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Digitalization and agricultural transformation in developing countries: Empirical evidence from Tanzania agriculture sector

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ABSTRACT

Agribusiness can potentially increase value for agriculture and the entire value chain, but it is hard to achieve these goals without digitalising the sector. The transformation reforms modern technology and digital infrastructure adoption to facilitate growth and inclusivity. These conditions make the agricultural digitization transformation more appealing. Therefore, using a survey of 400 smallholder farmers in four regions of Rukwa, Ruvuma, Morogoro and Tabora, this study examines the interplay between digitalization and agriculture transformation in Tanzania by focusing on the determinants and effects of digitalization on smallholder farmers' welfare. The study used the double hurdle model to estimate the determinants and extent of digitalization adoption; the Two-stage least square (2SLS) and the Control function approach (CFA) to estimate its effects on smallholder farmers' welfare. The findings revealed that access to credit (0.17428, $p < 0.01$), extension services (0.52884, $p < 0.01$), education and government support (0.10922, $p < 0.05$) are key determinants for agricultural digitalization. Moreover, digitalization was found to influence smallholder farmers' welfare significantly. The benefits of digitalization across smallholder farmers in all regions were observed in enhancing extension services (76.50 %), pest management (71.25 %), and accessibility of the market information (72.25 %), enhance an access to financial services (74.75 %). In sum, to promote digital technology adoption among smallholder farmers, policymakers in Tanzania and developing nations should prioritize financial inclusion through tailored microfinance programs, educational initiatives must integrate digital literacy, enhance extension services, subsidized technology access, and encouraging public-private partnerships to create incentives for sustainable agricultural development.

Introduction

Sustainable and resilient food systems play a pivotal role in global development and growth. According to World Bank (WB) statistics, the global population is projected to reach 9.7 billion by 2050, with a corresponding doubling of food demand [1]. Additionally, agricultural innovation emerges as a powerful catalyst, not only in alleviating extreme poverty but also in fostering collective prosperity and development. This is evident in the significant increase in incomes among economically challenged nations, surpassing the rates observed in other industries by two to three times [1]. The agricultural sector constitutes approximately 65 % of the labor force in impoverished societies worldwide. In Africa, it employs 70 % of the population and 60 % of the labor force, contributing 20 % and 17 % to exports and GDP, respectively (International Labour Organisation [[2], 2021; United Republic of Tanzania (URT], 2021). Regionally, it plays a substantial role in East Africa, contributing 40 % to the regional GDP and engaging over 80 % of the workforce [1]. In Tanzania specifically, agriculture employs 66.69 %, contributing nearly 30 % of the country's GDP, 25 % of foreign currency, and over 60 % of raw materials [3]. Despite its paramount importance in African countries, including Tanzania, the agricultural sector grapples with numerous challenges, such as a lack of essential market information for agricultural products and inputs, coupled with pervasive poverty, which hinders the sector's potential [3].

In this context, digitalization is essential in promoting agricultural transformation to improve farmers' welfare in developing countries. It equips farmers with relevant, timely information and services, thereby facilitating the cultivation of profitable and sustainable enterprises. Also, Abdulai [4] indicated that it enhances productivity, and profitability, and strengthens resilience for smallholders and communities, as

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well as climate change responses.

As a result, digitalization emerges as a potent force for improving rural incomes, food security, and national economies by enabling informed decision-making and connecting small-scale production to lucrative markets [5–7]. Likewise, this burgeoning digital transformation generates non-traditional actors within agricultural value chains, promotes trustworthy research and policy formulation, and enhances the equity and efficiency of agricultural supply networks. The convergence of technology and agriculture, also known as e-agriculture or agricultural digitization, is a burgeoning sector that drives agricultural and rural development [8].

Tanzania stands at the forefront of a digital and technological revolution driven by the widespread availability of mobile and communication technologies. The digital landscape has undergone substantial changes, with almost half of the population now connected to various telecommunication entities (Tanzania Communication Regulatory Authority [9], 2022). This surge in digital connectivity is evident through the widespread use of mobile connections, internet services, and active engagement on social media platforms. This transformative wave creates a dynamic ecosystem with the potential to reshape traditional trade patterns and create new opportunities. Recognizing the potential benefits, empowering farmers to embrace digital technology becomes a worthwhile pursuit, given its positive effects with desirable development outcomes. This includes the prospect of improved livelihoods leading to increased income, ultimately enhancing food and nutrition security. Notably, the Tanzanian government, through the Ministry of Agriculture, has taken notable strides in the past five years by introducing digital platforms like the Mobile Kilimo[2] (M-Kilimo) application, a call center for extension services, the Digital Fertilizer Subsidy Distribution and Payment System (DFSDS), and the Agricultural Trade Management System (ATMIS) [3,7]. These platforms aim to facilitate agricultural activities and provide crucial information on production, weather, and markets, thereby elevating the livelihoods of farmers.

Despite these commendable efforts, a relatively small proportion of smallholder farmers have accessed and utilized these digital platforms [10]. This limitation results in challenges related to weather predictions, access to extension services, and obtaining market and price information, all of which significantly impact their production and overall welfare [11]. This study embarks on an empirical exploration of the impact of digitalization on agriculture transformation in Tanzania. By delving into the relationship between digital adoption and socioeconomic prosperity among smallholder farmers, the research sheds light on the intricate dynamics of digital content dissemination, mobile applications, and the burgeoning digital agriculture landscape. Given that smallholder farmers constitute 98 % [3] of the entire producer base in the sector, understanding the profound impact of digitalization on their practices and livelihoods becomes crucial. This research contributes to the ongoing discourse on the intersection of digitalization and agricultural development in developing nations, where agricultural landscapes continue to undergo significant transformations.

Literature review

Determinants of adoption of digital technology among the farmers

The extant body of literature consistently indicates that a range of factors, such as education and income, exert significant influence on the adoption of digital technology and the digitization process in agricultural practices. The significance of education is emphasized by its ability to facilitate individuals in understanding and interpreting digital content, which is frequently essential for the efficient utilisation of technology [12–14]. Formal education plays a significant role in equipping farmers with the necessary skills, enabling them to effectively adapt to technological advancements, in contrast to their counterparts who have limited exposure to education.

Moreover, the significant influence of mobile phones has attracted considerable attention in the context of fishing communities. The authors Govindaraju and Mabel [15] provide an analysis of the substantial impact of mobile phones on the modernisation and development of the fishing industry, with notable effects on economic and social dimensions. The utilisation of mobile phones by fishermen has been observed to exhibit a positive correlation with improved economic well-being, as evidenced by an increase in income and notable changes in spending patterns.

The possession of assets, such as land and productive machinery, has been identified as a significant factor that encourages smallholder farmers to adopt digital agricultural infrastructure [5,16,17]. These resources provide farmers with the means to incorporate digital tools and technologies into their agricultural practices, thereby improving productivity and efficiency.

The socioeconomic background of farmers serves as the foundation for these adoption trends. Numerous studies have emphasized the significant correlation between socioeconomic variables and the utilisation of instant communication technology and the advancement of digital agricultural practices [18–21]. The aforementioned factors collectively influence the inclination of farmers to adopt digitalization, illustrating the complex interaction between the adoption of technology and wider socio-economic dynamics.

In a recent investigation carried out by Kitole et al., [6], an examination was undertaken to explore the factors influencing the adoption of technology and its subsequent effects on the welfare of fishermen in Lake Victoria, Tanzania. The study revealed that educational attainment, income levels, and age are significant factors that influence the adoption of technology within the fishing community. Interestingly, there is a notable distinction in terms of gender, as females demonstrate a greater inclination towards the adoption of technology in comparison to males. The aforementioned findings provide insights into the complex and diverse aspects of technology adoption and its consequences for various sectors within the fishing community.

Effects of adoption of digital technology on farmers' welfare

A multitude of scholarly investigations have explored the consequences of the adoption of digital technology in the domestic agricultural markets of developing countries, with a specific focus on its economic effects on small-scale farmers. While previous studies have primarily focused on the transformative impact of information technology in terms of market expansion and customer retention, there has been a scarcity of research examining the dynamics of crop management.

According to Sullivan and Drenman [22], the widespread availability of mobile phones presents agricultural communities with a valuable resource to improve various aspects of both pre-and post-harvest production processes. Consequently, this measure effectively mitigates the negative impact of insufficient management on output, enhancing overall revenues. In their study, Gruber and Kauntrompis [23] emphasize the significant impact of agricultural technology in facilitating the timely dissemination of market information regarding product prices. This, in turn, empowers farmers to make well-informed business decisions and ultimately achieve sustainable profitability. According to Matokeo [20], the increase in the adoption of digital devices is primarily driven by the desire to enhance one's income.

According to Aker and Mbiti [24], the increasing adoption of smartphones enables farmers to utilize agricultural digital applications, thereby improving crop management. The use of digital applications improve crop management through real-time monitoring and data-driven insights. Farmers utilize these applications to track weather patterns, assess soil health, and detect early signs of pests or diseases [25]. By receiving instant information, farmers can make timely

[2] Kilimo is a Swahili word meaning agriculture.

decisions, implement preventive measures, and optimize resource usage. Additionally, digital tools enable precision agriculture, allowing farmers to tailor their interventions, reduce input costs, and enhance overall crop productivity. The integration of technology enhances efficiency, accuracy, and sustainability in crop management practices.

The necessity of implementing technological interventions arises from the imperatives of modernising agriculture in the developing world, specifically the transition from subsistence farming to agribusiness models. The adoption of technology in various regions is driven by its effectiveness in providing accurate weather information, which is particularly important in areas where agriculture relies heavily on seasonal rainfall patterns. By utilising digitalized extension services, farmers have the opportunity to acquire valuable knowledge regarding seeds, fertilizers, and pest management strategies. This enables them to enhance agricultural outputs and improve their overall livelihoods [26]. Technological adoption is a fundamental process that facilitates the improvement of crop quality and efficient dissemination of information, thereby empowering smallholder farmers to strengthen their competitive position in dynamic agricultural environments.

Theoretical framework

The Technology-Organization-Environment (TOE) framework, proposed by Tornatzky and Fleischer in 1990, provides a solid and thorough foundation for examining the digitalization and transformation of the agricultural sector in developing countries, with a particular focus on Tanzania. This theoretical lens provides a structured method for analysing the interplay between technological innovation, organisational dynamics, and external environmental influences, enabling a nuanced examination of how these factors collectively shape the adoption and impact of digital technology in the agricultural domain.

The TOE framework offers a methodical framework for analysing the adoption of digital technology in the agricultural context. Within the "Technology" component, the framework encourages an examination of how farmers perceive digital platforms, mobile applications, and communication devices in terms of their compatibility with existing practices, usability, and potential benefits. This dimension is especially important for comprehending the practical aspects of technology adoption, as it sheds light on the characteristics and characteristics that promote or inhibit adoption among smallholder farmers.

Moving to the "Organisation" dimension, the TOE framework enables an examination of how the internal characteristics of agricultural organisations, such as the educational backgrounds, asset ownership, and socioeconomic profiles of farmers, interact with the adoption of digital technology. This section highlights how the socioeconomic characteristics of farmers can serve as digitalization facilitators or barriers. For instance, education and income levels impact the ability to interpret and utilize digital content, which may affect the adoption process. Thus, the framework provides a lens for understanding how the organisational context influences adopting and incorporating digital technology into existing agricultural practices.

The "Environment" component of the TOE framework expands the analysis to include external factors that influence technology adoption. In the case of this study, the agricultural landscape of Tanzania is examined in terms of its regulatory environment, market dynamics, and broader socio-cultural influences. By incorporating the socio-economic characteristics of farmers within this dimension, the framework helps to comprehend how factors such as infrastructure availability, access to information, and broader economic conditions interact with farmers' profiles to influence the decision to adopt digital technology. This holistic perspective illuminates how the external context influences the viability and impact of digitalization initiatives among smallholder farmers.

Despite the extensive body of research conducted thus far, there exists a significant research gap on the comprehensive investigation of the adoption of digitalization within the agricultural sector of developing nations. The objective of this study is to fill the existing research gap by specifically investigating Tanzanian farmers as a representative sample. The study will utilize the Technology-Organization-Environment (TOE) framework to analyse the complex relationship between technological attributes, organisational dynamics, external influences, and the socioeconomic characteristics of farmers. This research enhances our comprehension of the factors that impact the adoption of digital technology and its potential to bring about transformation among small-scale farmers (see Fig. 1). As a result, it fills a significant gap in knowledge within sub-Saharan regions and other similar contexts in developing countries.

Materials and method

The study employed a cross-sectional study design to gather data from farmers across multiple regions in Tanzania, including Tabora, Rukwa, Ruvuma, and Morogoro (see Fig. 2). Data collection was facilitated through structured questionnaires tailored to the farmer population. The selection of these specific regions was informed by Ministry of Agriculture data, which identified them as prominent contributors to national crop production. Notably, the Morogoro region holds the distinction for its significant role in paddy and maize production, Tabora for tobacco and cotton cultivation, Rukwa as a primary maize producer, and Ruvuma as a key cereal-producing area in Tanzania. The study thus encompassed a comprehensive investigation into farmers' practices, technology adoption (specifically, mobile phone usage for obtaining production and market insights), and various socio-demographic attributes, yielding a valuable collection of pertinent information.

Sample size

The sampling framework included 11,350 farmers from different cooperative societies in the regions under the study. The sample size as obtained using the Yamane's [27] formula as here down shown;

$$n = \frac{N}{1 + e^2(N)}$$

Whereby;

n = sample size
N = total number of registered farmers under agricultural cooperative societies, 11,350
e = error margin, 0.05

$$n = \frac{11,350}{1 + 0.05^2(11,350)}$$

$$n = 391.4$$

The determined sample size utilising the given formula was initially 391. However, to ensure result consistency in estimation and mitigate potential biases, the sample was appropriately adjusted to encompass 400 respondents. This adjustment was made in consideration of optimising data quality. In order to, uphold the integrity of the study and acquire reliable insights, a balanced distribution of respondents was maintained across regions (see Table 1). This approach involved obtaining an equal number of participants from each region, thereby contributing to the minimisation of potential biases and enhancing the overall robustness of the collected information.

Estimated results on determinants of adoption of digital technology

To comprehensively investigate the determinants and extent of digital adoption among farmers, the study adopts a Double Hurdle Model. This analytical framework proves to be highly suitable for

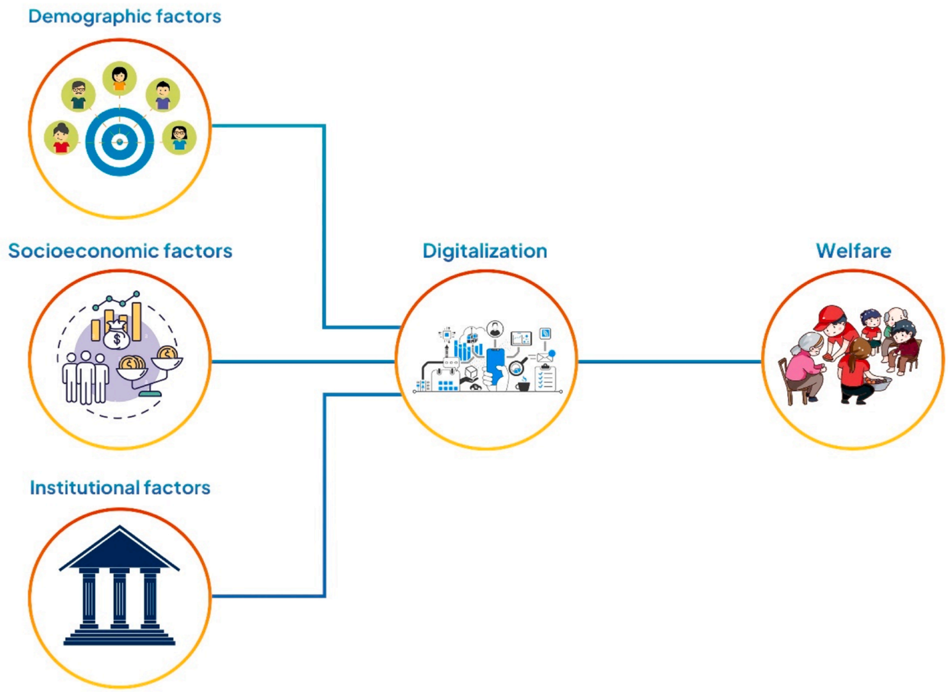

Fig. 1. Conceptual framework
Source: Authors' design 2022.

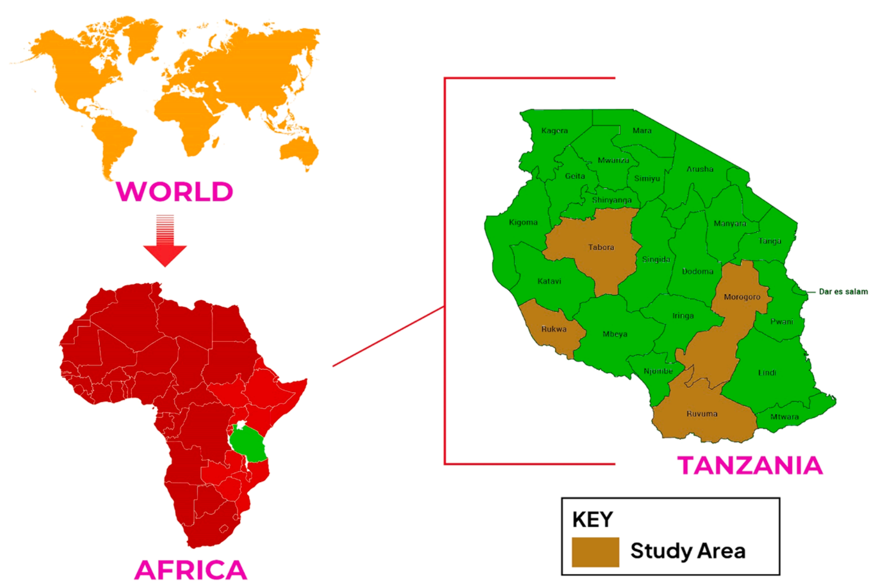

Fig. 2. Map of Tanzania showing regions under the study
Source: Authors' design, 2022.

Table 1
Distribution of respondents across regions.

Regions	Sample	Number of active farmers in cooperative societies
Tabora	100	2820
Rukwa	100	2843
Ruvuma	100	2839
Morogoro	100	2848
Total	**400**	**11,350**

understanding the complexities of digitalization adoption within the agricultural context [28]. The model entails two distinct stages, each addressing distinct facets of the digitalization process. Moreover, the Double Hurdle Model has been utilized in this study due to its ability in examining the dual decision-making process of participants in the adoption of digital technology among smallholder farmers.

Step 1: First hurdle – digitalization adoption decision

In the first hurdle, we model the binary decision of whether farmers adopt digitalization or not. Let's denote this binary outcome as Y_{1i}, where $Y_{1i} = 1$ if farmer i adopts digitalization, and $Y_{1i} = 0$ if not, given the set of predictor variables X_i that influence this adoption decision. Thus, the probit regression model can be used for this hurdle:

$$Pr(Y_{1i} = 1 \mid X_i) = \phi(\beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_k X_{ik})$$

Whereas ϕ is the standard normal cumulative distribution function, β_0 is the intercept of the probit model which represents the estimated impact on the log-odds of the event occurring when all independent variables are equal to zero, $\beta_1, \beta_2, \ldots, \beta_k$ are the coefficients of the predictor variables $X_{i1}, X_{i2}, \ldots, X_{ik}$.

Step 2: Second hurdle – the extent of digitalization adoption among farmers

In the second hurdle, we focus on the farmers who have adopted digitalization $Y_{1i} = 1$ and examine the proportion of their farming income that is attributable to digitalization. Let's denote this continuous outcome as Y_{2i}. Therefore, the linear regression model for this hurdle is given as:

$$Y_{2i} = \beta_0 + \beta_2 X_{i1} + \beta_2 X_{i2} + \ldots + \beta_2 X_{ik} + \varepsilon_{2i}$$

Whereby, β_0 is the intercept of the linear regression model, $\beta' s$ are the coefficients of the predictor variables $X_{i1}, X_{i2} + \ldots + X_{ik}$ and ε_{2i} is the error term.

Effects of digital adoption on smallholder farmers' welfare

The Two-Stage Least Squares (2SLS) approach is employed to address endogeneity in the relationship between digitalization adoption and farmers' income. The procedure involves two sequential steps, effectively isolating the influence of the endogenous variable on the outcome variable while accounting for the potential impact of correlated instruments and control variables.

In the first stage, the instrumental variable Z is regressed on digitalization adoption (D) along with the control variables (Xs). This yields a fitted value (D̀) for digitalization adoption that captures the exogenous variation provided by the instrumental variable. Mathematically, this stage can be expressed as:

$$D = \alpha_0 + \alpha_1 Z + \alpha_2 X_1 + \alpha_3 X_2 + \ldots + \alpha_k X_k + \varepsilon_1$$

where D̀ is the estimated value of digitalization adoption.

In the second stage, the fitted digitalization adoption value ($\widehat{\mathrm{D}}$) obtained from the first stage is used as an explanatory variable in a regression of farmers' income (Y) on $\widehat{\mathrm{D}}$ and the control variables (Xs). This step accounts for the endogeneity of digitalization adoption and mitigates the potential bias introduced by omitted variables or reverse causality. The second stage equation is given by:

$$ln(Y) = \beta_0 + \beta_1 \widehat{\mathrm{D}} + \beta_2 X_1 + \beta_3 X_2 + \ldots + \beta_k X_k + \varepsilon_2$$

The 2SLS estimator then provides consistent and unbiased estimates for the coefficients ($\beta_1, \beta_2, \beta_3, \ldots, \beta_k$) that represent the causal impact of digitalization adoption on farmers' income, while addressing the endogeneity concern through the instrumental variable *Z*. Furthermore, the two-step process of the 2SLS approach facilitates the identification of a causal relationship between digitalization adoption and farmers' income, accounting for potential endogeneity and enhancing the validity of the estimation.

Conversely, to effectively manage potential heterogeneity that could influence the income of farmers within the designated Tanzanian regions, the study strategically employed the Control Function Approach (CFA). This technique proves to be particularly adept at addressing endogeneity concerns across both linear and nonlinear models, through its concurrent processes. Initially, the CFA involves predicting the residuals to a reduced-form equation derived from estimated functions. Subsequently, these residuals are incorporated as additional explanatory variables in the second-stage regression.

In essence, the Control Function Approach leverages the predicted residuals as instrumental variables to account for unobserved characteristics that might otherwise confound the relationship between digitalization adoption and farmers' income. By skillfully integrating this approach, the study proficiently mitigates endogeneity and heterogeneity concerns, facilitating a more accurate and rigorous examination of the impact of digitalization on farmers' income in the selected regions of Tanzania.

In contrast to alternative methodologies like Two-Stage Least Squares (2SLS) and Instrumental Variable (IV) approaches, the Control Function Approach adopts a distinct approach in addressing endogeneity concerns. While both 2SLS and IV methods incorporate instrumental variables, the Control Function Approach utilizes control functions to mitigate endogeneity and generate reliable estimates. Typically presented in tandem to reveal result variations, CFA uniquely controls for heterogeneity, a factor not addressed in 2SLS.

Results

The general descriptive statistics of the farmers' socioeconomic characteristics are shown in Table 2 indicating the characteristics of smallholder farmers in Tanzania for the four surveyed regions of Ruvuma, Morogoro, Tabora and Rukwa.

The descriptive results of smallholder farmers shown in Table 2 indicate that an average farmers year of schooling is 9.43 years while the average age is 35.53 years. Moreover, the average farming experience across all farmers in four regions is more than 22.14 years. Also, the average household size for smallholder farmers is 10.46 members which is higher than the country's average household size of 3.80 members and far more than the global average person living a household of 4.90 [29]. On the other hand, the average distance from smallholder farmers' homes to the marketplace 34.56 km. Additionally, by engaging in farming activities, the average household income of farmers is Tanzanian shillings (Tshs) 620,560 equivalent to US$ 206.44 at the 2022 exchange rate.[3] Although women are often recognized as crucial contributors to agricultural growth in many developing countries, including Tanzania [30], Fig. 3 reveals a noteworthy distribution among smallholder farmers in the study as 58 percent are male, while 42 percent are female. This observation emphasizes the inherent gender sensitivity within agriculture in numerous developing countries [31,32], suggesting that men and women may encounter distinct experiences in agriculture, including differences in resource access, opportunities, and decision-making authority.

The results in Fig. 4 show that 221 (55.25 %) farmers in the selected regions use smartphones, while only 179 (44.75 %) farmers do not. A gender-based analysis indicates that females (59 %) are the majority users of smartphones compared to male (41 %) farmers. This result implies that women are more flexible to use smartphones than males. What's more, the results show that men are the main non-users (55 %) compared to their female counterparts (45 %). Thus, the fact that the majority of small-scale farmers own a smartphone means that they have easy access to digital agricultural content.

Additionally, the results in Fig. 5 revealed that 26.75 % of farmers used digital information during the post-harvest period, while 23.75 % used this digital information content for good planning and decision-

Table 2
Descriptive statistics for smallholder farmers.

Variables	Mean ($\overline{X}$)	Standard deviation (SD)
Years of schooling	9.43	1.24
Age of farmers	35.53	53.47
Farming experience	22.14	25.86
Household size	10.46	10.67
Farming income	620,560	1163,640.14
Distance to the marketplace (km)	34.56	2.84

[3] The exchange rate at the time of survey was 1 US$ = Tshs 3,006

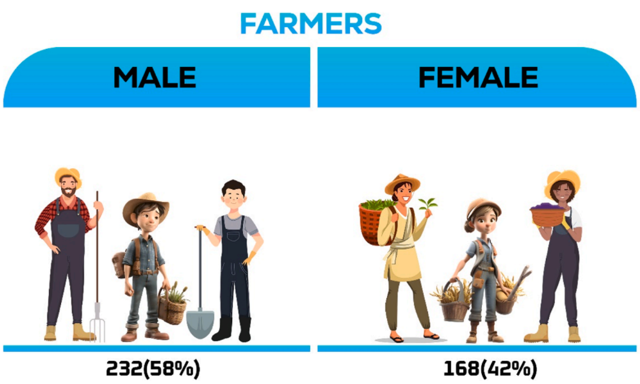

Fig. 3. Distribution of smallholder farmers by gender.

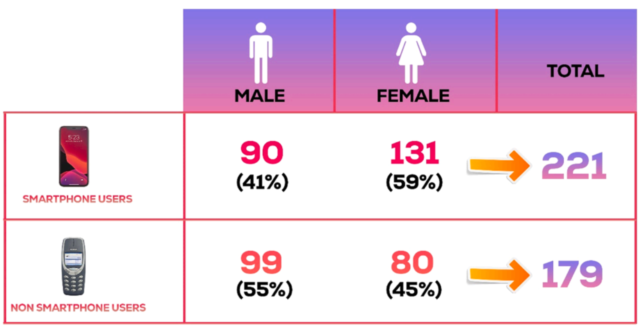

Fig. 4. Farmers' mobile devices for accessing digital information.

making before starting farming.

Moreover, a little number of farmers 6.25 % use digital information during preparation for farming while 19.5 % use it during the harvesting period. These findings in line with studies suggesting that most farmers tend to seek extra agriculture knowledge during farming with the anticipation of ensuring they have a large amount of output (productivity) and the desire for knowledge is even higher after harvesting as they tend to seek better information of the market prices for the produced crops [33–37].

Furthermore, one of the major reasons for the farmers' decision towards adopting digitalization in agriculture is the anticipated benefits of digitalization which adds significant value to their agricultural activities and production improvement. Therefore, this study has found that 78 % of farmers have been using digital information in their agricultural practices due to its ability to eliminate risks and uncertainty, while 74.75 % claim it has facilitated access to finance and services, and about 76.5 % in extension services. Other benefits of digitalization in agriculture are described in Table 3.

Table 4 reveals that male farmers have negative and insignificant impact on the adoption of digital technologies in both Hurdle I and Hurdle II. This result contradicts the findings of Mtega and Msunga [38], who suggested that gender disparities may impact farmers' access to and adoption of technology significantly. While the insignificance in this study challenges the gender disparity narrative, it underscores the need for nuanced investigations into the multifaceted factors influencing technology adoption in agricultural contexts.

In both tiers, household income emerges as a crucial determinant of digital technology adoption. In Hurdle I, higher income levels significantly increase the likelihood of adoption, highlighting the importance of financial capacity for gaining access to technology. In a similar agricultural context, Repo [39] found a positive relationship between income and technology adoption. In Hurdle II, income has a positive effect on the extent of adoption, corroborating [40] assertion that a higher income is associated with a greater degree of technology integration.

This finding is consistent with Sullivan and Drenman [22], who emphasized the logistical benefits of technology adoption in smaller households. This relationship, however, does not persist in Hurdle II, indicating that the size of the household does not significantly affect the degree of technology integration. The complex interaction of socio-demographic factors in determining adoption patterns is highlighted by the nuanced role of household size.

Table 3
Benefits of digitalization among smallholder farmers.

Benefits of adoption	Response	Frequency	Percentage
Timely market information	Yes	289	72.25 %
	No	111	27.75 %
Increase the volume of sales	Yes	221	55.25 %
	No	179	44.75 %
Reduces crop losses	Yes	209	52.25 %
	No	191	47.75 %
Increase market information	Yes	242	60.50 %
	No	158	39.50 %
Eliminate risks and uncertainty	Yes	312	78.00 %
	No	88	22.00 %
Improves pests management	Yes	285	71.25 %
	No	115	28.75 %
Improves crop management	Yes	239	59.75 %
	No	161	40.25 %
Access to finance and services	Yes	299	74.75 %
	No	101	25.25 %
Building financial inclusion	Yes	273	68.25 %
	No	127	31.75 %
Improves rural land governance	Yes	290	72.50 %
	No	110	27.50 %
Extension services	Yes	306	76.50 %
	No	94	23.50 %

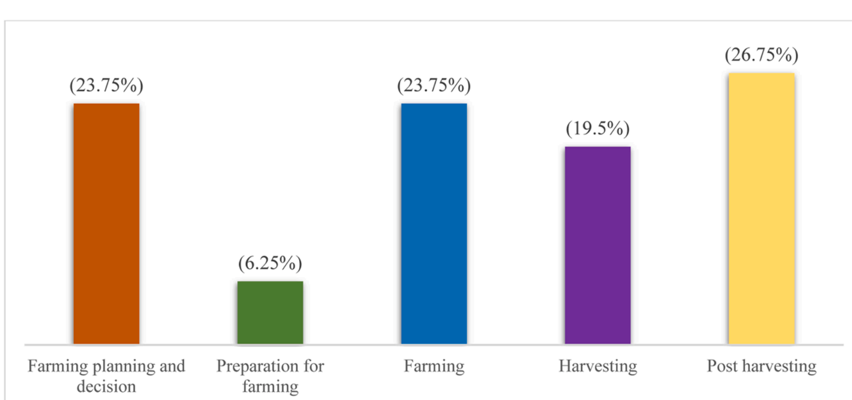

Fig. 5. Use of agricultural digital information among farmers.

Table 4
Double hurdle regression results on determinants and extent of digital technology adoption among smallholder farmers in Tanzania.

Explanatory variables		Hurdle I (Determinants)		Hurdle II (Extent)	
		Coefficient	Robust Std. Err	Coefficient	Robust Std. Err
Sex (Male)		−0.11316	0.36812	−0.04475	0.03645
Household income		0.23011***	0.00014	0.16395**	0.00922
Household size		−0.07101***	0.07836	0.04740**	0.0033
Access to finance		0.17428***	0.35793	0.09672**	0.03438
Asset ownership		0.12801***	0.05933	0.24646**	0.02127
Education level	No schooling	−0.23219***	0.00431	−0.10131**	0.00102
	Primary school	0.00783	0.09322	−0.03210	0.08321
	Secondary school	0.12448**	0.00893	0.09172***	0.00000
	Tertiary education	0.28109**	0.06431	0.11371**	0.00183
Unmarried farmers		−0.19485	0.38316	−0.05132	0.09174
Age of farmers		0.03029	0.01869	0.09275	0.30172
Farming experience		0.18347**	0.00557	0.17230***	0.00652
Government support		0.10922**	0.00438	0.20939**	0.04688
Mobile phone ownership		0.01024**	0.01001	0.14030***	0.00953
Social media engagement		0.30031**	0.10041	0.25101***	0.03144
Extension service		0.52884***	0.00067	0.48992***	0.01832
Distance to market		0.23165*	0.08152	0.42138**	0.03451
Regions	Rukwa	0.10622	0.30221	0.04711	0.21992
	Ruvuma	−0.05732	0.32170	−0.11418	0.09471
	Tabora	0.01422**	0.00019	0.10881***	0.00035
	Morogoro	0.16903**	0.01331	0.09517***	0.00042
Pseudo R square		**0.3578**			
Chi-square		**0.0000**			
Goodness-of-fit statistics		**AIC = 3262.146 BIC =3294.268**		**AIC = 3017. 841 BIC = 3109. 229**	

*** $p < 0.01$,.
** $p < 0.05$,.
* $p < 0.1$.

Farmers with greater access to financial resources are more likely to adopt digital technology at both levels of their operations. This result is consistent with the findings of Gakuru et al., [41], who highlighted the role of financial resources in overcoming barriers to technology adoption. Moreover, as observed in Hurdle II, access to finance contributes to a more comprehensive adoption of technology. Collectively, these findings demonstrate the significance of financial inclusion strategies in fostering the adoption of sustainable technologies.

In both tiers, the possession of assets emerges as a significant determinant of technology adoption. Hurdle I asset ownership influences adoption positively, consistent with Mpogole et al., [42], who emphasized the role of asset accumulation in enhancing technology affordability and access. This positive effect extends to Hurdle II, supporting the notion that asset ownership encourages a deeper integration of digital technologies into agricultural practices.

Education has varying effects on the adoption of technology across tiers. In Hurdle I, farmers with no formal education are less likely to adopt technology, consistent with Rashid and Elder [43] emphasis on the role of education in fostering technology literacy. However, the effect of education differs in Hurdle II, where secondary and tertiary education have a positive effect on the rate of adoption. While education may influence the initial decision to adopt, its influence on the degree of technology integration is nuanced and complex, as suggested by these findings.

Both the likelihood and extent of technology adoption are positively influenced by farming experience at both levels. This is consistent with Kitole et al., [6], who identified the experiential learning component of farming as a catalyst for technology engagement. The positive correlation between farming experience and technology adoption highlights the knowledge and abilities that veteran farmers bring to the process of adoption.

Government support significantly improves the adoption of technology in both tiers. The positive impact of government assistance is consistent with Samuel et al., [44] emphasis on the role of policy interventions in promoting the adoption of technology. In addition, government support contributes to more extensive adoption of technology in Hurdle II, indicating that supportive policies promote deeper incorporation of digital tools into agricultural practices.

The possession of mobile phones influences technology adoption in both tiers positively. This is consistent with the findings of Gillwald and Esselaar [45], who highlighted the transformative role of mobile phones in bridging information gaps and promoting technology adoption. The positive impact of mobile phone ownership extends to Hurdle II, indicating that mobile phone ownership contributes to greater use of digital technologies.

Social media participation is a significant factor in determining technology adoption in both tiers. This result is consistent with the findings of Osei-Akoto et al., [46], who emphasized the influence of social networks on technology adoption behavior. In addition, participation in social media has a positive effect on the extent of technology adoption in Hurdle II, highlighting the interactive nature of online platforms as a driver of comprehensive technology integration.

The effects of market proximity on technology adoption vary across tiers. In Hurdle I, market proximity does not significantly affect adoption, contrary to Rashid and Elder [43], who hypothesized that market proximity could affect technology access. In Hurdle II, however, a positive relationship emerges between market proximity and adoption. This nuanced finding highlights the intricate relationship between market access and technology integration.

Among the regions, Tabora and Morogoro stand out as major contributors to the adoption and spread of technology at both levels. This is consistent with Saleh [47], who emphasized regional differences in rates of technology adoption. Ruvuma emerges as insignificant in both tiers, challenging the regional influence observed by [48] on technology engagement.

The findings of this study both support and expand upon the conclusions drawn in previous research concerning the adoption of technology among smallholder farmers. The positive impact of household income on technology adoption aligns with the results found by Muto and Yamano [34]. Similarly, the influence of education on adoption behavior corresponds with the outcomes observed by Neményi et al. [13]. Noteworthy insights from Kitole et al. [6] emphasize the transformative potential associated with mobile phone ownership and engagement in social media.

While certain consistencies align with prior research, noteworthy deviations surface. Table 4 highlights a positive correlation between age and digital adoption although not statistically significant hence departing from Keogh and Henry's [5] emphasis on age's pivotal role in behavioral change and technology adoption. These results indicate that age influences smallholder farmers decision to adopt technology, and further determine their extent of adoption.

Results on Table 5 outline the outcomes of an in-depth analysis into the potential effects of digitalization on the welfare of smallholder farmers. Three distinct regression models of Ordinary Least Squares (OLS), Two-Stage Least Squares (2SLS), and Control Function Approach (CFA) have been applied to examine the association between digital adoption and various indicators of well-being among farmers.

The OLS regression model reveals a statistically significant positive correlation between years of schooling and farmers' welfare (β= 0.29219, $p < 0.1$). This suggests that increased education is linked with enhanced well-being. Notably, this relationship remains robust in the 2SLS model ($\beta = 0.31954, p < 0.05$) and is further reinforced in the CFA model ($\beta = 0.37332, p < 0.001$). These findings are congruent with the conclusions drawn by Rashid and Elder [43], who also highlighted the role of education in fostering improved economic outcomes among farmers.

Neither age nor its squared term exhibits a significant to farmers'

Table 5
Effects of digital adoption on smallholder farmers' welfare.

Variables	Regression 1 OLS	Regression 2 2SLS	Regression 3 CFA
Years of schooling	0.29219*	0.31954**	0. 37,332***
	(0.11045)	(0.0899)	(0.0130)
Place of residence (Rural)	0.34164	0.37026	0.40658
	(0.19447)	(0.2084)	(0.23327)
Sex (Male)	0.10258	0.13657	0.21678
	(0.21921)	(0.2619)	(0.3382)
Age	0.03679	0.03816	0.03718
	(0.0943)	(0.2913)	(0.1091)
Age square	0.00135	0.00145	0.00138
	(0.0462)	(0.2150)	(0.1481)
Agricultural Input prices	−0.31282	−0.38981	−0.45366
	(0.4115)	(0.3177)	(0.3381)
Access to credits	0.21374*	0.24763**	0.32846**
	(0.0968)	(0.0837)	(0.0721)
Household size	0.27219***	0.29170***	0.31596***
	(0.0073)	(0.0042)	(0.0010)
Total Household Expenditure	−0.19473**	−0.21873**	−0.20216***
	(0.0535)	(0.0588)	(0.0067)
Digitalization Adoption	0.34212***	0.38503**	0.41702***
	(0.0288)	(0.0745)	(0.0252)
Residuals			0.37026***
			(0.0014)
Digitalization*Residuals			0.34204**
			(0.0832)
Constant	0.55264	0.47808	0.79911
	(0.8319)	(0.3716)	(0.6811)
Durbin Wu-Hausman		0.76852	
R-squared	0.5577	0.57373	0.58704
Test for strength of instrument	F (1400) = 3.86481	Prob>F = 0.0000	

Standard errors in parentheses.
*** $p < 0.01$,.
** $p < 0.05$,.
* $p < 0.1$.

welfare in any of the models. This implies that age does not seem to have a distinct association with well-being outcomes, regardless of the extent of digital adoption. These results diverge from those of Rotondi et al. [18] and Sanga et al. [48], who proposed that older farmers might experience distinct welfare outcomes in response to technology adoption.

Access to credit resources yields a positive correlation to farmers' welfare in both the OLS ($\beta = 0.21374, p < 0.1$) and 2SLS ($\beta = 0.24763, p < 0.05$) models. This effect is further accentuated in the CFA model (Coefficient $= 0.32846$, $p < 0.01$). These findings are consistent with Gakuru et al. [41], who emphasized the role of credit accessibility in bolstering the financial well-being of farmers by means of technology-enabled opportunities.

Digital adoption emerges as a salient determinant for farmers' welfare in all three models. The OLS model ($\beta = 0.34212, p < 0.001$), the 2SLS model ($\beta = 0.38503, p < 0.01$), and the CFA model ($\beta = 0.41702, p < 0.001$) concur in highlighting the positive impact of embracing digital technologies on well-being. These outcomes substantiate the transformative potential of digitalization, in line with the conclusions drawn by Staal et al. [14] and, Ugochukwu and Phillips [8].

Moreover, the outcomes of this study align with the conclusions drawn from previous research regarding the interplay between digitalization and the welfare of smallholder farmers. The observed positive impact of digitalization on welfare resonates with the findings of Wyche and Steinfield [37] and, Yeates [17], who underscored the transformative potential of technology adoption. Similarly, the positive roles of education and credit access in augmenting well-being correspond with the insights presented by Sykuta [49].

Model specification

1.1 Test of endogeneity

The utilisation of the Durbin-Wu-Hausman test was a pivotal component within this study, serving the purpose of examining the presence of endogeneity. Notably, the findings unveiled in Table 6 elucidate that the probability value associated with the Durbin-Wu-Hausman test does not surpass the established significance threshold of 0.05. In light of this outcome, the research findings effectively negate the null hypothesis, thereby establishing the endogenous nature of the digitalization adoption variable. A noteworthy feature of this study was the strategic integration of an instrumental variable (specifically, distance to the nearest market) to meticulously address the issue of endogeneity. This methodological approach significantly bolsters the coherency and precision of the estimation technique employed in the research.

Strength of instruments

The present study has employed the Limited Information Maximum Likelihood (LIML) approach, with Table 7's final row assessing the instrument's effectiveness. With a 10 % rejection rate for a nominal 5 % Wald Test, an eigenvalue statistic of 61.32 surpasses critical values in Table 7. Consequently, the null hypothesis of weak instruments is rejected, indicating no presence of a weak instrument problem.

Discussion

The findings of the study shed light on various determinants influencing the adoption of digital technology among smallholder farmers in Tanzania. Household income emerges as a significant factor positively associated with digital adoption. This aligns with the existing literature, as higher income levels provide farmers with the necessary resources to invest in digital tools and technologies [18,25,48]. On the other hand, household size negatively affects the likelihood of adoption, indicating that smaller households are more inclined to embrace digital technologies. This may be attributed to the ease of managing and implementing technological advancements in smaller family units [32,47]. Additionally, factors such as access to finance, asset ownership, education level, and government support all play pivotal roles in fostering digital adoption among smallholder farmers. These findings resonate with studies emphasizing the importance of financial access, assets, and education in the adoption of agricultural innovations [16,35].

Moving to the impact of digital adoption on smallholder farmers' welfare, several variables exhibit noteworthy implications. Years of schooling positively correlate with farmers' welfare, emphasizing the role of education in enhancing overall well-being. This aligns with the notion that education equips farmers with knowledge and skills vital for navigating a rapidly evolving agricultural landscape [23,26]. Surprisingly, the place of residence (rural) does not significantly affect welfare, challenging the conventional assumption that rural areas may experience limited access to resources. The non-significant effect of sex (male) implies that gender does not inherently dictate welfare outcomes, emphasizing the need for gender-inclusive agricultural development policies [4,32].

The inclusion of age and its squared term introduces nuanced dynamics. While age itself does not significantly impact welfare, the positive coefficient for the squared term suggests a curvilinear relationship. This may imply that the benefits of age on welfare reach a peak and then

Table 6
Test for endogeneity.

Tests	Test scores	P - value
Durbin (score) chi2(1)	6.7806	0.0008
Wu-Hausman	3.86481	0.0012

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
Instrument strength by eigenvalue statistic.

	Critical values			
2SLS relative bias	0.05(5 %)	0.1(10 %)	0.2(20 %)	0.3(30 %)
	21.03	18.91	15.02	5.39
	0.1(10 %)	0.15(15 %)	0.2(20 %)	0.25(25 %)
2SLS size of nominal 0.05 Wald test	30.22	19.83	17.54	9.18
LIML size of nominal 5 % Wald test	9.07	7.36	5.69	3.32

eigenvalue statistic = 61.32.

plateau or decline, reflecting the intricate interplay between age and technological adaptability [11,30].

The negative impact of total household expenditure on welfare raises intriguing questions. It suggests that higher expenditures do not necessarily translate to improved welfare, urging a closer examination of how financial resources are allocated and utilized within households [7,50]. The positive and significant association between Access to Credits and welfare underscores the pivotal role of financial accessibility in enhancing smallholder farmers' overall well-being.

Most notably, the variable digitalization adoption consistently emerges as a significant and positive determinant of farmers' welfare across all models. This reaffirms the transformative potential of digital technologies in uplifting smallholder farmers' livelihoods. The positive relationship between digital adoption and welfare can be attributed to enhanced access to critical information, improved market linkages, and increased productivity facilitated by digital tools [4,6,8].

Intriguingly, the inclusion of a Control Function Approach (CFA) in the third regression introduces the interaction term between digitalization and residuals. The positive and significant coefficient for this term suggests that the combined effect of digital adoption and unobservable factors not captured by the model has an additional positive impact on farmers' welfare. This underscores the intricate interplay of both observable and unobservable factors in shaping the welfare outcomes of smallholder farmers.

Conclusion

The agricultural transformation in developing countries serves as a catalyst for growth and development, exemplified by initiatives like Tanzania's Agenda 10/30. This ambitious agenda aims for a 10 % growth in the agriculture sector and a 30 % contribution to the GDP by 2030, emphasizing the pivotal role of agriculture in fostering inclusive growth, poverty eradication, health improvement, and food security [3]. To achieve these goals, a mandatory shift from traditional to digitalized agriculture becomes imperative, ensuring the seamless flow of knowledge to mitigate uncertainties in production. This study underscores the significance of socioeconomic and institutional factors—such as extension services, government support, credit accessibility, and market proximity—in shaping smallholder farmers' decisions to adopt digitalization. Moreover, those adopting digital technologies demonstrate a higher likelihood of experiencing improved welfare compared to their non-adopting counterparts in farming activities.

Moreover, based on the study's findings, several recommendations emerge for policymakers and stakeholders aiming to harness digitalization's potential in the African agricultural landscape, which includes the enhancement of financial inclusion and facilitate digital technology adoption among smallholder farmers in Tanzania and other developing countries, policymakers should collaborate with financial institutions to design microfinance programs tailored to the agricultural sector. These programs should offer accessible credit facilities with favorable terms, encouraging farmers to invest in digital tools and technologies. Additionally, governments can explore partnerships with mobile banking services to provide convenient and secure financial transactions for farmers in remote areas.

Implementing targeted educational programs requires a multifaceted approach. In Tanzania, the Ministry of Education and Agriculture should collaborate to integrate digital literacy into the national curriculum, ensuring that students, especially those in rural areas, receive early exposure to technology. Furthermore, extension services should be revamped to include practical training on the use of digital tools. Partnerships with non-governmental organizations (NGOs) can facilitate the delivery of on-the-ground workshops and demonstrations, emphasizing the practical applications of digital technologies in farming practices.

Moreover, for a comprehensive approach, policymakers should design support packages that address the diverse challenges faced by smallholder farmers. In Tanzania, this could involve the establishment of farmer resource centers in rural areas, providing access to information, training, and assistance in navigating digital platforms. Government support programs should integrate initiatives for asset ownership, such as subsidized access to essential farming equipment and technology. Collaborations with private-sector partners can help ensure the sustainable implementation of these support packages.

Promoting existing digital platforms requires a concerted effort to increase awareness and facilitate user engagement. In Tanzania, the government, in collaboration with telecommunications companies, can launch targeted awareness campaigns through community radio stations and local events. Extension officers should be trained to guide farmers in using platforms like the Mobile Kilimo application and Agricultural Trade Management System, ensuring practical understanding and effective utilization. Regular workshops and demonstrations can further reinforce the benefits of these platforms.

Encouraging public-private partnerships is essential for bridging the digital divide in agriculture. In Tanzania, policymakers should create a conducive regulatory environment that incentivizes private companies to invest in agricultural technology. This could involve tax incentives, streamlined approval processes, and collaboration with international organizations to attract investments. Partnerships can extend to establishing community digital hubs, where private entities collaborate with local communities to provide access to digital tools, training, and ongoing support. Therefore, by implementing these detailed and practical recommendations, policymakers can contribute to creating a supportive ecosystem for digital technology adoption among smallholder farmers, fostering sustainable agricultural development in Tanzania and other developing countries.

Ethics approval

Ethical approval for this study was obtained from MINISTRY OF AGRICULTURE with Reference HA/48/231/01

Informed consent

Verbal informed consent was obtained from all subjects before the study.

CRediT authorship contribution statement

Felician Andrew Kitole: Conceptualization, Data curation, Formal analysis, Methodology, Visualization, Writing – original draft, Writing – review & editing. **Eliaza Mkuna:** Conceptualization, Formal analysis, Writing – review & editing. **Jeniffer Kasanda Sesabo:** Formal analysis, Methodology, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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