thailand.

Therefore, this study aimed to identify farmer typologies based on demographic, socioeconomic, agricultural, family, and digital characteristics using cluster analysis, compare multidimensional QoL among the identified farmer typologies, and characterize their implications for targeted rural development and QoL improvement strategies. By integrating a person-centered analytical approach with multidimensional QoL assessment, this study provides empirical evidence to support targeted interventions and policy development for improving the well-being of farming communities.

Research Objectives

1. To identify farmer typologies based on demographic, socioeconomic, agricultural, family, and digital characteristics using cluster analysis.
2. To compare multidimensional QoL among the identified farmer typologies.
3. To characterize the identified farmer typologies and discuss their implications for targeted rural development and QoL improvement strategies.

Research Methodology

Population and Sample

This cross-sectional study was conducted among farmers in Na San Subdistrict, Phra Phrom District, Nakhon Si Thammarat Province, Thailand. According to the Na San Subdistrict Municipality, the study population comprised 1,395 farming households across seven villages (Na San Subdistrict Municipality, 2025b). The required sample size was determined using Yamane's formula (Yamane, 1967), with a 5% margin of error, resulting in a required sample of 311 farming households. They were selected using simple random sampling from the household registration database, and one eligible farmer was selected from each sampled household, resulting in a total of 311 participants.

Eligible participants were farmers aged ≥ 18 years, with at least one year of farming experience, who could communicate in Thai and provided informed consent.

Instrument

Data were collected using a structured questionnaire developed from a literature review and relevant theoretical frameworks on farmers' QoL and digital inclusion. The questionnaire consisted of five sections: 1) demographic characteristics; 2) agricultural characteristics; 3) household and family characteristics; 4) digital inclusion; and 5) QoL. The QoL section assessed six domains: physical health, mental health, social relationships, environmental conditions, work participation, and economic welfare.

Digital inclusion was operationalized using three indicators representing digital access, digital resources, and digital capability: participation in digital training, internet accessibility, and smartphone/ tablet ownership. Participation in digital training during the previous year was scored as 1 = no participation, 2 = one to two training sessions, 3 = three to four training sessions, and 4 = five or more training sessions. Internet accessibility was measured using a five-point scale ranging from 1 (very good) to 5 (no access) and was reverse-coded so that higher scores indicated better internet accessibility. For descriptive presentation in Table 1, internet accessibility was further categorized as "good or very good" and "moderate or below." Smartphone/tablet ownership was coded as 1 = no and 2 = yes. A composite Digital Inclusion Score was calculated by summing the three indicators, resulting in a possible score ranging from 3 to 11, with higher scores indicating greater digital inclusion. The composite score was treated as a continuous variable in subsequent analyses. QoL was assessed using a five-point Likert scale ranging from 1 (lowest) to 5 (highest), with higher scores indicating better perceived QoL.

Content validity was evaluated by three experts using the Item–Objective Congruence (IOC) method, yielding IOC values ranging from 0.80 to 1.00. The questionnaire was pilot tested with 30 farmers who were not included in the main study. The pilot results demonstrated good internal consistency, with an overall Cronbach's alpha coefficient of 0.89. Cronbach's alpha coefficients for the six QoL domains were 0.81 for Physical Health, 0.84 for Mental Health, 0.78 for Social Relationships, 0.86 for Environmental Conditions, 0.79 for Work Participation, and 0.82 for Economic Welfare, indicating acceptable to good reliability across all domains.

Data Collection

Data were collected between February and March 2026 through face-to-face interviews conducted by the principal investigator. All participants signed a consent form before data collection began. Each interview lasted approximately 25–30 minutes. Completed questionnaires will be checked for completeness, personal information will be protected using unique identification codes, and securely stored before the data is entered and analyzed. Ethical approval was obtained from the Human Research Ethics Committee of Nakhon Si Thammarat Rajabhat University (Approval No. 011/2569).



Data Analysis

Data were analyzed using R version 4.5.3 (R Foundation for Statistical Computing, Vienna, Austria). Descriptive statistics were used to summarize demographic, agricultural, household, digital inclusion, and QoL of research participants. Continuous variables, including age, farming experience, cultivated area, monthly household income, and the Digital Inclusion Score, were standardized using z-score transformation prior to cluster analysis, whereas categorical variables were retained as nominal variables. Farmer typologies were identified using the K-prototypes clustering algorithm implemented in the *clustMixType* package. The K-prototypes algorithm combines Euclidean distance for continuous variables with a simple matching dissimilarity measure for categorical variables, allowing simultaneous clustering of mixed-type data. The overall dissimilarity between observations was calculated as the weighted sum of continuous and categorical components. The weighting parameter (λ), which balances the contribution of continuous and categorical variables, was estimated automatically using the *lambdaest* function in the *clustMixType* package. Candidate clustering solutions ranging from two to six clusters were evaluated. The optimal number of clusters was selected by jointly considering the average silhouette coefficient, the Davies–Bouldin index, cluster interpretability, and cluster stability. Cluster stability was assessed using 1,000 bootstrap resamples and the Jaccard similarity coefficient. Differences in QoL across the identified farmer typologies were examined using one-way analysis of variance (ANOVA), followed by Tukey's honestly significant difference (HSD) test for pairwise comparisons. Prior to ANOVA, the assumptions of normality and homogeneity of variances were evaluated using the Shapiro–Wilk test and Levene's test, respectively. Statistical significance was set at $p < .05$.

Findings

Characteristics of the Study Participants

A total of 311 farmers participated in the study. They had a mean age of 52.51 years (S.D. = 11.32), and 55.63% were female. Most participants were married (70.10%) and had completed primary education (43.73%). More than half cultivated rubber or oil palm (55.95%), with a mean farm size of 8.81 rai (S.D. = 5.62) and an average farming experience of 21.82 years (S.D. = 10.51). The mean household size was 4.22 persons (S.D. = 1.40). Overall, 79.10% of participants reported good or very good family relationships, 64.31% had good or very good internet accessibility, and 92.28% owned a smartphone or tablet. The mean Digital Inclusion Score was 7.84 (S.D. = 1.96).

Identification of Farmer Typologies

Cluster analysis identified three farmer typologies based on demographic, agricultural, household, and digital inclusion characteristics. Candidate clustering solutions ranging from two to six clusters were evaluated using the average silhouette coefficient, Davies–Bouldin index, cluster interpretability, and bootstrap stability analysis. The three-cluster solution demonstrated the most favorable balance between cluster separation, compactness, stability, and interpretability.



Specifically, the selected solution achieved an average silhouette coefficient of 0.405 and a Davies–Bouldin index of 0.799, indicating an acceptable clustering structure despite partial overlap among clusters in the reduced two-dimensional projection. Bootstrap resampling (1,000 iterations) yielded Jaccard similarity coefficients of 0.82, 0.79, and 0.85 for Clusters 1–3, respectively, indicating good cluster stability. Consequently, the three-cluster solution was retained for subsequent analyses. The final clusters comprised 101 (32.48%), 130 (41.80%), and 80 (25.72%) participants, respectively. Figure 1 presents a two-dimensional PCA projection of participants classified into the three identified farmer typologies, whereas Table 1 summarizes the characteristics of each cluster.

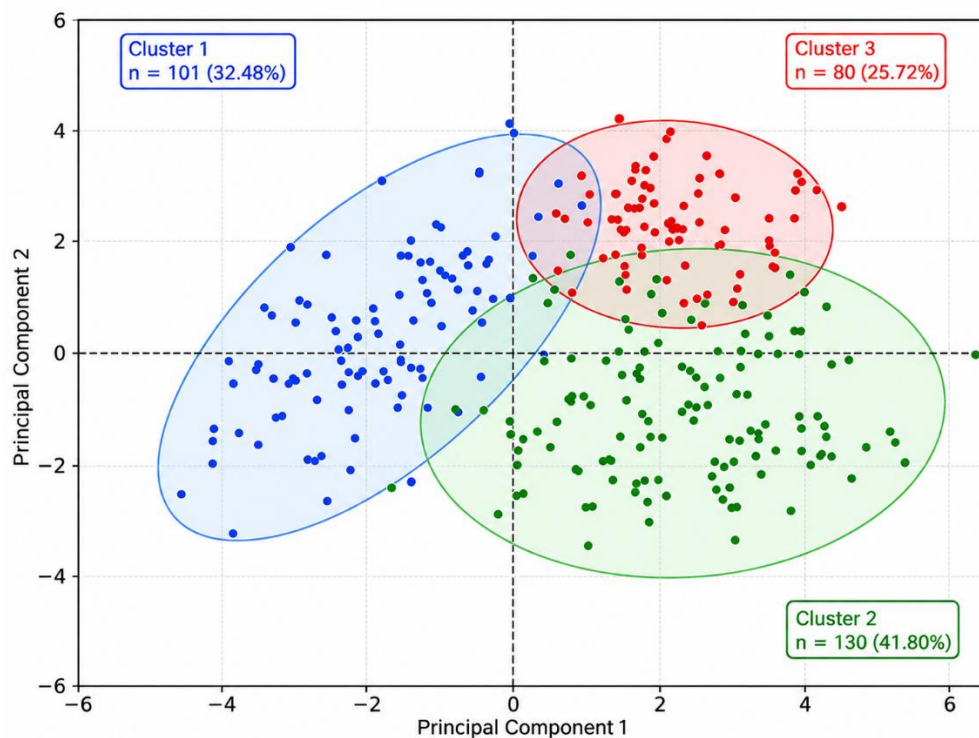


Figure 1. Two-dimensional PCA projection of the three farmer typologies identified by K-prototypes clustering.

Each point represents an individual participant. The shaded ellipses illustrate the dispersion of observations within each cluster. The PCA projection is presented solely for visualization purposes and does not represent the multidimensional clustering space used by the K-prototypes algorithm. Partial overlap among the ellipses reflects information loss associated with dimensionality reduction rather than poor cluster separation.

The characteristics presented in Table 1 are intended to describe the identified farmer typologies rather than to validate the clustering solution, because these variables were used in the clustering procedure. Cluster 1 consisted predominantly of older farmers with lower educational attainment, lower household income, smaller farm size, limited internet accessibility, and the lowest Digital Inclusion Score. Cluster 2 represented farmers with intermediate demographic, agricultural, and digital characteristics. Cluster 3 comprised relatively younger farmers with higher

educational attainment, larger farm size, higher household income, better internet accessibility, universal smartphone/tablet ownership, and the highest Digital Inclusion Score. Based on these characteristic profiles, the three clusters were labeled as Traditional Farmers with Limited Digital Inclusion, Intermediate Farmers with Moderate Digital Inclusion, and Digitally Connected Progressive Farmers, respectively. These typologies reflected distinct levels of socioeconomic, agricultural, household, and digital capacity, with corresponding differences in multidimensional QoL. The Traditional Farmers with Limited Digital Inclusion represented farmers with greater socioeconomic and digital constraints, whereas the Intermediate Farmers with Moderate Digital Inclusion showed intermediate levels of these characteristics. The Digitally Connected Progressive Farmers were characterized by relatively greater socioeconomic and digital capacity and consistently higher QoL across all domains. These distinct profiles provide a basis for developing targeted rural development and QoL improvement strategies tailored to the needs and capacities of each farmer typology.

Table 1 Characteristics of the Three Farmer Typologies Identified by Cluster Analysis

Characteristic	Cluster 1 (n = 101)	Cluster 2 (n = 130)	Cluster 3 (n = 80)
Farmer profile			
Sex, n (%)			
Male	39 (38.61)	61 (46.92)	38 (47.50)
Female	62 (61.39)	69 (53.08)	42 (52.50)
Age (years), Mean $\pm$ S.D.	58.30 $\pm$ 9.40	51.20 $\pm$ 10.10	45.70 $\pm$ 8.80
Marital status, n (%)			
Married	80 (79.21)	91 (70.00)	47 (58.75)
Single, widowed, or divorced/separated	21 (20.79)	39 (30.00)	33 (41.25)
Education, n (%)			
Primary school or below	72 (71.29)	63 (48.46)	21 (26.25)
Secondary school or above	29 (28.71)	67 (51.54)	59 (73.75)
Monthly household income, n (%)			
<5,000 THB	45 (44.55)	28 (21.54)	8 (10.00)
5,001–10,000 THB	39 (38.61)	58 (44.62)	22 (27.50)
>10,000 THB	17 (16.83)	44 (33.85)	50 (62.50)
Farming profile			
Type of farming, n (%)			
Rubber or oil palm plantation	63 (62.38)	74 (56.92)	37 (46.25)
Other farming	38 (37.62)	56 (43.08)	43 (53.75)
Farm size (rai), Mean $\pm$ S.D.	6.90 $\pm$ 3.10	8.80 $\pm$ 4.40	11.60 $\pm$ 5.80
Farming experience (years), Mean $\pm$ S.D.	28.60 $\pm$ 8.70	21.00 $\pm$ 8.90	15.20 $\pm$ 7.40
Household profile			
Living arrangement, n (%)			
Living with others	82 (81.19)	119 (91.54)	77 (96.25)



Characteristic	Cluster 1 (n = 101)	Cluster 2 (n = 130)	Cluster 3 (n = 80)
Living alone	19 (18.81)	11 (8.46)	3 (3.75)
Household members, Mean $\pm$ S.D.	3.80 $\pm$ 1.10	4.30 $\pm$ 1.30	4.70 $\pm$ 1.50
Family relationship, n (%)			
Good or very good	71 (70.30)	109 (83.85)	70 (87.50)
Fair to very poor	30 (29.70)	21 (16.15)	10 (12.50)
Digital profile			
Participation in digital training score, Mean $\pm$ S.D.	1.58 $\pm$ 0.67	2.36 $\pm$ 0.74	3.27 $\pm$ 0.59
Internet accessibility, n (%)			
Good or very good	37 (36.63)	90 (69.23)	73 (91.25)
Moderate or poor	64 (63.37)	40 (30.77)	7 (8.75)
Smartphone/tablet ownership, n (%)			
Yes	82 (81.19)	123 (94.62)	80 (100.00)
No	19 (18.81)	7 (5.38)	0 (0.00)
Digital Inclusion Score, Mean $\pm$ S.D.	6.02 $\pm$ 1.21	7.86 $\pm$ 1.12	9.84 $\pm$ 0.81

Notes. Values are presented as mean $\pm$ standard deviation (S.D.) or n (%). The variables shown were used to construct the farmer typologies and are presented to describe the characteristics of each cluster rather than to test statistical differences among clusters.

Comparison of QoL Across Farmer Typologies

To examine differences in QoL among the three identified farmer typologies, mean scores across the six QoL domains and the overall QoL score were compared using ANOVA, followed by Tukey's HSD post hoc test. The results are presented in Table 2.

Overall, statistically significant differences were observed among the three farmer typologies across all QoL domains and the overall QoL score (all $p < .001$; Table 2). QoL scores increased progressively from the Traditional Farmers with Limited Digital Inclusion to the Digitally Connected Progressive Farmers across all six domains. Work participation ($F = 792.64$), economic welfare ($F = 721.38$), and environmental quality ($F = 648.93$) yielded the highest ANOVA F statistics, whereas social relationships showed the lowest F statistic ($F = 129.36$). Tukey's HSD post hoc test confirmed that all pairwise comparisons among the three farmer typologies were statistically significant for every QoL domain and the overall QoL score (all $p < .05$).



Table 2 Comparison of QoL Across the Three Farmer Typologies

QOL domain	Traditional Farmers with Limited Digital Inclusion (n = 101)	Intermediate Farmers with Moderate Digital Inclusion (n = 130)	Digitally Connected Progressive Farmers (n = 80)	F	p-value	Tukey HSD
Physical health	2.71 ± 0.48	3.23 ± 0.45	4.08 ± 0.42	186.42	<.001	C1 < C2 < C3
Mental well-being	2.38 ± 0.54	3.08 ± 0.49	4.45 ± 0.39	391.57	<.001	C1 < C2 < C3
Social relationships	3.07 ± 0.51	3.68 ± 0.43	4.17 ± 0.38	129.36	<.001	C1 < C2 < C3
Environmental quality	1.78 ± 0.46	2.79 ± 0.42	4.30 ± 0.37	648.93	<.001	C1 < C2 < C3
Work participation	2.16 ± 0.52	3.88 ± 0.39	4.63 ± 0.33	792.64	<.001	C1 < C2 < C3
Economic welfare	1.42 ± 0.41	2.47 ± 0.46	3.91 ± 0.40	721.38	<.001	C1 < C2 < C3
Overall QoL	2.25 ± 0.32	3.19 ± 0.28	4.26 ± 0.27	914.85	<.001	C1 < C2 < C3

Notes. C1 = Traditional Farmers with Limited Digital Inclusion; C2 = Intermediate Farmers with Moderate Digital Inclusion; C3 = Digitally Connected Progressive Farmers. All pairwise comparisons were significant at $p < .05$ according to Tukey's HSD test.

Implications of Farmer Typologies for Targeted Rural Development and QoL Improvement

The identified farmer typologies revealed distinct combinations of demographic, socioeconomic, agricultural, household, and digital characteristics, accompanied by clear differences in multidimensional QoL. These profiles suggest that rural development interventions should be differentiated according to the specific characteristics and needs of each farmer typology rather than applying a uniform approach. Traditional Farmers with Limited Digital Inclusion were characterized by older age, lower educational attainment, lower household income, smaller farm size, limited internet accessibility, lower participation in digital training, and the lowest Digital Inclusion Score. This typology also recorded the lowest QoL scores across all six domains and overall QoL, indicating a need for integrated interventions emphasizing basic digital literacy, access to digital services, livelihood and income support, and improved access to agricultural and community resources.

Intermediate Farmers with Moderate Digital Inclusion demonstrated intermediate levels of demographic, agricultural, household, and digital characteristics, together with intermediate QoL across all domains. This profile suggests potential for further development through interventions that strengthen digital competencies, improve agricultural productivity and household economic capacity, and facilitate greater use of digital technologies for farm management, information access, and market participation. Such strategies may help address the remaining gaps in digital capacity and QoL within this group.

Digitally Connected Progressive Farmers were relatively younger and had higher educational attainment, larger farm sizes, higher household income, better internet accessibility, greater participation in digital training, universal smartphone/tablet ownership, and the highest Digital Inclusion Score. This typology also exhibited the highest QoL across all six domains and overall



QoL. For this group, rural development strategies may therefore focus on advanced digital agriculture, innovation adoption, digital market participation, knowledge sharing, and the development of farmers as local digital or innovation leaders. These approaches may support continued development while enabling this group to contribute to knowledge and technology diffusion within the wider farming community.

In Summary, the findings indicate that the three farmer typologies represent different levels of socioeconomic and digital capacity and corresponding QoL profiles. The findings therefore support a differentiated development approach: targeted support and basic digital inclusion for Traditional Farmers with Limited Digital Inclusion, capacity building and productivity enhancement for Intermediate Farmers with Moderate Digital Inclusion, and innovation-oriented and leadership-focused strategies for Digitally Connected Progressive Farmers. This typology-based approach provides an empirical basis for designing rural development and QoL improvement strategies that are responsive to the heterogeneous characteristics and needs of farming households.

Discussion

The findings of this study support the view that farming households should not be regarded as a homogeneous population because demographic, socioeconomic, agricultural, household, and digital characteristics interact to create distinct patterns of QoL. The principal contribution of this study lies in the identification of three distinct farmer typologies integrating demographic, socioeconomic, agricultural, household, and digital characteristics. The findings demonstrate that farmers can be classified into three meaningful groups with markedly different profiles and levels of QoL. Significant differences were observed across all QoL domains, with scores increasing progressively from Traditional Farmers with Limited Digital Inclusion to Intermediate Farmers with Moderate Digital Inclusion and Digitally Connected Progressive Farmers. These findings suggest that multidimensional farmer typologies provide a useful framework for understanding disparities in QoL and for designing more targeted rural development interventions than approaches that assume farming populations are homogeneous (Iles *et al.*, 2021; Suárez *et al.*, 2021).

The three farmer typologies identified in this study highlight the considerable heterogeneity that exists within farming communities. The observed differences in age, educational attainment, household income, farming experience, farm size, internet accessibility, and digital inclusion suggest that farmers' QoL is shaped by the interaction of multiple socioeconomic and digital factors rather than by any single characteristic. This interpretation is consistent with the Capability Approach, which emphasizes that well-being depends not only on the availability of resources but also on individuals' capabilities to access and utilize opportunities effectively. In rural agricultural settings, digital inclusion may strengthen these capabilities by improving farmers' access to agricultural information, extension services, markets, and social networks. However, the benefits of digital technologies are likely to depend on complementary factors such as education, economic resources, and farming capacity. This interpretation is also consistent with previous studies showing that demographic and socioeconomic characteristics strongly influence farmers' adoption of digital



technologies and their ability to benefit from digital agriculture (Khanna, 2021; Iles *et al.*, 2021). Consequently, digital inclusion should be viewed as one component of a broader socioeconomic context influencing farmers' well-being rather than as an isolated determinant. This finding also aligns with evidence that digital inequality is closely intertwined with broader socioeconomic inequalities contributing to disparities in rural development (Lei *et al.*, 2025).

One notable finding of this study was that QoL increased progressively across the three farmer typologies, with the highest scores consistently observed among Digitally Connected Progressive Farmers and the lowest among Traditional Farmers with Limited Digital Inclusion. This pattern suggests that greater digital inclusion is associated with more favorable QoL profiles among farmers. However, this association should be interpreted cautiously. Farmers in the Digitally Connected Progressive Farmers group were also younger, had higher educational attainment, higher household incomes, and larger farm sizes than those in the other typologies. These demographic and socioeconomic characteristics are themselves well-recognized determinants of health and well-being and may partially explain the observed differences in QoL. Therefore, the present findings should not be interpreted as evidence that digital inclusion alone leads to better QoL. Rather, digital inclusion is likely to represent one component of a broader set of interrelated factors influencing farmers' well-being. Nevertheless, greater access to digital technologies and information resources may facilitate farm management, improve access to agricultural knowledge and services, and strengthen farmers' capacity to respond to changing environmental and market conditions, thereby supporting better livelihood outcomes (Qin *et al.*, 2022; Bocean, 2024). Although the cross-sectional design precludes causal inference, the observed associations are consistent with previous studies reporting that digital inclusion is positively associated with well-being and livelihood outcomes in rural communities (Khanna, 2021).

The findings also illustrate that digital exclusion rarely occurs in isolation but is embedded within broader socioeconomic disadvantage. Conversely, Traditional Farmers with Limited Digital Inclusion exhibited lower educational attainment, lower household income, smaller farm sizes, lower Digital Inclusion Scores, and poorer QoL across all domains. This pattern suggests that digital exclusion may coexist with broader socioeconomic disadvantage rather than representing an isolated challenge. Lower educational attainment, limited economic resources, and smaller farm sizes may reduce farmers' opportunities to access digital technologies, participate in training activities, and adopt improved agricultural practices, which together may contribute to lower levels of well-being (Arangurí *et al.*, 2025; Khanna, 2021). However, because these characteristics are closely interconnected, it is not possible to determine the independent contribution of digital exclusion from the present cross-sectional data. Therefore, interventions should address these interrelated barriers comprehensively rather than focusing solely on improving internet infrastructure. Combining digital literacy training, user-friendly technologies, accessible agricultural extension services, and continuous technical support with broader socioeconomic development initiatives may be more effective in enhancing digital participation and improving farmers' QoL (Wang *et al.*, 2025; Qin *et al.*, 2022).



The present findings have important implications for agricultural and rural development policy and support a typology-based rather than one-size-fits-all approach. The three farmer typologies differed in socioeconomic and digital capacity and exhibited corresponding QoL profiles, indicating that development priorities should be tailored to the characteristics and needs of each group (Iles *et al.*, 2021; Lei *et al.*, 2025). Traditional Farmers with Limited Digital Inclusion, who had the lowest socioeconomic and digital capacity and QoL, may require integrated support combining basic digital literacy, affordable connectivity, agricultural extension, and livelihood support (Arangurí *et al.*, 2025; Khanna, 2021; Qin *et al.*, 2022). Intermediate Farmers with Moderate Digital Inclusion may benefit from capacity building in digital farm management, agricultural information access, market participation, and productivity-enhancing technologies (Khanna, 2021; Qin *et al.*, 2022). In contrast, Digitally Connected Progressive Farmers, who demonstrated the highest socioeconomic and digital capacity and QoL, may be better positioned to adopt advanced digital agriculture, precision technologies, and digital marketing (Bocean, 2024; Clapp & Ruder, 2020; Wang *et al.*, 2025). These differentiated strategies provide an empirical basis for targeted rural development and QoL improvement that recognizes the heterogeneity of farming households and the multidimensional nature of well-being (Suárez *et al.*, 2021). However, these findings should not be interpreted as evidence that digital inclusion directly causes higher QoL, as the cross-sectional design does not establish causality and digital inclusion is intertwined with other socioeconomic and agricultural characteristics.

This study extends the literature by identifying farmer typologies based on multidimensional demographic, socioeconomic, agricultural, household, and digital characteristics using a person-centered approach. The findings demonstrate that these typologies are associated with distinct QoL profiles and provide practical evidence for developing more targeted rural development interventions. Nevertheless, several limitations should be acknowledged. First, the cross-sectional design precludes causal inference. Second, although digital inclusion was an important characteristic of the identified typologies, differences in age, educational attainment, household income, and farm size may have confounded the observed associations with QoL. Third, the findings were derived from a single agricultural community using self-reported data, which may limit their generalizability. Future research should validate these typologies in diverse agricultural settings using longitudinal designs and objective indicators to better clarify the relative contributions of digital inclusion and other socioeconomic factors to farmers' QoL.

Recommendations

Practical Recommendations

1. For Traditional Farmers with Limited Digital Inclusion, local agricultural extension and community development agencies should provide basic digital literacy training on accessing agricultural information, digital services, and online markets, supported by hands-on assistance and user-friendly tools.



2. For Intermediate Farmers with Moderate Digital Inclusion, agricultural extension organizations should provide capacity-building programs on digital farm management, online agricultural information and market access, with follow-up technical support to facilitate continued technology use.

3. For Digitally Connected Progressive Farmers, agricultural agencies and local innovation networks should support the adoption of advanced digital agriculture, including precision farming, digital marketing, and data-driven farm management, while promoting peer learning and knowledge sharing.

Policy Recommendations

1. Government agencies and agricultural extension organizations should adopt a typology-based rural development framework to differentiate interventions and allocate resources according to farmers' socioeconomic, agricultural, household, and digital characteristics.

2. Agricultural development policies should integrate digital inclusion with existing rural development programs by addressing internet access, digital literacy, agricultural information, technical assistance, and the affordability of digital technologies.

3. Local governments and agricultural extension agencies should establish targeted referral mechanisms to identify farmers with limited digital inclusion and connect them with appropriate training, extension, livelihood, and digital services.

4. Agricultural policies should promote differentiated development pathways across farmer typologies, prioritizing basic digital inclusion and socioeconomic support for Traditional Farmers with Limited Digital Inclusion, capacity building and productivity enhancement for Intermediate Farmers with Moderate Digital Inclusion, and innovation, market integration, and knowledge-sharing opportunities for Digitally Connected Progressive Farmers.

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References

- Aranguri, M., Mera, H., Noblecilla, W. & Lucini, C. (2025). Digital literacy and technology adoption in agriculture: A systematic review of factors and strategies. *AgriEngineering*, 7(9), 296. <https://doi.org/10.3390/agriengineering7090296>
- Bocean, C. G. (2024). A cross-sectional analysis of the relationship between digital technology use and agricultural productivity in EU countries. *Agriculture*, 14(4), 519. <https://doi.org/10.3390/agriculture14040519>
- Brennan, M., Hennessy, T., Dillon, E. & Meredith, D. (2023). Putting social into agricultural sustainability: Integrating assessments of quality of life and wellbeing into farm sustainability indicators. *Sociologia Ruralis*, 63(3), 629-660. <https://doi.org/10.1111/soru.12417>



- Clapp, J. & Ruder, S. L. (2020). Precision technologies for agriculture: Digital farming, gene-edited crops, and the politics of sustainability. *Global Environmental Politics*, 20(3), 49-69. https://doi.org/10.1162/glep_a_00566
- Dou, B., Vandenberg, B. & Moons, P. (2026). Cluster analysis: an overview of traditional and novel approaches for health researchers. *European Journal of Cardiovascular Nursing*, zvag100. <https://doi.org/10.1093/eurjcn/zvag100>
- Iles, K., Ma, Z. & Nixon, R. (2021). Multi-dimensional motivations and experiences of small-scale farmers. *Society & Natural Resources*, 34(3), 352-372. <https://doi.org/10.1080/08941920.2020.1823540>
- Khanna, M. (2021). Digital transformation of the agricultural sector: pathways, drivers and policy implications. *Applied Economic Perspectives and Policy*, 43(4), 1221-1242. <https://doi.org/10.1002/aep.13103>
- Lei, M., Yang, X., Hong, S., Wang, D., Zhang, W. & Chen, H. (2025). Sustainable digital rural development: measurements, dynamic evolutions, and regional disparities-a case study of China. *Sustainability*, 17(9), 4250. <https://doi.org/10.3390/su17094250>
- Liu, S. & Wang, H. (2025). Constructing Multidimensional User Personas for Community-Based Chronic Disease Patients Based on Digital Literacy, Health Status, and Social Support: A Cross-Disciplinary Study for Digital Health Product Design. *Creative Engineering*, 1(2), 151-172.
- Minh, N. A., Palaniappan, G., Mitchell, J., Tim, N. H. & Binh, N. T. (2024). A Gendered Analysis on Access to Rice Farming Technology in the Vietnamese Mekong Delta: From Policy to Practice. *JL & Soc. Deviance*, 28, 77.
- Na San Subdistrict Municipality. (2025a). *Local development plan (2023-2027)*. Na San Subdistrict Municipality.
- Na San Subdistrict Municipality. (2025b). *Population and household registration records*. Na San Subdistrict Municipality.
- Niu, L., Yuan, L., Ding, Z. & Zhao, Y. (2023). How do support pressure and urban housing purchase affect the homecoming decisions of rural migrant workers? Evidence from rural China. *Agriculture*, 13(8), 1473. <https://doi.org/10.3390/agriculture13081473>
- Qin, T., Wang, L., Zhou, Y., Guo, L., Jiang, G. & Zhang, L. (2022). Digital technology-and-services-driven sustainable transformation of agriculture: Cases of China and the EU. *Agriculture*, 12(2), 297. <https://doi.org/10.3390/agriculture12020297>
- Suárez, A. E., Gutiérrez-Montes, I., Ortiz-Morea, F. A., Ordoñez, C., Suárez, J. C. & Casanoves, F. (2021). Dimensions of social and political capital in interventions to improve household well-being: Implications for coffee-growing areas in southern Colombia. *Plos one*, 16(1), e0245971. <https://doi.org/10.1371/journal.pone.0245971>
- Veenhoven, R. (2024). Quality of life (QOL), an overview. *Encyclopedia of quality of life and well-being research*, 5668-5671. https://doi.org/10.1007/978-3-031-17299-1_2353
- Wang, S., Yang, Y., Yin, H., Zhao, J., Wang, T., Yang, X., ... & Yin, C. (2025). Towards Digital Transformation of Agriculture for Sustainable Development in China: Experience and Lessons Learned. *Sustainability*, 17(8). <https://doi.org/10.3390/su17083756>



Yamane, T. (1967). *Statistics: An Introductory Analysis* (2nd ed.). Harper & Row.

Zhou, J., Yang, Y., Li, S., Mao, N., Chen, X., Wang, D., ... & Hu, X. (2025). Patterns of social participation among older adults and their association with self-rated health: the mediating role of activities of daily living. *Aging Clinical and Experimental Research*, 37(1), 221.
<https://doi.org/10.1007/s40520-025-03131-3>

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