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Impact of Rural Out-Migration on Agricultural Technology Adoption of Rural Households in Southern Ethiopia

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Abstract

Using the new economics labor migration theory as a theoretical framework and the multinomial treatment effects negative binomial regression as an analytical model in southern Ethiopia, this study investigated the effects of rural out-migration on the intensity of agricultural technology adoption. In the year 2021, data were collected from 415 sample houses using stratified random sampling. Regression analysis showed that while the influence of migration from rural to urban areas is negligible, participation in international migration greatly increases the likelihood of technology adoption in rural families by 38.9%. The intensity of agricultural technology adoption by rural households is negatively and significantly correlated with male-headed households and household age, while the frequency of extension visits, non-farm participation, saving, membership in cooperatives, sales of livestock, and tropical livestock unit are positively and significantly related to the intensity of agricultural technology adoption. The outcome is consistent with the labor migration theory's risk and credit hypotheses. To encourage the adoption of agricultural technology and stop the recent surge of rural out-migration in southern Ethiopia, policymakers should provide access to capital, public services, and viable off-farm employment in rural areas.

Keywords

Migration, self selection bias, negative binomial regression, technology adoption.

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Introduction

Migrants move from areas with limited economic activity to areas with better economic opportunities, and the primary cause of migration is the economic discrepancy between migrant-sending and migrant-receiving areas (World Bank, 2020). Between 2000 and 2019, the number of international migrants in the world increased from 174 to 272 million people (UNDESA, 2020). Between 2000 and 2019, the total amount of remittances from international migrants increased from 121.6 billion to 714.2 billion United State dollars in the world (UNCTAD, 2020). Further, about 77 percent of the remittance flow is directed to developing countries. Added to this, the number of internal migrants has been mounting and reached 1.3 billion in developing countries in 2016 (FAO, 2019).

Despite the continuous flow of labor from the rural agricultural sector to urban non-agricultural sectors and capital in the form of remittance from urban non-agricultural sectors to the rural agricultural sector, the impact of rural out-migration on agricultural technology adoption in migrant-sending origin areas is the source of debate (United Nations, 2016). Put differently, the impact of rural out-migration on agricultural technology adoption in migrant-sending rural areas is expected to be dichotomous. On the one hand, there is an optimistic view of rural out-migration which claims that rural out-migration promotes agricultural investment in migrant-sending rural areas through remittance (Stark,1985). On the other hand, there is a pessimistic view of rural out-migration which considers migration as a loss of human capital to migrant-sending origin areas (Rozelle et al. 1999; Lucas, 1987).

With an estimated 115 million population in 2020, Ethiopia is the second-most populous country in Africa, and the 12th in the world (World Bank, 2021). Both rural-urban and international migration have different patterns in Ethiopia under different

political regimes (Adugna, 2021). First, during the emperor's regime (1941-1974), both rural-urban and international migration were insignificant in Ethiopia (Lyons, 2009), and only an estimated 20,000 people out-migrated to western countries primarily to get an education (Terrazas, 2007). Second, during the military government (1974-1991), international migration increased mainly due to political repression, civil war, and the mid-1980s famine in Ethiopia. But rural-urban migration was limited due to the restrictions on rural out-migration mainly through forced villagization (Alemu, 2005). Third, during the current government (1991 onwards), both rural-urban and international migration have been mounting in Ethiopia. While the percentage of rural-rural migrants decreased from 35.6 to 23.4, the percentage of rural-urban migrants increased from 21.6 to 32.2 between 1999 and 2021 (LMS, 2021). Regarding international migration, while the stock of international migrants increased from 611 thousand to 1.1 million people, the inflow of remittances increased from 53 to 404 million US dollars between the period 2000 and 2020 (World Bank, 2021). About 42, 26.9 and 25.6 percent of Ethiopian emigrants originated from rural areas of Oromia, Amhara, and SNNP regions respectively (LMS, 2021).

Regarding the destination of migrants, 30.7, 12.4, 8.9, and 8.3 percent of migrants from Ethiopia were directed to Saudi Arabia, South Africa, United Arab Emirates, and the United States respectively (LMS, 2021). Generally, international migrants from Ethiopia use three major migration corridors. First, the eastern corridor is the busiest route of migration, and Ethiopians migrate to the Middle East following this route since the 1990s. Most of the migrants who traveled following this path are young, female, and unmarried traveling mainly as houseworkers. Female migrants make near 95 percent of all formal migrants from Ethiopia in the Middle East (MoLSA, 2018). Second, Ethiopian migrants use the northern migration corridor only in rare cases to transit through Sudan to Libya and Europe (Massey et al., 1998). Third, the southern migration corridor runs from the Horn of Africa to South Africa. While Ethiopia and Somalia are the major sources of migrants to South Africa, Ethiopia alone accounts for two-thirds of the migrants (Horwood, 2009). Hadiya and Kembata from southern Ethiopia largely migrate to South Africa (Zewdu, 2015). The migration from Hadiya and Kembata-Tembaro zones to South Africa started in 2000 (Kanko et al., 2013). Though migration from these two zones to South Africa started in recent years, the level of outflow is very high, and more than 39.4 percent of rural households have at least one international migrant (Tsedeke and Ayele, 2017).

While few studies (Mendola, 2005; Williams, 2014; Shi, 2020; Sun et al., 2021) have examined the link between rural out-migration and technology adoption, they found mixed results, focused on the adoption of a single technology and not controlled for self-selection bias into migration. This study examined the impact of rural out-migration on the intensity of technology adoption using the new economics labor migration theory as a theoretical framework, and multinomial treatment effects negative binomial model as an analytical model. The rest of this study is organized as follows. The second section presents the literature review. The third section describes the materials and method. The fourth section presents results and discussion while the fifth section deals with the conclusion.

Literature review

Theoretical review

There are various theories of migration (Ravenstein, 1885; Lewis, 1954; Lee, 1966; Harris-Todaro, 1970; Stark, 1985) that predict the relationship between rural out-migration and agricultural technology in economic literature. Lewis's (1954) two-sectors migration theory insists that the withdrawal of labor from the rural agricultural sector to the urban industrial sector improves the productivity of both, and will lead to economic development. This theory assumes that there is a surplus of labor in the rural agricultural sector and a shortage of labor in the urban industrial sector. According to this theory, the rural areas of developing countries are characterized by smallholder farmers, rapid population growth, and low agricultural productivity. Hence, the transfer of labor from the agricultural sector to the urban industrial sector would improve production in receiving urban and sending rural areas (Ranis, 2003).

The human capital theory of migration (Harris and Todaro, 1970) primarily focuses on the causes, and impacts of rural out-migration on migrants and migrant-receiving urban areas. This theory claims that rural out-migration is primarily caused by wage differences between migrant-sending and receiving areas. According to the neoclassical theory of migration, migration decisions are made at an individual level. However, the new economics labor migration theory (Strak, 1985) primarily

focuses on the impact of rural out-migration on migrant-sending rural areas, and this theory has shifted the unit of analysis from individual to household level in migration studies. This theory states that the limited access to insurance and credit services in rural areas is the primary cause of participation in rural out-migration. There are two hypotheses regarding the impact of rural out-migration on agricultural technology adoption by rural farmers; the risk hypothesis and the credit hypothesis. According to these two hypotheses, agricultural investment depends on both the level of risk aversion and the credit constraints of rural farm households. The risk and credit hypotheses state that rural out-migration increases the adoption of new agricultural technology by reducing the risk aversion and credit constraint of households. In other words, remittance from rural out-migration will not only be used for household consumption and rather but will also be used to finance the adoption of agricultural technologies by rural households (Stark, 1985).

On the one hand, the risk hypothesis assumes that rural out-migration is an important tool to ensure rural households against the risk of agricultural losses. In other words, if a rural household adopts agricultural technology and the crop fails, migrants will direct more remittances to households in the origin areas to cover the losses. Hence, the presence of a migrant member in the household will increase the likelihood of agricultural technology adoption even if the remittance is unobserved. Remittance is observed if and only if the household faces crop failure (Lucas and Stark, 1985; Tylor and Wyatt, 1996). Therefore, the risk hypothesis states that the number of migrants and the likelihood of agricultural technology adoption by rural farmers are positively correlated.

On the other hand, the credit hypothesis states that capital is a very scarce factor of production in rural areas and agricultural productivity and technology adoption depends on credit constraint. The adoption of new agricultural technology requires finance but the unbanked rural household faces liquidity constraints. This implies that remittance from migrants to migrant-sending households will increase the likelihood of new technology adoption by lessening the credit constraint of farmers. According to the credit hypothesis, ceteris paribus, remittance from migrants increases crop production efficiency and the likelihood of agricultural technology adoption by smallholder farmers. So, the household undertakes the migration of its members to get remittances and finance agricultural investments. The basic assumption of these hypotheses is that rural households are unbanked and unable to borrow money to finance their agricultural investments against future harvests (Tylor, 1999).

Besides, the new economics labor migration theory assumes that there are four motives of remittance from migrants namely; altruism, insurance contract, loan contract, and investment (Lucas and Stark, 1985). The altruism motive insists that migrants send remittances because they care about their families (Stark, 2009) while the insurance motive claims that migrants send remittances to protect their families against shocks (Rosenzweig and Stark, 1989). The loan contract motive claims that remittances are the repayment of informal loans which is taken by migrants from their family to enhance their human capital and finance the cost of migration. Finally, the investment motive argues that migrants send remittances to households in the origin areas to return and inherit the investment (Lucas, 1985). Therefore, the new economics labor migration theory assumes that the primary causes of rural out-migration are the lack of credit and insurance markets, and rural out-migration affects the technology adoption behavior of migrant-sending households by lessening the risk aversion level and credit constraint of households. This study applied the new economics labor migration theory as a theoretical framework

Empirical review

This section presents an empirical review of the impact of rural out-migration on agricultural technology adoption. The theoretical literature predicts that rural out-migration promotes agricultural technology adoption in origin areas by reducing the risk aversion level and the credit constraints of rural households. However, previous studies on the link between rural out-migration and agricultural technology adoption found mixed results. On the one hand, some previous studies on the link between rural out-migration and agricultural technology adoption found a positive and significant association (Mwungu et al., 2018; Maguza-Tembo et al., 2017; Tesfaye and Tirivayi, 2016). Added to these, a study conducted by (Tshikala, 2014) on the link between remittance from migration and agricultural technology adoption obtained a positive and significant association. Still, a study conducted by (Abebaw et al., 2019) on the effect of rural-urban migration on agricultural investment showed that participation in rural out-migration increases expenditure on livestock and pesticides. Moreover, a study conducted by Bhandari

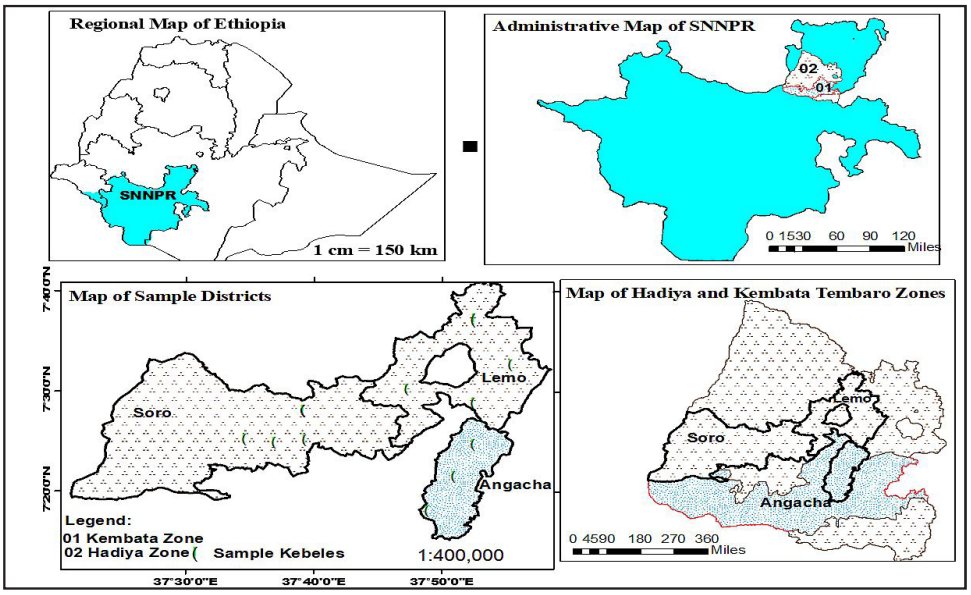
and Reddy, (2015) on the impact of migration on technology adoption in Kenya using data from the world bank and the two-stage least square estimation technique found that rural out-migration positively affects the use of improved seeds by farmers. In addition, a study conducted by Sun et al., (2021) on the impact of rural-urban migration on rice farmers' agricultural machinery expenditure indicated that rural-urban migration significantly increases households' expenditure on agricultural machinery.

On the other hand, Williams (2014) examined the impact of migration on technology adoption, natural resource conservation, and household welfare in Nepal using cross-sectional data and a three-stage least square technique of estimation, and the results indicated that migration and remittance decrease the number of natural resource conservation practices adopted by farmers. Similarly, Zegeye (2021) conducted a study on impact of remittance on technology adoption in Ethioppia using cross-sectional data and probit model, and the study found that remittance significantly reduces agricultural technology adoption in Ethiopia. Yet, Mesele et al. (2022) investigated the determinants of agricultural technology adoption using cross-sectional data and multinomial logit model, and found that households with lower remittance have a higher propensity to adopt agricultural technology. Though few studies have examined the impact of rural out-migration on technology adoption, they found mixed results, focused on the adoption of a single technology, and did not control the problem of self-selection bias. This study examined the impact of migration on the intensity of technology adoption by controlling self-selection biases.

Materials and methods

The study area

The Southern Nations, Nationalities, and People's (SNNP) regional state is one of the nine regional states in Ethiopia. The SNNP regional state accounts for 10 and 20 percent of the land area and the population of Ethiopia respectively. There are fifteen zones in SNNP regional state, and this study was conducted in the Hadiya and Kembata-Tembaro zones of the SNNP regional state. These two zones are the most densely populated and the primary sources of both internal and international migrants in Ethiopia (Degelo, 2015). Hosanna and Durame are the capital towns of the Hadiya and Kembata-Tembaro zones and are located 267km and 260km southwest of Addis Ababa respectively. The population of the Hadiya and Kembata-Tembaro zones was 1,747,356 and 996,969 people while the total land size was 3,593.31 and 1,355.90 square kilometers respectively (CSA, 2021). There are eleven and seven districts in Hadiya and Kembata-Tembaro zones respectively. While Soro and Lemo districts were selected from the Hadiya zone, the Angacha district was selected from the Kembata-Tembaro zone for this study purposively. These three districts are the leading sources of migrants (Kanko et al., 2013). The location of the sample districts is presented in Figure 1.



Source: Author compilation, 2021

Figure 1: Map of study area, and sample districts in Hadiya and Kembata Tembaro Zones.

Soro district is placed between 7°23' and 7°46' north latitudes and 37°18' and 37°23' east longitudes. The altitude of the district ranges from 840 to 2850 meters above sea level. The farming system of the district is a mixed system of crop production and livestock husbandry (SDARDO, 2021). Lemo district is located between 7°22' and 7°45' north latitudes, and 37°40' and 38°00' east longitudes. The altitude of the district ranges from 1900 to 2720 meters above sea level. Crop production and livestock husbandry are the chief livelihood source of the population (LDARDO, 2021). Anigacha district is found between 70°30' and 70°34' north latitudes and 370°83' and 370°88' east longitudes. The altitude of the district ranges from 1501 to 3000 meters above sea level. Crop and livestock productions and animal husbandry are the key sources of livelihood for the population in the district (ADRADO, 2021).

Data sources and collection tools

Cross-sectional data were collected from 415 sample rural households in three districts namely; Lemo, Soro, and Angacha in southern Ethiopia using structured questionnaires. Focus group discussions and interviews with key informants were also held to support the data collected using the questionnaire. Also, secondary data were gathered from the Central Statistical Authority of Ethiopia, the World Bank, the Food and Agriculture Organization, the United Nations Development Program, the Ethiopian Ministry of Labor and Social Affairs, the United Nations Department of Economic and Social Affairs, and other published and unpublished documents to get background information about the research area. The training was given to data collectors, and they gathered primary data using a survey questionnaire. A list of fourteen portfolios of agricultural technologies that include improved seed, chemical fertilizers, row planting, mulching, crop rotation, irrigation, compost, crop residuals, chemicals, terracing, animal fodder, inter-cropping, tree planting, and improved livestock were prepared, and each sample household was asked whether he/she adopted a particular technology or not. As a result, the outcome variable is a count variable with values between 0 and 14. Cross-sectional data on various socio-economic, demographic, and farm characteristics of rural households were also collected to quantify the impact of rural out-migration on the intensity of agricultural technology adoption in a migrant-sending rural area.

Sampling procedures and sample size

Sample zones and districts were selected purposively while sample Kebeles were selected using the proportionate random sampling technique. First, from the fifteen zones in the SNNP region, Hadiya and Kembata Tembaro zones were purposively selected for this study. This is because the two zones are the most densely populated, and the primary sources of both internal and international migrants in southern Ethiopia (Zewdu, 2015; Degelo, 2015). Second, from the 11 districts in the Hadiya zone, Soro and Lemo districts were selected while from the 7 districts in the Kembata-Tembaro zone, the Angacha district was selected for this study. Still, these districts are the main sources of international migrants in the Hadiya and Kembata-Tembaro zones (Kanko et al., 2013). There are 33, 33, and 17 rural Kebeles in Lemo, Soro, and Angacha districts, respectively. Third, 11 sample Kebeles were selected from the sample districts using proportionate random sampling, and accordingly, four Kebeles (Sundusa, Sonda, Shara, and Bona), three Kebeles (Kerekicho, Garba Fandide, and Bobicho), and four Kebeles (Haise, Shurmo, Jawe, and Sena) were selected from Soro, Angacha, and Lemo districts respectively. Fourth, sample *gots*[1] were randomly selected from each sample Kebele to prepare a sampling frame that contains the lists of households with no migrants, rural-urban migrants, and international migrants. Sample households were included in the study using a stratified random sampling technique from each sample got. As a result, 193, 85, and 137 sample households with no migrants, rural-urban migrants, and international migrants were used in this study respectively. This study employed the following Cochran (1963) formula to obtain an adequate sample size with 95, 50, and 5 percent confidence levels, degree of variability in the population, and the level of precision respectively.

$$\boldsymbol{n = \frac{Z^2pqN}{e^2(N-1)+Z^2pq}}$$

where *e, p, q, n, N*, and *Z* are the measure of precision, the assumed level of variability in the population, one minus the level of variability in the population, the sample size of the study, the total population and the value of standard normal distribution respectively. The total households (*N*) in the three districts, degree of variability, and level

[1] Gots are the lowest level of administration in the study area which mostly contain more than 50 households. From a total of 147 gots in all sample Kebeles, 36 sample gots were included in the study.

of precision in this study were 69277, 0.5, and 0.005 respectively. Based on the above formula, a sample size of 383 was determined for the present study. But by adding ten percent of this figure to account for incomplete responses, a total of 421 questionnaires were distributed to enumerators and this study finally used data from 415 completed questionnaires.

Methods of data analysis

Both descriptive and econometric analyses were employed to analyze the data collected from sample households. To quantify the impact of rural-urban and international migration on the intensity of agricultural technology adoption, the value of the outcome variable which is the count of technologies adopted by each household lies between 0 and 14. The treatment variable is participation in rural out-migration which is a nominal variable with three categories[2]: households without migrants (j = 0), with rural-urban migrants (j = 1), and with international migrants (j = 2). Some control variables are also included while measuring the impact of rural out-migration on the outcome variable.

Specification of analytical model

The objective of this study is to quantify the impact of rural out-migration on the intensity of agricultural technology adoption by rural households. The new economics labor migration theory claims that households participate in rural out-migration by sending at least one family member to urban areas to reduce risks and overcome liquidity constraints. The implication of this theory is rural out-migration affects agricultural investment and the welfare of migrant-sending households in origin areas via remittance. In this study, to examine the impact of rural out-migration on the intensity of agricultural technology adoption, the number of technologies adopted by households is used as the outcome variable whereas the participation in rural out-migration is used as a treatment variable. The number of potential portfolios of agricultural technologies in this study is 14 and the value of the outcome variable lies between 0 and 14. As a result, the outcome variable is a count variable that follows a Poisson distribution.

In the empirical literature, though there are various competing models which are used to quantify the impact of an endogenous independent variable on a continuous outcome variable (Cameron and Trivedi 1998), there are very few extensions of such models which are used to examine the impact of an endogenous multinomial treatment on a non-negative count outcome variable. Recently, a multinomial treatment effects negative binomial model was developed by (Deb and Trivedi, 2006) to quantify the impact of endogenous variables on the count outcome variable. The multinomial treatment affects negative binomial regression controls for biases due to both observed and unobserved factors. That means if both the count outcome variable and the treatment variable are both endogenous variables, the use of multinomial endogenous Poisson regression produces unbiased and consistent estimates. On the one hand, participation in rural out-migration is not random and there is a problem of self-selection into migration. On the other hand, rural out-migration and the intensity of technology adoption may be affected by the same unobserved factors and this will lead to a biased and inconsistent estimate of the impact of rural out-migration on the intensity of technology adoption.

The estimation of the multinomial treatment effects negative binomial model involves two steps namely; the estimation of the participation equation and the estimation of the impact equation. First, the participation equation is estimated where rural out-migration is regressed on all covariates. Second, a negative binomial regression model is estimated to assess the impact of rural out-migration on the mean number of technologies adopted by a rural farmer. Assume that the ith household chooses one treatment from a set of choices that contains a control group, and EV_{ij}^{*} refers to the indirect utility of selecting the jth treatment, j = 1,2,3…J, and it is given by;

$$EV_{ij}^{*} = z_i'\alpha_j + \delta_j I_{ij} + \mu_{ij} \quad (1)$$

where Z_i' is a vector of covariates, α_j and δ_j are parameters to be estimated, μ_{ij} is the error term which is identically independently distributed, I_{ij} is a latent factor that includes the unobserved characteristics of the households which affect both the participation in rural out-migration and the intensity of technology adoption by households. These latent factors may include motivation, the propensity to work, and perception. It is assumed that the latent factors are independent of the error term, μ_{ij}. Suppose that d_j is a discrete variable that shows the observed treatment choices, and $d_i = (d_{i1}, d_{i2}…d_{iJ})$. Assume further that

[2] Households with both rural-urban and international migrants are categorized under households with international migrants since their numbers are very few. Besides, rural-urban migrant is less likely to remit if his or her family has another international migrant.

$I_i = (I_{i1}, Ii2 \ldots I_{iJ})$, and the probability of treatment can be given by;

$$P_r(d_i|z_i, I_i) = g(z_i'\alpha_1 + \delta_1 I_{ij}, z_i'\alpha_2 + \delta_2 I_{ij}, \ldots . z_i'\alpha_J + \delta_J I_{ij}) \quad (2)$$

where g is a multinomial probability distribution and is assumed to have a mixed multinomial logit model structure. In a mixed multinomial logit model where participation also depends on latent factors, the probability of choosing the j[th] an alternative is given by;

$$P_{ij} = \Pr(M_i = j/Z_{i,}I_i) = \frac{e^{(Z_i'\alpha_j + \delta_j I_{ij})}}{1+\sum_{k=1}^{J} e^{(Z_i'\alpha_j + \delta_j I_{ij})}} \quad (3)$$

where P_{ij} is the probability of choosing a given status of rural out-migration, j is the number of categories for rural out-migration (j = 0,1,2), I_i is a latent factor and it is assumed that each choice is affected by a unique latent factor. The outcome variable in this multinomial treatment effects negative binomial regression is a count variable which is the number of technologies adopted by rural farmers (y_i = 0,1,2…14), and the expected outcome equation for the i[th] household is given by;

$$E(y_i|d_i, X_i, I_i) = X_i'\beta + \sum_{k=1}^{J} \gamma_{ij}\, d_{ij} + \sum_{k=1}^{J} \lambda_j\, I_{ij} \quad (4)$$

where X_i is a vector of exogenous covariates which affect the number of technologies adopted by the i^{th} farmer, β, γ_{ij} and λ_j are vectors of parameters to be estimated, and d_{ij} is the multinomial treatment variable with three categories. The coefficient of d_{ij} measures the impact of participation in rural out-migration on the mean number oftechnologies adopted by accounting for the problem of endogeneity. If the value of γ_{ij} is positive and significant, participation in rural out-migration increases the intensity of technology adoption by rural households. But if the value of γ_{ij} is negative and significant, participation in rural out-migration reduces the intensity of technology adoption by rural households. Hence, equation (4) simultaneously estimates the participation equation and the outcome equation by controlling for biases due to observed and unobserved factors.

Description of variables, and expected sign

The outcome variable is the count of technologies adopted by the i[th] household and it is a count variable with values between 0 and 14. The treatment variable is rural out-migration which is a nominal variable with three categories: households without migrants (j = 0), rural-urban migrants (j = 1), and international migrants (j = 2). Age, education, tropical livestock unit, saving, extension visit, non-farm participation, land renting out, soil fertility, cooperative membership, sales of livestock, age-square, and gender are used as control variables. Added to these, a dummy for return migrants and family size are used as exclusion restriction variables or instrumental variables. These instrumental variables are selected in such a way that they affect the participation equation or rural out-migration directly, but they do not directly impact the outcome equation which is the intensity of agricultural technology.

The age and education level of the household head are continuous variables and they are measured in years. Studies conducted by Massresha et al. (2021) and Fadeyi et al. (2022) on factors influencing technology adoption by small-holder farmers found that age and education are positively and significantly related to agricultural technology adoption. But a study conducted by (Dhraief et al., 2019) on factors affecting agricultural technology adoption found that the age of the household head and technology adoption are negatively and significantly associated. The same author found that non-farm participation and agricultural technology adoption are positively and significantly associated. This study also hypothesized a positive association between the non-farm participation of households with the intensity of agricultural technology adoption. A study conducted by (Ullah and Saqib, 2022) on determinants of technology adoption found extension visits and access to credit positively associated with agricultural technology adoption. Thus, the frequency of extension visits is expected to induce the technology adoption behavior of rural households. The same study found that the education level of the household head is negatively and significantly associated with agricultural technology adoption. Sales of livestock and land renting out provide rural households with income. They use farm income to acquire inputs, hire labor and acquire farmland. A study conducted by Fadeyi et al. (2022) on factors affecting technology adoption indicated that farm income positively and significantly impacts agricultural technology adoption by rural farmers. This study also hypothesized that participation in livestock and land markets is positively related to the intensity of agricultural technology adoption.

Besides, studies conducted by Feyisa (2020) and Massresha et al.(2021) on determinants of agricultural technology adoption by smallholder farmers indicated that the number of tropical livestock units and the frequency of extension visits are positively and significantly related

to agricultural technology adoption. This study also hypothesized that tropical livestock units and the frequency of extension visits are positively related to the intensity of agricultural technology adoption. In this study, the gender of the household head is used as a dummy variable which assumes 1 for males and 0 for females. A study conducted by Massresha et al. (2021) on factors affecting technology adoption found that the likelihood of technology adoption in male-headed households is significantly higher compared to female-headed households. Besides, the saving of households is also expected to be positively associated with the intensity of agricultural technology adoption in rural households (Table 1).

Furthermore, a study conducted by Simtowe et al. (2011) on determinants of technology adoption found that cooperative membership is positively and significantly associated with agricultural technology adoption, and this study also hypothesizes that cooperative membership is positively related to technology adoption by small-holder farmers. A study conducted by Sun et al. (2021) on the effect of rural-urban migration on farmers' expenditure on agricultural machinery found positive and significant effects. Added to this, studies conducted by Mendola (2005 and Shi (2020) also indicated a positive and significant association between rural-urban migration and technology adoption. But a study conducted by Williams (2014) found a negative and significant association between technology adoption and remittance from migration.

Results and discussion

Descriptive and Mean Difference Test results

The mean age of rural to urban migrants, and international migrants are 23 and 26 respectively in the study areas while the mean years of schooling of rural to urban migrants and international migrants are 9.3 and 8.6 years respectively as presented in Table 2. This suggests that most of the rural out-migrants are young and better educated. The mean monthly income of rural-urban migrants and international migrants are Birr 892.5 and 12185.2 whereas the mean annual remittance from rural-urban migrants and international migrants to origin areas are Birr 862.9 and 22,527.2 Ethiopian birrs respectively.

Though the mean annual remittance from international migrants is higher, international migration is associated with a significant initial cost of migration. Further, the majority of the migrants in the study areas are male (75 percent) and unmarried (97 percent). Among all participants in rural out-migration, 94 percent of households

	Description	Measurement	Expected Relation
Outcome Variable	Count of technologies adopted	Scale	
Instrumental variables	Family Size	Scale	+
	Return Migrant (1 for presence, & 0 otherwise)	Nominal	+
Control Variables			
AGE	Age of household head in years	Scale	-
EDUC	Education level of household head in years	Scale	+
TLU	Tropical livestock units	Scale	∓
SAVING	Dummy for saving (1 for savers, 0 otherwise)	Nominal	+
NFP	1 for non-farm participation, & 0 otherwise	Nominal	∓
EXTN	Frequency of extension visits per year	Scale	+
LR	Land Renting Out (1 for rent, 0 otherwise)	Nominal	+
SL	Sales of livestock (1 for sales, & 0 otherwise	Nominal	+
SF	Soil fertility (1 for fertile land, & 0 otherwise)	Nominal	+
CM	1 for cooperative membership & 0 otherwise	Nominal	+
EDUCH	Highest education level in the family	Scale	+
AGE-SQ	Square of household age	Scale	+
GENDER	1 for male-headed, & 0 otherwise	Nominal	+
ANGACHA	1 for Angacha district, & 0 otherwise	Nominal	∓

Source: Author compilation, 2021)

Table 1: Variables description, measurement, and expected relationship.

	International		Rural-Urban		Total	
	Mean	Std. dev	Mean	Std. dev	Mean	Std. dev
Age of migrants	26.1	5.7	22.5	3.1	24.8	5.2
Education of migrants	8.6	2.2	9.3	1.8	8.8	2.1
Income at destination	12185.2	5566.4	2523.3	892.5	8676.1	6454.5
Annual remittance	22527.2	39979.5	1560.3	862.9	15203.8	33735.1
				Number		Percent
Marital status of migrants	Unmarried			215		97
	Married			7		3
Gender of migrants	Male			166		75
Remittance status	Recipient of remittance			209		94

Source: author computation, 2021

Table 2: Descriptive statistics of continuous and discrete attributes of migrants.

received remittance in the last year. While a study conducted by Abire and Sagar (2016) on determinants of international migration in southern Ethiopia indicated that male migrants constituted about 72.5 percent of international migrants in Hadiya and Kembata-Tembaro zones, a study conducted by Debnath (2022) on the benefit of remittance found that 92 percent of households with rural-urban migrants received remittance in rural India.

Also, South Africa is the primary destination for international migrants while Addis Ababa is the leading destination for domestic rural-urban migrants in the study area. Added to this, female migrants primarily travel to the Middle East whereas male migrants mainly move to South Africa due to the nature of job opportunities in destination areas. As indicated in Table 3, 33.8 percent of migrant-sending rural households have two or three migrant family members while 60 percent of migrant-sending rural households have one migrant family member in the study area. Moreover, 33 percent of rural households have at least one international migrant in the study areas. A study conducted by Tsedeke and Ayele (2017) on determinants of international migration in southern Ethiopia also found that 39 percent of households in the Hadiya and Kembata-Tembaro zones have at least one international migrant. As indicated in Table 3, the decision to out-migrate is made at the family level for the majority of migrants, and this supports the prediction of the new economics labor migration theory which claims that the decision to out-migrate is made at the household level. This theory also predicts that migrants send remittances to origin areas for four motives namely; altruism, insurance contract, loan contract, and investment (Lucas and Stark, 1985).

The use of remittances from rural-urban migrants and international migrants by migrant-sending rural areas is presented in Table 4. On one hand, remittances from rural-urban migrants are primarily used for household food consumption, clothing, and health expenditure by remittance-receiving rural households. For instance, more than two-thirds of remittances from rural-urban migrants are used for household food consumption. It seems that a higher proportion of remittances from domestic rural-urban migrants are used for consumption compared to agricultural investment. A study conducted by Debnath (2022) on the use of remittance in India also found that rural households spend remittance from rural-urban primarily on food, clothing, education, and health.

On other hand, rural households spend remittances from international migrants primarily on housing, food, livestock, and inputs. Therefore, international remittance-receiving rural households use remittance mainly for housing which includes the purchase of urban houses, construction of houses in rural areas, and purchase of urban land for house construction. For instance, more than half of remittances from international migrants are used for housing rural households. Besides, more than 15 percent of remittances from international migrants are also used for the purchase of livestock and agricultural inputs. The implication is international remittance-receiving households use remittance for asset augmenting, agricultural investment, and household consumption in the study area. This suggests that the uses of remittances by remittance-receiving rural households depend on the size of remittances or sources of remittances.

In this study, each sample household is presented with a list of fourteen portfolios of agricultural technologies that include improved seed, chemical

	Major destinations	Frequency	Percentage
Rural-Urban migrants (85)	Addis Ababa	47	55.29
	Hawassa	13	15.29
	Other cities	25	29.41
International Migrants (137)	Republic of South Africa	97	70.8
	Middle East	38	27.74
	Others countries	2	1.46
Migrants per household		Frequency	Percent
	1	133	59.9
	2	50	22.5
	3	25	11.3
	4	10	4.5
	5 and 6	4	1.8
	Total	222	100
Decision to migrate	Self	6	2.7
	Relatives	9	4.1
	Friends	11	5
	Family	196	88.3
	Total	222	100

Source: author computation, 2021

Table 3: destination of migrants, migrants per household, and decision to migrate

	Rural-Urban migration	International migration	
Use of remittance	Percent	Use of remittance	Percent
Food	69.87	Food	14.77
Clothing	19.21	Clothing	4.74
Education	3.02	Education	2.18
Health	4.27	Health	4.94
Inputs	1.76	Inputs	6.77
Housing	1.21	Housing	51.05
Livestock	0	Livestock	8.45
Labor	0	Labor	0.35
Mobile	0.66	Mobile	4.3
TV & Radio	0	TV& Radio	1.51
Solar	0	Solar	0.52
Other	0	Other	0.42

Source: author computation, 2021

Table 4: Percentage share of remittances used by migrant-sending households.

fertilizers, row planting, mulching, crop rotation, irrigation, compost, crop residuals, chemicals, terracing, animal fodder, inter-cropping, tree planting, and improved livestock, and was asked whether he/she adopted each technology or not. The descriptive result in Table 5 shows the count of various technologies adopted by rural households in the study area. While most of the households use fertilizers and chemicals, 45.06 percent of households use row planning in Hadiya and Kembata-Tembaro zones.

Similarly, 54.94 percent of households use improved seeds whereas 30.36 percent of households have improved livestock variety. Since Hadiya and Kembata-Tembaro zones are known for limited agricultural land, farm households grow oats, alfalfa, and desho grasses for their livestock. As indicated in Table 5, 58.07 percent of households use animal fodder in the study area. In addition,

Technologies	Count	Percentage	Technologies	Count	Percentage
Improved seeds	228	54.94	Crop residue	218	52.53
Fertilizers	411	99.04	Chemicals	386	93.01
Row planting	187	45.06	Soil terracing	285	68.67
Mulching	186	44.82	Fodder	241	58.07
Rotation	187	45.06	Inter-copping	262	63.13
Irrigation	28	6.75	Tree planting	270	65.06
Manure	249	60.00	Livestock	126	30.36

Source: author computation, 2021

Table 5: Distribution of the number of technologies adopted by rural households.

Technologies adopted	Migration status				Total	
	Without migrants		With migrants			
	Count	%	Count	%	Count	%
1-4	25	12.95	8	3.60	33	7.95
5-8	145	75.13	86	38.74	231	55.66
9-12	23	11.92	110	49.55	133	32.05
13-14	0	0.00	18	8.11	18	4.34
Total	193	100	222	100	415	100

Source: author computation, 2021

Table 6: Frequency distribution of agricultural technologies adopted by migration status.

households construct soil terracing (68.67percent) in Hadiya and Kembata-Tembaro zones primarily to grow desho, oats and alfalfa.

Moreover, the number of agricultural technologies used by rural households is compared by migration status, and the results are presented in Table 6. The result shows that the number of technologies used by about three-fourths of households without migrant family members lies between 5 and 8. However, the number of technologies used by about half of households with migrant family members lies between 9 and 12. This may suggest that migrant-sending rural households are more likely to adopt agricultural technologies compared to rural households without migrant family members.

The credit hypothesis predicts that participation in rural out-migration enhances technology adoption of migrant-sending households by lessening the liquidity constraints of households. Similarly, the risk hypothesis of the new economics labor migration theory predicts that participation in rural out-migration promotes technology adoption of migrant-sending households by reducing their risk aversion level. Though it seems from the descriptive result that the intensity of agricultural technology adoption is higher for households with rural out-migrants, the extent and the statistical significance of the impact of participation in rural out-migration on the intensity of agricultural technology adoption is quantified and presented in the next section under econometric results.

Multinomial treatment effects negative binomial regression model

This study also examined the determinants of the intensity of agricultural technology adoption and quantified the impact of rural labor out-migration on the intensity of agricultural technology adoption using the new economics labor migration theory as a theoretical framework, and the multinomial treatment effects negative binomial model as an analytical model. The multinomial treatment effects negative binomial regression was employed since it controls for biases due to both observed and unobserved factors (Deb and Trivedi, 2006). The outcome variable is the number of agricultural technologies adopted by households which is a count variable with values between 0 and 14. The key independent variable or the focal variable is participation in rural out-migration which is a nominal variable with three categories: households without migrants, with rural-urban migrants, and international migrants. Hence, the impact of participation in rural out-migration on the intensity of agricultural technology adoption is examined by including some control variables, and the result is presented in Table 7.

As presented in Table 7, the multinomial treatment

effects negative binomial regression estimates the participation equation and the outcome equation simultaneously. First, it estimates the determinants of participation in rural out-migration, and the result is presented on the left-hand side in Table 7. Second, the outcome equation which is the determinant of the intensity of agricultural technology adoption by farmers is quantified by using the predicted value of rural-urban migration, and international migration from the first estimation as additional independent variables. The Wald test result showed that the chi-square value is statistically significant at 1 percent, and this suggests that the estimated model best fits the data at the hand.

The presence of return migrants and family sizes are used as instrumental variables in quantifying the impact of rural labor out-migration on the intensity of agricultural technology adoption by rural households. The instrumental variables are included in the participation equation but are excluded from the outcome equation. The coefficients of return migrants and family size are positive and statistically significant at 1 percent. That means the presence of return migrants in the village and family size increase the likelihood of participation in rural-urban and international migration by rural households. Besides, tropical livestock unit, saving of household, frequency of extension visits, land renting out, cooperative membership, and being female-headed household are directly and significantly associated with participation in international migration while the highest education level in the family and land fertility are indirectly and significantly related to international migration in Hadiya and Kembata-Tembaro zones. Likewise, the age of the household head, being from the Angacha district, age-square of household head, and land renting are significantly

Multinomial treatment effects NB regression			Number of observations = 415			
Log pseudolikelihood = -1054.7696			Wald $chi^2(48)$ = 861.01 (0.000)			
	Rural-Urban migration		International migration (robust)		Technology adoption	
	Coeff.	Std. error	Coeff.	Std. error	Coeff.	Std. error
Rural-Urban					0.056	0.036
International					0.389	0.031***
Angacha District	-1.255	0.582**	-0.410	0.598	0.120	0.027***
Age of HH Head	0.501	0.260*	-0.046	0.260	-0.022	0.011**
Education of HH Head	0.087	0.069	0.037	0.078	0.001	0.003
Tropical Livestock Units	-0.007	0.172	0.481	0.159***	0.011	0.004**
Saving of HH Head	0.68	0.565	1.136	0.546**	0.049	0.025*
Non-Farm Participation	-0.216	0.489	-0.645	0.497	0.042	0.022*
Extension Visits	-0.054	0.123	0.494	0.126***	0.014	0.004**
Land Renting	1.119	0.558*	1.566	0.594***	0.044	0.028
Sales of Animals	-0.915	0.594	-0.617	0.604	0.048	0.025*
Land Fertility	-0.253	0.535	-1.169	0.542**	0.030	0.023
Cooperative Membership	0.281	0.644	1.479	0.619**	0.075	0.024***
Highest Education	-0.063	0.109	-0.229	0.102**	0.002	0.005
Age Square	-0.005	0.002*	0.001	0.002	0.0023	0.001**
Male_Headed	-1.261	0.916	-1.841	0.878**	-0.064	0.038*
Family Size	0.678	0.198***	0.690	0.198***		
Return Migrants	6.774	0.853***	6.276	0.938***		
Constant	-19.480	6.844	-8.047	6.422	2.176	0.283***
Lnalpha					-30.697	0.272***
Lambda_Outcome2					-0.019	0.003***
Lambda_Outcome3					-0.0003	0.0025
Alpha					4.660	1.270
Likelihood Ratio Test of Exogeneity						
Likelihood Ratio Value = 54.618			Probability of LR =0.000			

Note: ***, **, and * denote the statistical significance level at 1%, 5% and 10% respectively
Source: author computation, 2021

Table 7: Estimation results of multinomial treatment effects negative binomial model.

related to rural-urban migration in the study area.

The coefficient of participation in international migration is positive and significant at 1 percent and this suggests that the result supports the credit and risk hypotheses of rural out-migration. The risk and the credit hypotheses claim that participation in rural out-migration is caused by the lack of insurance and credit markets in rural areas. According to these two hypotheses, participation in rural out-migration induces a positive technology adoption behavior of households in migrant-sending rural areas by reducing the insurance and credit constraints of households. While the coefficients of intervention variables, rural-urban migration, and international migration, are interpreted as a percentage, the coefficients of other covariates in the outcome equation are interpreted like the coefficients of negative binomial regression (Deb and Trivedi, 2006). Hence, participation in international migration by households increases the likelihood of technology adoption by 38.9 percent and is statistically significant at a 1 percent level of significance.

However, participation in rural-urban migration increases the likelihood of technology adoption in rural households only by 5.6 percent and is statistically insignificant, and this may be due to the significant difference between the average remittance from international and rural-urban migrants in the study areas. This finding is consistent with the findings of some previous studies on the impact of participation in rural out-migration on the decision to adopt agricultural technology by migrant-sending rural households (Tesfaye and Tirivayi, 2016; Maguza-Tembo et al., 2017; Mwungu et al., 2018). But the finding of this study contradicts the findings of Williams (2014), Zegeye (2021), and Mesele et al. (2022) who found a negative and significant association between participation in migration and technology adoption by migrant-sending rural households. But the previous studies did not control for self-selection bias due to unobserved factors, and they focused on the adoption of a single technology.

Besides, the age of the household head, gender of the household head, frequency of extension visits, saving of households, non-farm participation, tropical livestock unit, and cooperative membership are significantly related to the intensity of agricultural technology adoption in Hadiya and Kembata-Tembaro zones. As observed in Table7, being from the Angacha district increases the log count of agricultural technology adoption of households by 0.120, and statistically significant at a 1 percent level. This suggests that the mean count of agricultural technology adoption by households is higher in the Angacha district compared to Lemo and Soro districts.

While the age of the household head is indirectly and significantly related, the age square of the household head is directly and significantly associated with the log count of agricultural technology adoption. By implication, the intensity of agricultural technology adoption is lesser at lower ages of household heads and more at higher ages of the household head. This shows the importance of experience to induce the technology adoption behavior of rural households. This finding is consistent with a study conducted by Masresha et al. (2021) while it contradicts the finding of a study conducted by Dhraief et al. (2019).

Further, non-farm participation has a direct and significant influence on the log count of agricultural technologies adopted by rural households, and this is consistent with the prior expectation. As presented in Table 7, participation in non-farm activities increases the log count of the agricultural technologies adopted by households, on average, by 0.042, and statistically significant. This suggests that participation in non-farm activities can promote agricultural technology adoption by lessening the liquidity constraints of rural households. Likewise, the coefficient of the dummy for household saving is positive and statistically significant. However, being male-headed households decreases the log count of agricultural technology adoption of households, on average, by 0.064, and statistically significant. The intensity of agricultural technology adoption is higher for female-headed households compared to male-headed households in the study area. This finding is consistent with Olawuyi and Mushunje (2019) who found a negative and significant association between being in a male-headed household and the intensity of agricultural technology adoption.

The coefficient of tropical livestock unit is positive and statistically significant at a 5 percent significance level, citrus paribus. If the tropical livestock unit increases by one unit, the log count of agricultural technologies adopted by households increases by 0.011, and this could be because livestock is the source of both food and income for agrarian rural households. Similarly, the frequency of extension visits is positively and significantly related to the log count of agricultural technology adoption

by rural households. In other words, as the frequency of extension visits increases by one unit, the log count of agricultural technologies adopted by rural households increases, on average, by 0.0135, and statistically significant at a 1 percent significance level, citrus paribus. This implies that the frequency of extension visits can induce a positive technology adoption behavior in rural households by increasing access to information. This finding is consistent with Ullah and Saqib (2022), Feyisa (2020), and Massresha et al. (2021) who found a direct and significant effect of the frequency of extension visits on agricultural technology adoption of rural households.

Moreover, the coefficient of the dummy for cooperative membership is positive and statistically significant at a 1 percent significant level and it suggests that being cooperative membership increases the log count of agricultural technology adoption of rural households by 0.075. This could be because cooperative membership improves access to information which induces a positive technology adoption behavior in households. This finding is in agreement with a study conducted by Simtowe et al. (2011) who found a positive and significant association between cooperative membership and agricultural technology adoption. Still, the coefficient of participation in the livestock market is positive and significant, and this suggests that participation in the livestock market through sales of livestock increases the likelihood of agricultural technology adoption by households in the study area. In the same vein, a study conducted by Fadeyi et al. (2022) on factors affecting technology adoption indicated that participation in the livestock market via sales of livestock is positively and significantly associated with agricultural technology adoption by rural farmers.

Lastly, the alpha parameter is significantly different from zero, and this suggests that the specification and estimation of negative binomial regression for the outcome equation are more appropriate compared to Poisson regression for the count data under consideration. The likelihood ratio test result indicates that the null hypothesis of exogeneity is rejected at a 1 percent significance level, and the specification and the estimation of the multinomial treatment effects of negative binomial regression are appropriate.

Conclusion

There are few studies on the impact of rural out-migration on migrant-sending households' adoption of agricultural technology using the new economics labor migration theory (stark, 1985) as a theoretical framework, despite the abundance of studies on the impact of rural out-migration on migrants and migrant-receiving urban areas using the human capital theory of migration (Harris-Todaro, 1970) as a theoretical framework. Furthermore, despite the fact that there are few studies that have looked at the impact of rural out-migration on agricultural technology adoption in migrant-sending origin areas, the ones that have done so have tended to be narrow in scope, yield mixed results, and fail to account for self-selection bias resulting from unobserved factors. Therefore, using the new economics labor migration theory as a theoretical framework and the multinomial treatment effects negative binomial regression as an analytical model, this study investigated the impact of rural out-migration on the intensity of agricultural technology adoption of migrant-sending rural households in southern Ethiopia. Utilizing stratified random selection, data was gathered from 415 sample rural households in 2021.

Descriptive results showed that most of the rural out-migrants are better-educated, unmarried, male, and young. More than half of rural-urban migrants are directed to Addis Ababa whereas more than two-thirds of international migrants are directed to South Africa in the study area. Besides, one-third of rural households in the Hadiya and Kembata-Tembaro zones have at least one international migrant member while more than half of rural households have at least one migrant member. While remittance from rural-urban migrants is primarily used for consumption expenditure by rural households, remittance from international migrants is used for asset augmenting, and agricultural investment in addition to consumption expenditure.

According to descriptive findings, the majority of rural out-migrants are younger, male, unmarried, and better educated. In the research area, more than two-thirds of international migrants directed to South Africa whereas more than half of rural-urban migrants directed to Addis Abeba. Moreover, more than half of rural households have at least one migrant member, with one-third of rural households in the Hadiya and Kembata-Tembaro zones having at least one international migrant member. Remittances from overseas migrants are utilized for asset augmentation, agricultural investment, and consumption expenditure by rural households, but remittances from rural-urban migrants are predominantly used for consumer expenditure. Regression analysis showed that while the influence of migration from rural to urban

areas is insignificant, participation in international migration significantly increases the likelihood of technology adoption in rural households by 38.9%. The intensity of agricultural technology adoption by rural households is negatively and significantly correlated with male-headed households and household age, while the frequency of extension visits, non-farm participation, saving, membership in cooperatives, sales of livestock, and tropical livestock unit are positively and significantly related to the intensity of agricultural technology adoption. The outcome is consistent with the labor migration theory's risk and credit hypotheses. To encourage the adoption of agricultural technology and stop the recent surge of rural out-migration in southern Ethiopia, policymakers should provide access to capital, public services, and viable off-farm employment in rural areas. Future research will look at how rural out-migration affects rural labor and land markets, as well as income inequality in migrant-sending rural areas.

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The Relationship Between Digital Performance and Production of Greenhouse Gas Emissions in EU Countries: Correlation Analysis and ANOVA Method

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Abstract

Agricultural activities produce the significant amounts of greenhouse gas emission. The importance of an ever-changing climate means that digital technologies and their environmental impact are more frequently discussed in the context of the 5th Industrial Revolution. It is important to minimize environmental threats and reduce production waste on the way to a sustainable path. The main scientific aim of the paper is to examine, based on correlation analysis and ANOVA method, the relationship between two variables, digital performance of individual EU countries expressed by the indicator Digital Economy and Society Index and production of Greenhouse Gas Emissions, specifically how digital technologies affect the environment and how to transform digital technologies to supporting the European Green Deal and accelerate sustainable growth. The reasons are that digital technologies can play an important role in reducing greenhouse gas emissions. According to the results, it has been proven that exists a positive correlation between two variables regarding as a weak correlation between DESI and GHG emissions. Analysis of variance indicates the highly significant differences between variables. Countries with the higher DESI index produce more Greenhouse gas emissions as well but in a weak manner.

Keywords

Agriculture, correlation analysis, digital economy and society index, digital performance, European Green Deal, greenhouse gas.

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Introduction

Today, we can see a typical example of how the COVID-19 pandemic has highlighted the importance of digital asset economies and how networks, data, connectivity, as well as digital skills sustain our economies and societies by allowing us to continue working. Expanding the use of information technology is needed to ensure its proper functioning by adapting to new requirements in line with the EU strategic priorities, but also by linking them to best practice in the field (Bălăcescu et al., 2021).

Digital transformation is not only a single step for upgrading specific functions in an organization, it is an integration of information technologies in process or activity that trigger fundamental changes in organizations. Digital transformation has become the crucial factor to enable organizations to be more competitive, innovative, and prosperous (Feroz et al., 2021). The digital transformation of businesses opens up new opportunities and accelerates the development of new and reliable technologies. The digital transformation depends on the level of the economy (measured by GDP) and the availability of the country's resources. The changing climate attracts more attention to environmental challenges. In response to these, new strategies have been created to protect the health of citizens and transform the economy to be resource efficient. Countries face a big opportunity, where merging the environmental path and economic growth can accelerate competitiveness whether other countries are unwilling to transition to green digital transformation. The leaders of the EU attach importance to the transition of clean digital technologies to becoming greener as a crucial factor for climate and environmental

sustainability. The policy alignment of green digital technologies has significant potential and should support digitalization that accelerates environmental protection (European Green Digital Coalition, 2021).

The changing climate is an existential threat to the world. A European Union has presented its main activities to support digital transformation to be greener by using smarter technologies. This initiative strives to achieve a climate-neutral continent by 2050, which is a key objective of the European Green Digital Coalition (European Commission, 2021). Following, digital technologies are a crucial factor in determining climate neutrality and environmental sustainability. We can state that digitalization may be beneficial to the environment in the future. Given the importance of digital technologies in supporting the competitiveness of businesses and the innovative digital economy European Commission created index Digital Economy and Society Index (DESI) to measure the digital competitiveness of European Union (EU) member states. DESI covers five key areas of digital development: connectivity, human capital, use of internet, integration of digital technology, and digital public services. Index provides a comprehensive overview of digital development in the EU and allows member states to benchmark their digital performance and helps to prioritize investments in areas where they lag behind other countries and to assess the impact of their digital policies against other countries. It also serves as a tool for policymakers to identify areas for improvement and to develop policies to enhance the digital competitiveness of their country.

Understanding the relationship between digital economy and greenhouse gas emission can be the critical aspect of economic and social development and can inform policy decisions and help countries achieve sustainable development goals. Digital technologies may offer opportunities to reduce greenhouse gas emissions through improved energy efficiency (optimize energy systems), smart transportation systems, and more effective waste management practices, promote the use of renewable energy sources. All this could lead to a reduction in greenhouse gas emissions.

The greenhouse gas emissions refer to the release of gases such as carbon dioxide, methane, and nitrous oxide into the atmosphere, which contribute to global warming and climate change. Greenhouse gas emissions are typically associated with human activities, such as transportation, electricity generation, industrial processes, and agriculture. While DESI and greenhouse gas emissions are not directly related, there may be some indirect connections between them. For example, a country with a high level of digitalization may have more efficient transportation systems, better energy management, and more effective waste management, which can help reduce greenhouse gas emissions. Similarly, digital technologies can enable the development of smart grids, renewable energy systems, and other solutions to help mitigate climate change.

The first part of the paper deals with a critical analysis of the literature, basically in the area of Digital transformation, European Green Deal and Digital economy and society index. This section mentions the importance of using digital technology in organizations and its benefits for the sustainable future. The next part contains empirical analysis of the relationship between two specific indicators, the Digital Economy and Society Index (DESI), which monitors Europe's overall digital performance and measures the progress of individual EU countries in terms of their digital competitiveness and indicator Greenhouse gas emissions, which measures total national emissions. For data collection process, official European Union reports and for data analysis was used statistical software SPSS Statistics. The final part of the paper concludes the main results of the study and presents the relationship between digital performance and the progress of EU countries with the change in climate and environmental challenges that may turn into opportunities.

Theoretical background

The European Green Deal

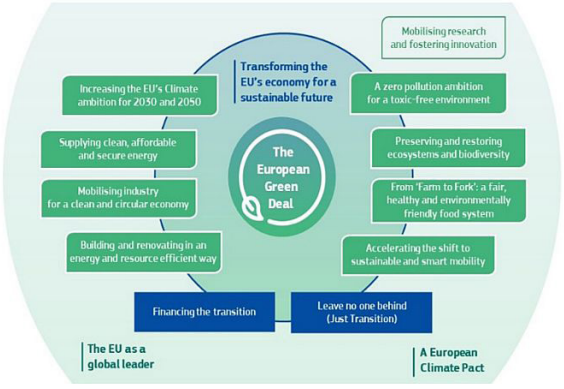
Climate change and environmental degradation pose an existential threat to Europe and the world. To overcome these challenges, a Green Agreement for Europe was established to transform the Union into a modern, competitive, resource-efficient economy where these goals are set: it will reach zero net greenhouse gas emissions by 2050; economic growth will be decoupled from resource use, and no individual or region will be left out (Krämer, 2020).

Under the agreement, actually the 27 Member States of the European Union have committed themselves to transforming Europe into the first climate-neutral continent by 2050. This will open up new opportunities to innovate, invest,

and create new jobs. Following Franklin Roosevelt's New Deal, based on social and cultural programs to overcome the Great Depression in the 1930s and to promote similar solidarity in a similar way, the European Commission presented the Green Deal of the EU as a 'new growth strategy that aims to transform the EU into a fair and prosperous society' (Ossewaarde and Ossewaarde-Lowtoo, 2020).

The agreements should reduce emissions in the long term, tackle energy poverty, reduce dependence on foreign energy supplies, and improve the health and living conditions of the population. Great emphasis is placed on the environmental area (mainly in the area of reducing CO2 emissions, reducing greenhouse gas emissions, but also increasing the share of energy from renewable sources), but the required changes can be perceived as a change for a better future with economic and social benefits. Emission reductions are connected with: unemployment rates below 7% and rates of youth unemployment below 15% across EU member states by 2030; strengthening convergence and cohesion; average annual growth rates of EU GDP above 2% until 2030; inflation rates in line with price stability as defined by the ECB; etc. (Wolf et al., 2021).

In Figure 1 we can see elements of the European Green Deal, an integral part of the strategy developed by the current Commission and aimed at, inter alia, implementing the UN 2030 Agenda for Sustainable Development and the Sustainable Development Goals (United Nations, 2020, Wrzaszcz and Prandecki, 2020).



Source: Own processing based on European Commission (2019)

Figure 1: The ambitions of the European Green Deal.

A key goal of the European Green Deal is to make Europe the first climate-neutral continent by 2050, and smarter and greener use of technologies will help it. Technology can improve energy and resource efficiency, facilitate the circular economy, lead to a better allocation of resources; reduce emissions, pollution, biodiversity loss, and environmental degradation. At the same time, the ICT sector must ensure the environmentally sound design and deployment of digital technologies (European Commission, 2021).

From digitization to digital transformation

Digital transformation is considered a comprehensive system that includes the process of digitization and digitalization and embraces the ability of digital technology to capture and analyze data. Digital transformation is an iterative technological process of constant change that leads to automating and optimizing business processes in organizations (Lombardi, 2019).

Digitization

The concept of digitization is handled with automated routines and tasks based on the process of converting data from analogue to digital format. Clerck (2017) pointed out the importance of connecting digitization and automation and highlighted the fact that transforming analogue data to digital format is done for a reason, which is automating business processes and workflows. To measure the benefits of digitization, a report by PricewaterhouseCoopers determined six key attributes. Measuring ubiquity, affordability, reliability, speed, usability, and skills helps to recognize the level of digitization in a company (Sabbagh et al., 2012). The positive impacts of digitization are seen on economic strength, societal well-being, and effective governance. Digitization is not the ultimate aim of digital transformation but is a major milestone to attain in the complex process of digital transformation. Without digitization, neither digitization nor digital transformation can be achieved.

Digitalization

The concept of digitalization uses digital technologies and digitized data (digitized and natively digital) that generally improve the way of communication in organizations. Digitalization generates revenue, improves business processes by their transformation, and creates an environment for digital business, whereby digital transformation is essential. Digitalization is considered the milestone toward a fully digital business using digitized data (processed by digitization) and cutting-edge technologies (El Hilali et al., 2020).

Digitalization can help improve the availability of information on the characteristics of products sold in the EU. For instance, an electronic product passport (e.g. Smart CE marking) could provide information on a product's origin, composition, repair and dismantling possibilities, and end-of-life handling (European Commission, 2021). For the EU organizations to run their business, the driving forces of digitalization are extremely important to accomplish internal communication or share information with business partners, government, and customers. The same driving forces have a tremendous impact on reducing business operating expenditures (OPEX), such as payroll, office supplies, utilities, marketing, or taxes (Trașcă et al., 2019).

Digital transformation

Digital transformation follows the process of digitization and digitalization and is driven by digital technologies where the effect of these enables 'unprecedented things' to be achieved (Brynjolfsson and McFee, 2014). The significant impact of digital transformation on business processes across all industries enables managers to focus on the connectivity of machines and devices to enable operations to be more efficient and quickly respond to market changes (Clerck, 2017). Westerman et al. (2011) define digital transformation as 'the use of technology to radically improve the performance or reach of enterprises'. They identified three axes to focus on in a digital transformation of a given business: customer experience, operational processes, and business model. Rogers (2016) determined five domain strategies that are the most influenced: customer, competition, data, innovation, and value proposition. The authors Uhl and Gollenia (2016) discussed the impact of these and found that the keys to succeed in transforming an organization to fully digital are customer centricity, innovation capability, operational excellence using data capabilities, and competitive mindset.

Digital transformation is expected to have high annual growth, simplify and streamline established processes, ensure higher data security, and increase the company's competitiveness and profitability. To ensure intelligent production, automation is necessary, which leads to the transition to advanced technologies. The synergy of production and information technologies brings great progress (Ustundag and Cevikcan, 2017). A convergence of different digital technologies such as Internet of Things (IoT), additive manufacturing, big data, artificial intelligence, cloud computing, and augmented and virtual reality have made significant progress and moved beyond the ability and understanding of the individual (Rindfleisch et al., 2017; Nambisan, 2017). This development is referred to as the fourth industrial revolution. The advent and widespread adoption of information and communication technologies in various domains of human endeavor have established a connection between the digital economy and novel viewpoints on the drivers that shape its progress and prosperity (Košovská et al., 2022). The process from digitization to a fully digital organization requires a thoughtful approach with a specific plan, a list of stakeholders, identified benefits, but also with potential complications.

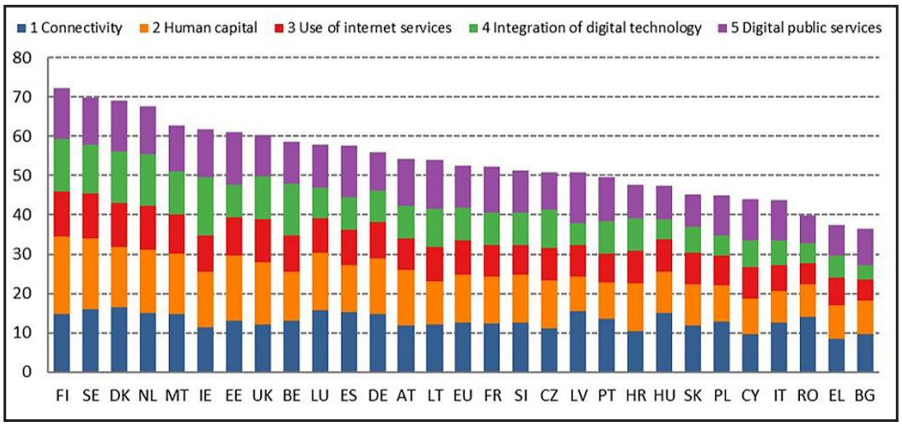
Digital Economy and Society Index

To characterize and compare the progress of individual countries of the European Union, it is used in digitization the Digital Economy and Society Index (DESI). It is a composite index that summarizes relevant indicators on Europe's digital performance and tracks the evolution of EU member states across five main dimensions. Through DESI, we can monitor Europe's overall digital performance and track the progress of EU countries in digital competitiveness. By providing data on the state of digitization of each Member State, it helps them identify areas requiring priority investment and action. DESI country reports contain quantitative data obtained from DESI index indicators in all its five dimensions (which group 37 indicators overall), knowledge of country policies and best practices:

- Connectivity – Fixed broadband take-up, fixed broadband coverage, mobile broadband, and broadband prices;
- Human capital – Internet user skills and advanced skills;
- Use of Internet – Citizens' use of Internet services and online transactions;
- Integration of digital technology, business digitization, and e-Commerce;
- Digital public services – e-Government.

The ranking of member states in the Digital Economy and Society Index for 2020 is shown in Figure 2.

As we can see in Figure 2, the most advanced digital economies in the EU are Finland, Sweden, Denmark, and the Netherlands. On the other hand, Bulgaria, Greece, Romania, and Italy have



Source: European Commission (2020)

Figure 2: Digital Economy and Society Index 2020.

the lowest scores on the index. Based on data before the pandemic, the Czech Republic is the strongest in the integration of digital technologies, where its results exceed the EU average. The score here is high due to good results in the field of electronics trade. The share of people employed in the field of information and communication technologies and the number of graduates in this field has grown significantly (European Commission, 2020).

Materials and methods

According to the aim of the paper, research of the relationship between two indicators, DESI index and Greenhouse gas emissions is provided. Investigating the relationship between the DESI index and greenhouse gas emissions can help identify areas where digital technologies can be leveraged to address climate change and reduce environmental impact. For example, digital platforms can enable the sharing of resources and reduce the need for physical travel, while remote work and virtual meetings can reduce emissions from transportation.

The DESI was developed according to the guidelines and recommendations in the OECD Handbook on the construction of composite indicators: methodology and user guide. The data collection process for the Digital Economy and Society Index (DESI) is conducted by the European Commission, in collaboration with national statistical offices and other relevant stakeholders. The process involves the collection of data from various sources, including surveys, administrative data, and statistical databases. The European Commission selects a set of indicators that are relevant for measuring the digital competitiveness of EU member states. These indicators are grouped into five categories: connectivity, human capital, use of internet, integration of digital technology, and digital public services. The data is validated and checked for errors and inconsistencies to ensure the quality and accuracy of the data and aggregated and calculated to produce scores for each indicator and overall scores for each category and country. The data collection process for DESI is conducted on an annual basis, with the results being published in the form of a report that provides an overview of the digital competitiveness of EU member states. The report also includes recommendations for policymakers and other stakeholders to improve the digital development of their country. The limitation of the index DESI is that measures the digital competitiveness of EU member states, and therefore does not provide insights into the digital development of non-EU countries. This limits the usefulness of DESI for businesses and policymakers interested in global digital trends.

The total DESI score for each country consists of the results of five areas. There are overall weights attributed to the main dimensions of DESI, which reflect the priorities of EU digital policy. The indicators for each area are as follows:

Connectivity (25 %): Overall fixed broadband take-up; At least 100 Mbps fixed broadband take-up; Fast broadband (NGA) coverage; Fixed Very High-Capacity Network (VHCN) coverage; 4G coverage; Mobile broadband take-up; 5G readiness; Broadband price index.

Human capital (25 %): At least basic digital skills; Above basic digital skills; At least basic software skills; ICT specialists; Female ICT specialists; ICT graduates.

Use of Internet services (15 %): People who never used the internet; Internet users; News; Music, videos and games; Video on demand; Video calls; Social networks; Doing an online course; Banking; Shopping; Selling online.

Integration of digital technology (20 %): Electronic information sharing; Social media; Big data; Cloud; SMEs selling online; e-Commerce turnover; Selling online cross-border.

Digital public services (15%): e-Government users; Pre-filled forms; Online service completion; Digital public services for businesses; Open data.

The DESI index was used from the European Commission report for the years 2020, 2019 and 2018. Results 2020 report data for the year 2019. The United Kingdom is still included in the 2020 DESI, and EU averages are calculated for 28 Member States. Data on greenhouse gas emissions were used for comparison with the DESI index, given that there is an effort to reduce them in the future, as mentioned in the European Green Deal (European Commission, 2020).

Greenhouse gases are those that trap heat in the atmosphere. Carbon dioxide (CO_2) is the main greenhouse gas emitted by human activity. The main human activity that emits CO_2 is the burning of fossil fuels (coal, natural gas and oil) for energy and transport. Changes in CO_2 emissions from the combustion of fossil fuels are influenced by many long-term and short-term factors, such as: population growth, economic growth, changing energy prices, new technologies, etc. The general procedure for calculating greenhouse gas emissions from fossil fuels (in this case, natural gas) according to the U.S. Environmental Protection Agency (EPA) is as follows:

- Determine the amount of natural gas consumed (in units of volume or weight).
- The hydrocarbon content of the natural gas is determined. As a rule, standard emission factors for each type of hydrocarbon are used.
- Calculate the total amount of carbon dioxide (CO_2) produced by the combustion of natural gas, as: Amount of natural gas consumed (in units of volume or weight) x emission factor for the hydrocarbon type x CO_2 emission factor for the hydrocarbon type (United States Environmental Protection Agency, 2021).

Then correlation is used to describe the linear relationship between two continuous variables, DESI index and Greenhouse gas emissions. The digital economy has the potential to play an important role in reducing greenhouse gas emissions by enabling more efficient and sustainable ways of working and living. By using correlational analysis to explore the relationship between DESI and greenhouse gas emissions, we can identify whether there is a correlation between digital development and reduced emissions. If we find a negative correlation between these two variables, we can infer that states with higher levels of digital development tend to use energy more efficiently, which could lead to lower greenhouse gas emissions. This can provide valuable insights for policymakers and businesses looking to develop strategies for reducing emissions while promoting economic growth.

The correlation coefficient is measured on a scale that varies from + 1 to 0 to – 1. The complete correlation between two variables is expressed by either + 1 or -1. Very relation labels the strength of association for absolute values of r 0-0.19. Regarded as a weak correlation is the strength of correlation for absolute values of r 0.2-0.39, 0.40-0.59 as moderate, 0.6-0.79 as a strong, and 0.8-1 as very strong correlation. When one variable increases, as the other increases the correlation is positive; when one decreases as the other increases, it is negative. The complete absence of correlation is represented by 0. In terms of research, a correlational study is generally used to study quantitative data and determine trends between the DESI index and Greenhouse gas emissions. The correlational study helps to isolate the variables and identify the interaction between them. For the purpose of the study, a statistical software SPSS Statistics is used. The statistical method, analysis of variance (ANOVA), determines if there are statistically significant differences between selected variables based on the variance observed between them. ANOVA is based on the assumption that the data being analyzed is normally distributed, and that the variances of the groups being compared are approximately equal (Kaufmann and Schering, 2014). A p-value index measures the probability that the observed difference may occur by chance. The lower the p-value indicates the low probability of null hypothesis. In other words, the null hypothesis has a low support in the observed data and should be rejected.

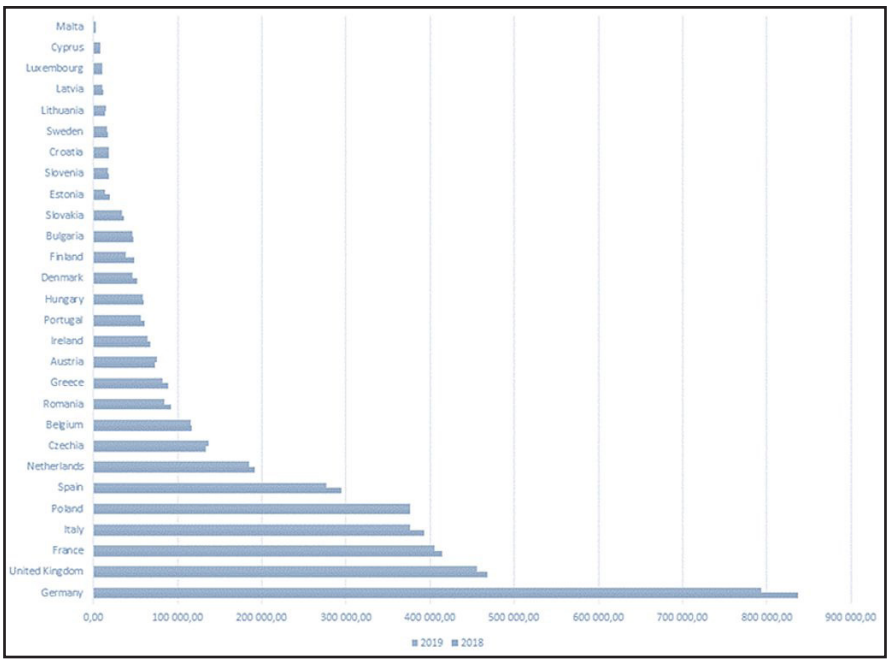
Results and discussion

Over the past 20 years, Greenhouse gas emissions, especially from fossil fuels and industry, have been continuously increasing. At the beginning of the century, global emissions were roughly 23 billion metric tons, but by 2018 they had reached a record high of 43.91 billion metric tons. In 2019, the reduction of emissions was affected by COVID-19, which amounts to an unprecedented 2,500 million metric tons worldwide. Most countries around the world were put under strict lockdowns, meaning transportation and industrial activities were significantly reduced. This was mainly due to the strict lockdowns put in place.

Figure 3 presents the comparison of greenhouse gas emissions in the European Union 28 in 2018 and 2019. The member states are ranked according to their level of greenhouse gas emissions from the countries with the least pollution (Malta, Cyprus, and Luxembourg) to the largest polluters (France, Germany, and the United Kingdom).

At first glance, it might seem that emissions are largely related to a country's development and living standards. However, this is not entirely true. For example, many highly developed countries in Europe have relatively low greenhouse gas emissions, for example Sweden, Luxembourg, or Finland. There are several potential factors, influencing the production of greenhouse gas emissions: climate and geography, energy efficiency, carbon pricing and policies, lifestyle and culture and investment in innovation. While Finland and Sweden have colder climates and rely heavily on renewable energy sources like hydroelectric power, wind power, and biomass, which emit fewer greenhouse gases than fossil fuels, then Germany relies heavily on coal for its energy needs and renewable energy sources such as wind and solar power still make up a relatively small proportion of the country's energy mix. Germany has a large and diverse manufacturing sector, including industries such as steel, cement, and chemicals, which are energy-intensive and produce significant greenhouse gas emissions.

Highly developed countries such as Denmark and Sweden have more efficient buildings, transportation systems, and industrial processes, which can reduce energy consumption and emissions. Denmark is known for its energy-efficient buildings, which use a combination of insulation, ventilation, and renewable energy sources to reduce energy consumption. The country also has a strong public transportation system, including a network of cycling paths and a well-developed public transit system in its capital city, Copenhagen. Sweden has made significant investments in energy efficiency and renewable energy, particularly in its buildings sector.

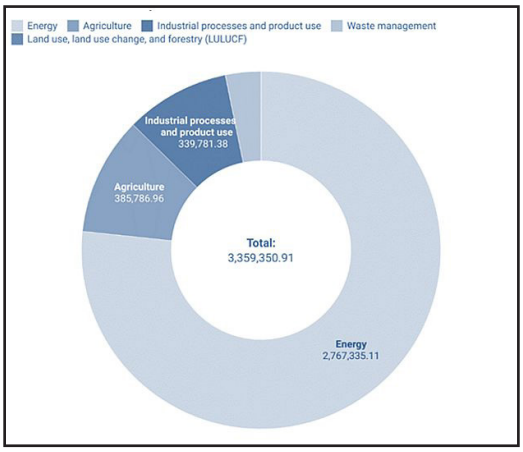


Source: Own processing based on Eurostat (2021)

Figure 3: Comparison of greenhouse gas emissions in thousand tons in EU 28 in 2018 and 2019.

In 2019, emissions have decreased across all sectors, which is particularly attributed to the effect of the global pandemic COVID-19. The largest producer of greenhouse gases in the European Union is, in absolute terms, Germany, which is also the most populous country in the Union. In the coming years, improvements in energy efficiency are expected to be the main driver of the decline in overall greenhouse gas emissions. Due to technological innovations, less energy was consumed while more goods and services were produced. Furthermore, the energy consumed relied relatively less on carbon-intensive fuels and more on renewables. The EU has decoupled its economic growth from greenhouse gas emissions, as these technical developments make it possible to increase economic growth while generating fewer emissions.

To better understand the driving forces behind the reduction in GHG emissions is projected in Figure 4 to see more detail on the sources of human activities. Figure 4 shows GHG emissions broken down by source sectors classified by emitting economic activities. Eurostat statistics recognize five key sectors: Agriculture; Energy; Waste management; Industrial processes and product use; Land use, land use change, and forestry.



Source: Own processing based on Eurostat (2021)

Figure 4: Global Greenhouse gas emissions by source sector in thousand tonnes in EU 28 in 2019.

The primary source of GHG emissions is the energy sector (27.67 billion metric tons), and global energy demand is expected to continue to increase in the coming decades, as populations and economies grow. Agriculture sector produces 3.8 billion metric tons and Industrial processes and product use produce 3.39 billion metric tons. Despite the decline in GHG emissions in 2019, we expect a continuous decline in GHG emissions in coming years. In the energy sector, there are significant interventions that will lead to climate change in general.

For each year, 2018 and 2019, the correlation coefficient (R) and the determination coefficient (R Square) between DESI and GHG emissions were calculated separately. Table 1 illustrates the summary of the model.

Regarding the correlation coefficient, there is an existing correlation between the considered variables, but a positive linear correlation is weak between DESI and GHG emissions. The estimated value of the determination coefficient is 0.065 in 2018 and 0.045 in 2019, which means that the proportion of variation of GHG emissions is 6,5% explained by the variation of DESI in 2018 and the variation of GHG emissions is 4.5% explained by the variation of DESI in year 2019.

According to Table 2, statistical analysis of variance (ANOVA) was used to compare the means of the observed variables using SPSS software. It involves calculating the sum of squares (SS) for each group, which measures the amount of variation in the data that can be attributed to differences between groups. We are to statistically evaluate whether the increase in the average of GHG emission values has been influenced by the DESI index in or whether it is only a random phenomenon. Thus, we test the null hypothesis that the mean values of all groups are equal, and we perform the testing on the basis of an analysis of the relationships between the variances in the individual groups.

Model Summary 2018 and 2019								
Model	R	R Square	Adjusted R Square	Change Statistics				
				R Square Change	F Change	df1	df2	Sig. F Change
2018	0.255	0.065	0.029	0.065	1.802	1	26	0.191
2019	0.213	0.045	0.009	0.045	1.236	1	26	0.276

Source: Author´s calculation (2022)

Table 1: Model Summary 2018 and 2019.

Source of Variation	SS	df	MS	F	P value	F criteria
Between Groups	14901.34	1	14901.34	381.88	0.0000	4.02
Within Groups	2107.124	54	39.02082			
Total	17008.46	55				

Source: Author´s calculation (2022)

Table 2: ANOVA.

The P-value determines the probability that the difference may occur by chance. In Table 2, the significance of the factor is $p < 0.001$. There is a statistically significant level of observed variables. The low level of the p-value means that in 99.99% of the occurrences the correlation is weak. The null hypothesis has very little support in the observed data and can be rejected at the significance level $\alpha = 0.05$.

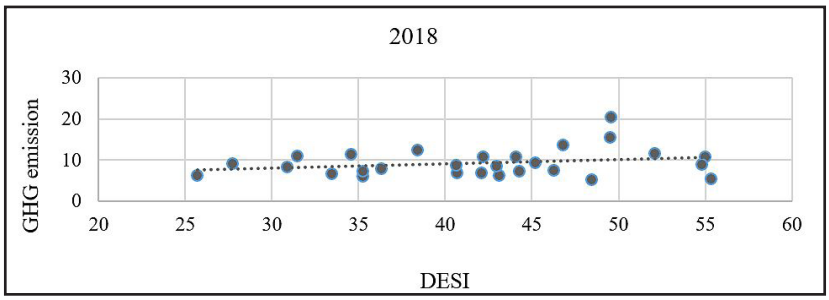
To understand how digital technologies influence the environment and to recognize the importance of transitioning digital technologies to support The European Green Deal and accelerate sustainable growth, we analyzed aspects of Greenhouse gas emissions and the Digital Economy and Society Index (DESI). Correlation analysis explains the significance of linear correlation based on assumption; if there is a change in one variable, this will reflect in the other, based on the dependence of each other. The correlation coefficient measures the strength of two continuous variables. This analysis follows the assumption that a higher degree of digitization should improve environmental aspects. To complement the calculation results, a graphical representation of these relationships in individual years is also given.

Carbon dioxide is mostly associated with global climate change, which will lead to global warming in the next decades. The DESI index reflects the pace of technology and development and the extent of digital transformation in the country. A positive correlation between variables indicates a positive relationship. If one variable increases, the other variable increases too. Weak correlation means that the two variables of interest have a weak linear relationship and when one variable increases the other variable increases as well but in a weak manner.

An outlier country of Germany (DE) is a point that does not fit the general trend of the data set. Finland, Sweden, Denmark, and the Netherlands are leaders in the digital performance in the European Union (European Commission, 2020). Countries with the highest values of Greenhouse gas emissions (Germany, UK, and France) display a medium or low score of digital performance. In 2019, Germany is an outlier of the linear trend line despite the 6 % decline in emissions year on year. The reduction in emissions is primarily caused by the COVID-19 pandemic that pushed down the use of fossil fuels. Malta ranks 6th out of the 28 EU countries in the Digital Economy and Society Index in 2019 and reduces GHG emissions year per year.

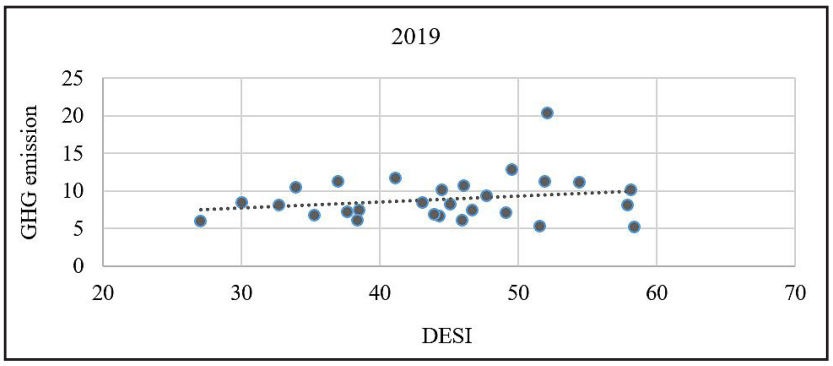
Digitization is a key factor in increasing energy and material efficiency. The Internet supports logistics, and artificial intelligence can help optimize and streamline processes. For many sectors, this is a simple step in business activities, but one of the most problematic sectors in terms of reducing emissions is the transformation of the food system and agriculture. In addition, it will be difficult to introduce more sustainable agricultural practices around the world. The main obstacles that can slow down progress are, in particular, poor spatial planning and regulation, a focus on rapid profits, insufficient funding, or a lack of knowledge. This can be a topic for further discussion, for further research within a specific industry.

The findings of this study have to be seen in light of some limitations. DESI indicator measures the digital competitiveness of EU member states, and therefore does not provide insights into the digital development of non-EU countries. The second limitation of the research can be the causation. While it may be possible to identify a correlation between DESI indicators and greenhouse gas emissions, establishing a causal relationship between the two can be challenging. There may be other factors, such as economic development or population growth, that contribute to greenhouse gas emissions, making it difficult to attribute changes solely to changes in DESI indicators.



Source: Own processing based on European Commission data, 2021

Figure 5: Correlation analysis of Greenhouse gases and DESI, 2019.



Source: Own processing based on European Commission data, 2021

Figure 6. Correlation analysis of Greenhouse gases and DESI, 2019.

Conclusion

Despite the fact that climate fluctuations have always occurred in the past, today's pace and scale changes are alarming. The goal is to make Europe the first continent to be connected by oil-independent transport, houses that do not waste energy, electricity produced mainly from renewable sources, environmentally friendly agriculture, and an industry based on innovative technologies and energy-effective processes. The member states of the European Union have committed themselves to making Europe a carbon-neutral continent by 2050. After this year, they will only emit enough emissions to eliminate them. By achieving carbon neutrality, the EU wants to contribute to the global fight against global warming, to which it has committed itself by signing the Paris Climate Agreement.

At present, when businesses and countries are dealing with the aftermath of Covid-19, digitalization is currently one of the most important trends that change society and business. Therefore, attention needs to be paid to digital performance and to digital competitiveness as one of the EU's priorities. Based on the DESI index, we can compare countries in the level of digital performance. The results for 2020 show that the most advanced digital economies in the EU are Finland, Sweden, Denmark, and the Netherlands.

In connection with the European Green Deal and its future goals, we focused on the connection between digital technologies (digital performance) and the reduction of Greenhouse gases, whether there is a relationship between countries with high levels of digital performance and a downward trend in emissions. Empirical research reveals that, based on the correlation coefficient in 2018 and 2019, there is an existing correlation between the variables considered, but positive linear correlation is weak between DESI and GHG emissions. When one variable increases, the other variable tends to increase as well, but in a weak or unreliable manner. According to the aim of this paper, the hypothesis is rejected. The countries with a higher DESI index produce more greenhouse gas emissions as well, but in a weak manner. Although the analysis of variance indicates the highly significant differences between variables, there is a need to assess where these differences occur, which requires the follow-up analysis called post hoc analysis. Even though, based on the information found, the paper does not provide confirmation of a strong positive relationship between the two variables under study and the calculated

low value of the correlation coefficient informs of a weak relationship, this finding may provide a basis for further research. Another research of the correlations can be done, for example, by means of regression analysis. Therefore, based on our results, we cannot say that countries with high level of digitalization have low GHG emissions. Countries with the highest values of Greenhouse gas emissions (Germany, France and Poland) display a medium or low score of digital performance. For example, Germany is the largest emitter of Greenhouse gas in the European Union, which is also the most populous country in the Union and does not fit the general trend of the dataset with medium score of DESI index.

Nonetheless, these results must be interpreted with caution and a number of limitations should be borne in mind such as limitation on European countries only and establishing a causal relationship between the two.

In the future, it would be advisable to continue to monitor the relationship with other evidential bases proving the dependence of observed variables and evaluate their development also due to restrictions of the European Green Deal. These findings can support the correlation.

The pandemic has clearly shown us that digital services are our future. The goal for the near future will be to strengthen Europe's capacity for new digital technologies that can help optimize production, reduce emissions and waste, boost organizations' competitive advantages, and bring new services and products to consumers. Digital technologies should be a key factor in determining climate neutrality and environmental sustainability. We can state that digitalization will be beneficial to the environment.

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The Effect of Foreign Direct Investment and Trade Openness on Economic Growth: Evidence from Five African Countries

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Abstract

Through some empirical studies, the flow of FDI and trade openness have proven to support economic growth in developing countries. This paper examines the significance of FDI and trade openness in five African countries (Ghana, Morocco, Kenya, Uganda, and Zambia). The study employed the panel data analysis method using data from the World Bank for the period 1994-2019 for the five selected countries. The result from the Random effect model indicated that FDI positively supports growth, whereas trade openness harms economic growth in these countries. The outcome further revealed that Uganda enjoys more significance than the other countries using the countries' dummies through the pooled model estimation. We recommend that various governments focus more on exports, reduce imports, attract more FDI through incentives, and create a regulatory environment that is friendly to FDI.

Keywords

GDP, FDI, Trade openness, Economic growth, Africa.

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Introduction

Foreign direct investment (FDI) and international trade are potential macroeconomic indicators supporting economic growth in developing and developed nations. Fast-growing trade operations catalyze rising local demands, which in turn help to build large-scale industries and boost export levels (Khan and Khilji, 2011). Developing nations previously had laws restricting trade, but as time passed and globalization emerged, all these nations came to see the value of trade liberalization (Zaman et al., 2018). Many advanced and developing nations started to open their economies to global integration in the 1980s (Güriş and Gözgör, 2015). Most countries have not fully uncovered the significance of FDI and trade openness as the barriers to free trade still exist. International trade has been significant for most developing countries on the African continent as they can leverage consumption of certain goods and services they cannot produce. The relationship between FDI and trade may be the result of FDI's influence on trade through the promotion of export expansion, or it may be the result of trade's influence on investment through the establishment of related services abroad and the adoption of a liberal trade policy regime because of export expansion (Thanh et al., 2019). Trade openness and FDI support technology and technical know-how in developing economies. By taking advantage of comparative advantages brought about by trade openness, open economies have cleared the way for the import of new technology and ideas from the rest of the world, leading to a better division of labour, new techniques of production, and new goods (Tahmad and Abdel, 2018). The recent global pandemic has caused many economies worldwide into recession, reducing the flow of FDI in African countries. Based on the projected gross domestic product (GDP) expansion and some investment-specific parameters, the flow of FDI to the African continent is expected to decrease by 25% to 40% in 2020 and recover in 2022 (UNCTAD, 2020). African countries have identified FDI as accumulating capital to support economic development. Numerous literature

and empirical findings found that FDI stimulates growth in developing countries. FDI is one of the explanatory variables that the modern domestic growth theory emphasizes as a determinant driving economic expansion (Zarria, 2021). According to the World Bank, FDI is also advantageous to the home country because it aids in market expansion, cost reductions, and other tariff reductions (UNCTAD, 2010). The higher aggregate inflow of FDI in Africa has raised expectations about its potential contribution to their development (OECD, 2011).

However, a resident of one economy (the direct investor) wants to acquire a long-term interest in a business located in another economy (Patterson et al., 2004); the goal of the foreign investment category is FDI (the direct investment enterprise). Since foreign investors frequently maintain tight control over the operations of affiliated companies due to ownership advantages linked to their proprietary assets and long-term interest, the underlying rationale for all such analytical exercises to capture the overall impact of FDI inflows has been the fundamental insight that FDI's impact and implications for the development of host economies are very different from those of foreign portfolio capital inflows that are more transient (Francis, 2010). The flow of FDI on the African continent increased rapidly in the 2000s. FDI inflow to the continent in the second half 1990s, and after increasing to a record of US$ 10.5 billion in 1999, decreased to US$ 9.1 billion in 2000 (Basu and Srinivasan, 2002). However, according to the World Bank, due to COVID-19, there has been a sharp decline in foreign private investment in Africa, with foreign direct investment (FDI) flows to the continent expected to shrink by about 16% in 2020. According to UNCTAD's World Investment Report 2022, FDI to African nations reached a record $83 billion in 2021. This was more than twice as stated in 2020 when the COVID-19 epidemic significantly negatively impacted regional investment. Despite the rapid expansion, just 5.2% of all foreign direct investments (FDI) worldwide went to Africa, up from 4.1% in 2020. While FDI increased moderately in most African nations in 2021, a financial transaction within a single company in South Africa accounted for about 45% of the total.

Conversely, according to the World Bank, trade is the aggregate of exports and imports of goods and services measured as a share of GDP. This ratio is frequently referred to as the trade openness ratio. Still, the term "openness" may be misleading because a low ratio may be caused by factors like the size of the economy and geographic distance from potential trading partners rather than high (tariff or non-tariff) barriers to foreign trade (OECD, 2011). However, the OECD indicated that the total value of goods and services traded internationally demonstrates how integrated a nation is into the global economy. Smaller nations are typically more interconnected; they specialize in fewer export industries and depend on imports more than larger nations to meet domestic demand. Additionally, trade integration is not solely determined by size. Geography, history, culture, trade policy, economic structure (particularly the proportion of non-tradable services), and integration in global production chains are additional factors that explain differences between nations. Measured trade may also include a sizeable portion of re-exports and intra-firm trade linked to the presence of multinational corporations (OECD, 2011). In the 1960s and 1970s, trade openness encouraged convergence, but after 1980, trade benefits largely went to the wealthier economies, with little benefit going to the less developed economies (Dowrick and Jane, 2004). Most of the trade's dynamic gains are derived through productivity growth, with increased investment making up a very modest portion. The simple outcome-oriented measures of trade openness only capture one aspect of trade openness: countries' share of trade, whereas the policy-oriented measures of trade openness used in earlier studies have been claimed to be subjective (Njindan, 2017).

Numerous researchers have jointly tested FDI and trade openness on economic growth through different methods and obtained different outcomes. The empirical results from past studies indicated that FDI and foreign trade could positively and negatively impact economic growth. According to (Sayef and Sofien, 2019) empirical findings of 24 Asian economies through the fixed and random effect models discovered that exports and foreign direct investment are harming the growth trajectory. Conversely, an empirical analysis based on 16 years of panel data from Southeast European nations by Fetahi-Vehapi et al. (2015), their estimation findings show that the baseline per capita income and other explanatory variables are necessary for the favorable effects of trade openness on economic growth; otherwise, there is weak evidence between these two variables. However,

Naveed and Shabbir (2006) used developed countries and discovered that openness is important and has a favorable impact on GDP per capita growth, but FDI seemed to have little impact. Furthermore, Sabir et al. (2019) used panel data for low, lower-middle, upper-middle, and high-income nations. Their findings support the notion that institutional quality influences FDI favorably across all nations. Consequently, Alam and Sumom (2020) investigated the causal relationship between trade openness and economic growth using 15 Asian nations. Their result demonstrated that trade openness has a favorable effect on economic growth. Chen and Gupta (2006) provided evidence through an empirical result that trade openness had a strong positive effect on Southern Development Community's economic growth. Additionally, Victor (2019) found a positive impact of trade openness in the Economic Community of West African States. Bajwa and Siddiqi (2011) stated that there is a long-term negative relationship between GDP and openness, as evidenced by the long-term elasticity magnitude between both being negative from 1972 to 1985. Conversely, empirical results of Brueckner and Lederman (2015) show that trade openness has a significant positive impact on Sub-Saharan African economies. Then Kumar´s and Rani´s (2018) results show that trade openness positively impacted growth, whereas FDI has a negative effect. On the other hand, the panel data analysis found trade openness to support high economic growth (Ulaşan, 2015). Liargova and Skandalis (2012) indicated that trade openness contributes positively to FDI in these nations in the long run in 36 developing countries. According to Quazi (2007), FDI in Latin America is strongly and significantly influenced by economic freedom. However, study by Kumari and Sharma (2017) indicated that fixed effect estimates show that market size, trade openness, interest rate, and human capital produce significant coefficients in connection to FDI inflow. The results show that the biggest factor affecting FDI inflow is market size. Conversely, Majeed and Ahmad (2009) confirmed that openness positively impacts FDI flows to developing nations. Ali´s (2016), findings indicated a significant link between trade openness and foreign direct investment inflows. Positive and significant effects of trade openness on FDI inflows to South Asian nations. Boğa (2019) stated that in the long run, it has been discovered that factors such as GDP growth, trade openness, local credit, natural resources, and telecommunications infrastructure all affect FDI inflows in Sub-Saharan African nations. However, only GDP growth and trade openness determine FDI inflows in the medium term. Zekarias (2016) concluded that FDI is a key driver of economic growth and a catalyst for conditional economic convergence in Eastern Africa.

Despite the significant number of works devoted to the study of FDI, trade openness, and economic development in developing countries, the findings have been ambiguous and contradictory. However, this study seeks to contribute to the existing hypothesis theory that FDI and trade openness support economic development. Consequently, the study is significant to the uncovered significance of FDI and international trade in developing economies. While the effects of FDI and trade openness have been captured in most studies on major economies in Africa, the impact of FDI and Trade openness on economic development in Uganda and Zambia remains insufficiently studied. Therefore, this study aimed to investigate the significance of FDI and trade openness in five African countries.

Materials and methods

To understand this study's goal through exploring the relationship between foreign direct investment and trade openness with the gross domestic product as a proxy for economic growth. This study aimed to investigate the significance of FDI and trade openness in five African countries. The study used annual data from 1994 to 2019 from the World Bank for five developing nations on the African continent, which include Ghana, Kenya, Morocco, Uganda, and Zambia. The reason for choosing these specific countries is because of regional balance since each of the countries is located within the various sub-regions of the African continent. Moreover, these countries depend heavily on FDI inflows for developmental projects. Consequently, these countries often experience a balance deficit from international trade, so assessing the impact of FDI and trade openness on economic growth is significant. The data may be limited due to variations in the availability of uniform data for all the countries. Lack of uniformity in the observations time range for all variables for the respective nations causes restrictions. The rationale for using data from 1994 to 2019 is because there was available data on FDI and trade openness for the selected countries. However, there were some missing data yearly for some of the countries in the early 90s, and it is ideal

for the study to be restricted to the available data. The chosen approach is based on the methods used in past literature (Wiredu et al., 2020; Batrancea et al.,2021; Mohan,2007), in which GDP was used as the proxy for economic growth. The model specification to be estimated in this study are as follows:

$\gamma_{it} = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + ... + \beta_d x_{di} + \varepsilon_i$
(Linear econometric equation)

$lnGDP_{it} = \beta_0 + \beta_1 FDI_{it} + \beta_2 Trade_{it} + \varepsilon_{it}$

The subscript t = time and i = country

Where $lnGDP_{it}$ is the log of Gross domestic product in US$. The gross domestic product also measures the market. FDI_{it} is foreign direct investment inflow in the current US$, whereas it also represents total inflows. $Trade_{it}$ represents (export plus import) ratio to GDP. Gross domestic product is used as a proxy to assess the selected countries' economic growth. Furthermore, we first tested for the significance of the variables towards economic growth through the pooled model for a better understanding.

Consequently, a panel diagnostic test was performed to determine whether the pooled model was adequate over the fixed and random effect model. The panel diagnostic test shall determine whether the fixed or random effect model will be used as our final model. The model equations for fixed and random effects can be written as follows:

$Y_{it} = \alpha_i + \beta X_{it} + \varepsilon_{it}$ = fixed effect model

$lnGDP_{it} = \alpha_i + \beta_1 FDI_{it} + \beta_2 Trade_{it} + ... + \varepsilon_{it}$

In a fixed effect model, the levels are either predetermined or based on the data's experimental design. Often, a fixed impact has "few" levels. In the case of the fixed effect, conditional expectation (mean) of interest.

$Y_{it} = \alpha_i + \beta X_{it} + \mu_{it} + \varepsilon_{it}$ = *random effect model*

$lnGDPit = \alpha i + \beta 1 FDIit + \beta 2 Trade_{it} + ... + \mu_{it} + \varepsilon_{it}$

The levels in a random effect model come from the distribution of a random variable, most likely a normal one. An effect caused by randomness frequently has "many" levels. Estimates of the random effect's variance are made. The assumption is that fixed and random effect models are uncorrelated.

α in the pooled model equation is the constant term for the group of countries. The Pooled model assumes that the group has the same mean. However, the α_i in both Fixed and Random effect models indicates the unknown intercept of each country. μ_{it} is the 'Between' variance, whereas ε_{it} is the' Within' variance. Y_{it} is the explained variable, X_{it} represents explanatory variables, and β is the coefficient of the explanatory variable. The description of the group mean by numbers (1-5) is indicated in Table 1.

ID (group)	Country
1	Ghana
2	Zambia
3	Morocco
4	Uganda
5	Kenya

Source: Authors calculations

Table 1: Countries representation by ID number.

These ID numbers are unique identification codes for each country in our analyses. The study also employed the ADF unit root test to assess time series properties. This test helps to identify whether the time series is stationarity or non-stationarity. Conversely, multicollinearity was performed to investigate if some variables were not a perfect combination of each other.

Countries description

Ghana is in the West African region with a GDP of US$ 77.59 billion as of 2021, a GDP per capita of US$ 2,445, and a population of 31.07 in 2020. However, Kenya is in the Eastern part of Africa with a GDP of US$ 110.35 billion in 2021 and a GDP per capita of US$ 2,007 with a population of 53.77 million as of 2020. Consequently, Morocco is situated in the North of Africa with a GDP of 132.73 billion in 2021, GDP per capita of US$ 3,497, and a population of 36.91 million as of 2020. Conversely, Uganda is also found in the Eastern part of the continent, with a GDP of US$ 37.60 billion, GDP per capita of US$858 in 2021 and a population of 45.74 million in 2020. Furthermore, Zambia is often considered part of southern African countries with a GDP of US$ 21.20 billion per capita of US$ 985 in 2021 and a population of 18.38 million in 2020.

Results and discussion

Table 2 displays the summary statistics of the time series variables, including their means, medians, standard deviations, minimum, and maximum.

The summary statistics cover all independent countries concerning this study. The output shows that trade openness has the highest mean and median

Variable	Mean	Median	S.D.	Min	Max
GDP	34.1	25.9	31.0	3.40	120.
Trade	61.1	60.1	18.5	27.8	116.
FDI	1.02	0.625	1.08	0.0100	3.88

Source: Authors calculations

Table 2: Summary statistics.

values, followed by GDP and FDI, respectively. However, Table 3 indicates the correlation matrix among the selected variables. The correlation coefficients at 5 % critical value (two-tailed) equal 0.1723 using all the observations.

GDP	Trade	FDI	
1.0000	0.1703	0.6847	GDP
	1.0000	0.3650	Trade
		1.0000	FDI

Source: Authors calculations

Table 3: Correlation matrix.

The output in Table 3 indicates that there is a positive relationship among the variables toward economic growth in each of the countries.

Collinearity test

Collinearity diagnostic test using Belsley-Kuh-Welsch (BKW) test is displayed in Table 4. The collinearity test shows the variance proportions of the variables using the lambda and Cond values. According to BKW, Cond greater or equal to 30 indicates strong near linear dependence and Cond between 10 and 30 shows moderately strong. Parameters estimates whose variance is mostly associated with problematic Cond values may be considered problematic.

The lambda is equal to eigenvalues of the inverse covariance matrix (smallest is 0.0375096), whereas Cond represents the condition index. Based on the result of the collinearity test in Table 4 shows no evidence of excessive collinearity.

ADF unit root test

However, testing for unit root the outcome shows that the variables are non-stationarity at a level whereas they became stationarity series at first difference. The ADF unit root test was carried out as the groups with a null hypothesis of all groups having unit root. The Dickey-Fuller test for all the variables was tested using the variant with constant, which has the equation $(1\text{-}L)\ y = b0 + (a\text{-}1) * y\ (\text{-}1) + e$. Under the variant with constant has a Choi meta-test, which includes inverse chi-square, inverse normal and logit test. Tables 5 and 6 indicate the details of the unit root results at a level and first difference.

The outcome of the unit root test at the level indicated a unit root presence in the variables because the p-values are greater than the 5 % significant level, and we failed to reject the null hypothesis. The assumption that a unit exists in the variables equals 1, and the asymptotic p-value is used to assess it. Any p-value greater than 5 % indicates a unit root presence.

Regression result

Table 7 indicates the regression coefficient outcome from the Pooled model. The coefficients of FDI and trade are significant at 1% in the Pooled ordinary least squares (OLS) output. FDI had a positive impact on the GDP trend towards economic growth. It also means that an increase in FDI will expand growth by 0.72% in these countries. However, the trade openness coefficient was negative, showing that trade harms the selected countries' economic growth. The coefficient of trade means that a rise in trade will lead to a 0.01% decrease in GDP.

$$lnGDP_{it} = 2.984 + 0.722(FDI_{it}) - 0.011(Trade_{it})$$

The Pooled model R-squared shows that 51% of the variation is explained in GDP by the regressors (FDI and trade). The p-value of the F-statistics is significant at a 1% level. However, some studies over the years found that FDI positively correlates with economic growth, confirming our findings about FDI. For instance, Adedeji and Ahuru (2016) found FDI inflows to support economic growth positively in Sub-Saharan African countries. On the other hand, Gui-Diby (2014) also indicated that FDI inflows have a significant impact on economic growth in 50 African countries, and there was some dynamic in results because from 1980 to 1994, FDI inflows had a negative effect. In contrast, there was positive support from 1995 to 2009. Conversely, Ayenew (2022), Cinar and Nulambeh (2018), and Wiredu et al. (2020) also found trade openness to positively support growth which does not confirm the coefficient of trade openness in our model. The significance

Lambda	Cond	Constant	GDP	Trade	FDI
3.356	1.000	0.006	0.017	0.006	0.017
0.448	2.736	0.046	0.110	0.033	0.172
0.159	4.597	0.003	0.797	0.013	0.664
0.038	9.458	0.944	0.076	0.949	0.147

Source: Authors calculations

Table 4: Belsley-Kuh-Welsch collinearity diagnostics.

Variables	Inverse Chi-square (10)	Inverse normal test	Logit test	Number of sample size
Trade	12.029 = p-value (0.283)	-0.901= p-value(0.1837)	-0.869 = p-value (0.196)	1994-2019
Log of GDP	1.784 = p-value (0.998)	2.421 = p-value (0.992)	2.378 = p-value (0.988)	1994-2019
Trade	11.717 = p-value (0.304)	-0.134 = p-value (0.447)	-0.103 = p-value (0.459)	1994-2019

Source: Authors calculations

Table 5: ADF unit root at level.

Variables	Inverse Chi-square (10)	Inverse normal test	Logit test	Number of sample size
Trade	82.213= p-value (0.0000)	-7.722 = p-value (0.0000)	-10.503= p-value (0.0000)	1995-2019
Log of GDP	47.352 = p-value (0.0000)	-5.255 with a p-value of (0.0000)	-6.030 = p-value (0.0000)	1995-2019
FDI	98.395 = p-value (0.0000)	-8.376 = p-value (0.0000)	-12.569=p-value (0.0000)	1995-2019

Source: Authors calculations

Table 6: ADF unit root after first difference.

Variables	Coefficient	Std. Error	t-ratio	p-value
constant	2.984	0.221	13.52	2.39e-26***
FDI	0.722	0.063	11.44	2.93e-21***
Trade	−0.011	0.004	−2.902	0.0044***

R-squared	0.51
Adjusted R-squared	0.50
F-statistic (2,127) = 66.3	P-value (F) 1.88e-20
Number of observations	130

Note: significant codes: *** 1%
Source: Gretl output using World Bank data

Table 7: Pooled model estimation.

of FDI inflows towards economic expansion is because of institutional reforms, investment incentives, and openness of the various economies to foreign investors. Formerly, investments were concentrated in the extractive industry, and FDI is now permeating the manufacturing and services sectors. For example, according to the United Nations, in 2016, the manufacturing industry accounted for around one-fifth of greenfield FDI projects, while the services sector accounted for about three quarters. In actuality, FDI is increasingly a significant funding source for economic diversification. However, for a deeper understanding, we further dummy the countries and re-assess their responses as individuals through the Pooled OLS, and the outcome is indicated in Table 8. The output shows that both variables (FDI and trade) have significance in the individual countries. However, the significant level differs among the countries.

The coefficient of the variables with the countries dummy indicates that if trade openness and FDI inflows expand, growth will increase by 2.51% in Ghana, 2.39% in Zambia, 2.52% in Morroco, 3.6% in Uganda, and 3.5% in Kenya, respectively. The flow of FDI to Ghana has increased over the years due to the government's investment and trade policy reforms. However, Ghana has been a net importer for many years, reflecting the negative significance of trade openness in the country's economy. East Africa's greatest

Variables	Coefficient	Std. Error	t-ratio	p-value
FDI	0.655	0.0497	13.17	2.90e-25***
Trade	−0.008	0.004	−2.031	0.0444**
DCountry_1	2.510	0.339	7.397	1.89e-11***
DCountry_2	2.395	0.289	8.305	1.52e-13***
DCountry_3	2.515	0.183	13.72	1.46e-26***
DCountry_4	3.558	0.303	11.73	8.80e-22***
DCountry_5	3.499	0.229	15.22	4.61e-30***

R-squared	0.76
Adjusted R-squared	0.75
F-statistic (6,123) = 66.3	P-value (F) 3.28e-36
Number of observations	130

Note: significant codes: *** 1%, ** 5%
Source: Gretl Output using World Bank data

Table 8: Pooled model estimation with country dummies.

economy at the moment is Kenya. Currently, the nation generates almost 50% of the GDP of East Africa (Nicholas, 2022). As a result, it has been the top choice for many international investors looking to set up investment in Africa.

Consequently, the Morroco economy is witnessing a greater impact of FDI and trade liberalization because of the strong policies to support its economy. The Morrocan government implemented several structural, institutional, and regulatory reforms in financial and trade liberalization . The promotion of investment, including tax relief, judicial system reform, trade liberalization, industrial property strengthening, banking sector modernization, infrastructure development, and development of several free zones (Sfar and Mtar, 2017). Conversely, Uganda experiences a higher impact on trade openness and the flow of FDI from the pooled model because most of the agricultural projects that foreign companies invest in involve producing flowers for export markets. According to the Uganda Bureau of Statistics, the growth and processing of oil seeds into finished products, the growing, processing, spinning, and knitting of cotton, and the production and processing of livestock products like milk and hides.

Additionally, Zambia's key recipients of FDI inflows in the agriculture industry, tourism, and copper and cobalt extraction. Foreign direct investment (FDI) has traditionally been mostly contributed to by businesses or groups of businesses from nations like the United Kingdom and South Africa; however, FDI inflow from other nations has dramatically increased in the Zambian economy (Jere et al., 2017). International trade has been a major challenge for most African countries as they import more than they export.

Panel diagostic test

Assessing whether the pooled model is adequate, a panel diagnostic test was performed to check the quality of the model against the fixed and random effects model. The pooled model assumes the group has the same mean, whereas the fixed and random effects model identifies the groups to have different means. The diagnostic test is shown in Table 9.

Panel diagnostic test	Null hypothesis	P-value	Conclusion
F-test	Pooled model is adequate	1.16954e-18	Ho is rejected; the fixed effect model is adequate.
Breusch-Pagan specification test	Pooled model is adequate	1.21861e-86	Ho is rejected; the random effect model is adequate.
Hausman specification test	The random effect model is consistent	0.867017	Ho is not rejected; the random effect model is adequate.

Source: Gretl output using World Bank data

Table 9: Panel diagnostic test of the Pooled model.

Under the panel diagnostic test, using F-test compares the pooled model against the fixed effect model and a low p-value count against the null hypothesis, which states that the Pooled model is adequate. The p-value must be greater than the 5% significant level for an acceptance of the null hypothesis. The Breusch-Pagan specification test compares the Pooled model to the random effect model, whereas the Hausman specification test compares the random effect model to the fixed effect model. However, the F-test proves

that the fixed effect model is more appropriate than the Pooled model. The Breusch-Pagan specification also indicated that the random effect model is better than the Pooled model. In contrast, the Hausman specification result also displayed the random effect model as appropriate for the final model. Hence, the model estimation through the random effect in the final model.

Table 10 shows the output of the fixed effect model. The coefficients have the same sign as in the Pooled model. The joint on named regressors test statistic of 87.2382 with a p-value of 2.58129e-24, which is statistically significant at a 5% level. However, the test for differing group intercepts null hypothesis of the group having a common intercept is rejected because the p-value was 1.16954e-18 which is significant at 5%.

The least squares dummy variables (LSDV) estimator R-squared indicated 76% variation explained in the dependent variable (GDP) by the regressors (FDI and trade). The F-statistics of the overall model are significant. The coefficient of FDI indicates a positive impact on economic growth in the selected countries, whereas trade openness negatively affects growth. However, the outcome of the variable coefficients in the random effect model is indicated in Table 11.

$lnGDP_{it} = 2.898 + 0.657\ (FDI_{it}) - 0.008\ (Trade_{it})$

The 'Between' variance of 0.581599 and 'Within' variance of 0.260766 with theta used for quasi-demeaning equal to 0.869799, and correlation (y, yhat)2 is 0.510049 from the random effect model means that country have different group means. Conversely, the Joint test on the regressors' asymptotic test statistic Chi-square was 178.414 with a p-value of 1.81096e-39, which means that the joint test's F-test is significant at a 1% level. The coefficients of FDI and trade in the Pooled model were higher than those in the random effect model. Consequently, the coefficients have the same signs as indicated in the Pooled OLS output: FDI coefficient with a positive sign and trade coefficient with a negative. The pooled and random effect results show that trade openness harms the country's economic growth. At a 5% significant level, the null hypothesis that the errors are normally distributed cannot be rejected since the p-value is 0.068 and greater than the critical value.

The pooled, fixed effect and random effect models confirmed a positive and statistically significant impact of FDI inflow on the selected countries' economies from 1994-2019. We affirmed the hypothesis that FDI supports economic growth in an economy in the long run. The findings about FDI conform with several studies in the Past (Haque et al., 2022; Aneyew, 2022; Zekarias, 2016). Consequently, our results did not confirm the hypothesis that Trade openness positively stimulates economic growth in the long run because the coefficient in the models had a negative sign which means that it harms development. Studies also found a negative impact on trade openness (Adu-Gyamfi et al., 2020).

Variables	Coefficient	Std. Error	t-ratio	p-value
constant	2.895	0.251	11.52	2.87e-21***
FDI	0.655	0.049	13.17	2.90e-25***
Trade	−0.008	0.004	−2.031	0.0444**

LSDV R-squared	0.76
Within R-squared	0.59
LSDV F (6, 123) =66.3	P-value (F) 3.28e-36
Number of observations	130

Note: significant codes: *** 1%, ** 5%
Source: Gretl Output using World Bank data

Table 10: Fixed Effect model estimation.

Variables	Coefficient	Std. Error	z	p-value
constant	2.898	0.419	6.922	4.46e-12***
FDI	0.657	0.049	13.33	1.58e-40***
Trade	−0.008	0.004	−2.088	0.0368**

Note: significant codes: *** 1%, ** 5%
Source: Gretl Output using World Bank data

Table 11: Random effect estimation.

Conclusion

The study investigates the linkage of FDI inflows, trade openness, and economic development in five selected nations (Ghana, Kenya, Morocco, Uganda, and Zambia) for 26 years. The data was collected from the World Bank on annual frequency from 1994 to 2019 and analyzed using summary statistics, correlation matrix, ADF panel unit root test, panel diagnostic test, and random effect estimation for the final findings. The individual significance using the countries dummy through a Pooled model shows that Uganda enjoys a high significance level from FDI and trade openness, followed by Kenya, Morocco, Ghana, and Zambia, respectively. The Hausman test of the panel diagnostic test revealed that the random effect estimation is the most preferred over the fixed effect model. The results from the random effect model indicated that FDI positively affects economic growth, whereas trade openness negatively impacts growth in the selected countries. The findings concluded that FDI inflows have a positive impact on the economies of the countries under study, which confirmed the hypothesis that FDI stimulates growth, but not in the case of trade openness in the selected countries. This implies that the hypothesis that trade openness facilitates economic development is not validated in this study.

The findings have a higher practical implication for these economies. The policymakers in these countries should encourage and support domestic firms by providing incentives enabling them to produce on a large scale for domestic consumption and exports. Furthermore, governments need to ensure that their economies are attractive and favorable for investment to encourage the growth of FDI. This can be accomplished through infrastructure development and liberalization of national policies to create a regulatory environment that is friendly to FDI by easing restrictions on foreign ownership and market entry and enhancing market efficiency. Additionally, the limited observation because of a lack of uniform time range for the variables regarding the individual countries may hinder the dynamism of the findings. Future research works can consider other variables and increase the sample size for more in-depth analysis.

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Development of Organic Production in Ukraine: Potential, Current Threats and Consequences for Global Food Security

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Abstract

The article aims to analyze the potential of organic production in Ukraine in war conditions and determine its consequences for world food security. Methodological approaches based on cluster and rating analysis of regions based on their potential in the field of organic production are proposed and provide an appropriate evaluation algorithm, mathematical tools, and strategic alternatives for all variants of data obtained in the calculation process. With the help of the given methodological approaches, the development of strategies for organic production for the primary clustering of regions, namely in Kyiv, Odesa, and Cherkasy oblasts, is proved. The system of forming a regional model of organically oriented multidisciplinary agriculture is appropriate for these regions. This will create the preconditions for organic food production, organic livestock, and related sectors of environmentally oriented economic activities. The development of an innovative component for implementing SMART-specialization projects is possible. It is substantiated that the most affected regions (Kharkiv, Luhansk, Donetsk, Kherson, Mykolaiv, Zaporizhia) from hostilities and occupation are potential for organic production and have significant areas for agricultural production. It is projected that the other war in Ukraine will reduce the production of farm products, including organic, which will lead to food security in most countries.

Keywords

Organic production, world food security, agricultural products, potential, war.

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Introduction

The situation in Ukraine can lead to a global crisis in the world, due to the deterioration of agricultural lands and other lands, the destruction of agricultural and critical infrastructure. Ukraine has the largest area in Europe (603.6 thous. sq. km), a significant share of agricultural land (about 70% of the country's total area), favourable geographical location and labour resources for farming.

Russia's war against Ukraine led to the loss of a significant part of Ukrainian agricultural products due to the production and conduct of intense hostilities. Russia's ongoing war against Ukraine could lead to a global food crisis in the world. That is why the strategy of organic product development should be reflected in the process of socio-economic development of Ukraine's regions during the war, in particular in a separate territory, as an alternative direction of competitiveness, improving the quality of life of a rural population, development of depressed areas and one of the alternative ways of economic growth.

Most scientists influence the diversification of agricultural production, cultivation of various species, and population growth on food security (Oppong, et al., 2014; Blizkovsky, et al., 2020). However, the study of the impact of hostilities on global food security in current conditions has not

received sufficient attention. Ukrainian scientists note that Ukraine has significant domestic potential for agricultural production, allowing it to strengthen global food security (Popadynets et al., 2021).

Despite the low productivity and high costs for the production of organic products in the region for display in the production of pesticides, GMOs, and other substances of non-biological origin, the development of the organic output brings significant economic long-term benefits to the country. According to UNEP, such benefits include:

- Direct economic benefits for farmers, traders, and producers from the products themselves (e.g., higher prices and reduced costs);
- Economic benefits for society - employment (throughout the value chain);
- Economic benefits for society - increased exports (e.g., organic products and/or reduced imports, such as energy and agrochemicals);
- Direct economic benefits for producers from the sale of public goods and services (e.g., biodiversity conservation and landscape care or capture-oriented carbon pricing mechanisms);
- Long-term benefits from increasing natural capital, especially from soil improvement;
- Costs for society (for example, water purification and medical care);
- increase capital (for example, cooperation between consumers, pride in doing something valuable, increasing trust in the value chain, as well as deeper understanding between consumers and owners) (UN Environment Program, 2018).

This is Senyshyn (2017) believes that "if the development of organic food production and organic farming in the coming years does not become a strategic task of Ukraine, the import and its own shadow production of genetically processed food can destroy the gene pool of the Ukrainian people. Therefore, we strive to emphasize the need to intensify the production of organic products in Ukraine, taking into account the experience of production of these products in European countries". Thus, the stage in substantiating strategic directions for the development of organic food products is the harmonization of national and international legislation. We propose to divide the strategic principles of the development of organic food products into macro-, meso- and micro-levels.

Thus, as noted by Kulish (2019), "Organic production in Ukraine is an up-and-coming area that can increase the competitiveness of agricultural products, significantly improve the country's image on the world stage, and promote market infrastructure and sustainable development of the country as a whole. However, the identified problems require the development of effective measures of state support to increase production and sales of organic products, which requires further research in this area ". Thus, only with the help of well-established cooperation between the state and business is it possible to sustainably increase the production of organic products, ensuring its competitiveness in the world. An effective mechanism of state support will ensure sustainable organic food production.

Ushakova-Kirpach (2020) believes that "In the context of increasing trends in human population, exacerbation of the global food problem and growing global demand for food, the interest of academia and economic elites in the efficient production of environmentally friendly agricultural products is growing. Given the geopolitical and climatic conditions, Ukraine has a huge potential in the market of organic products, which is developing rapidly in the world and especially in the European Community. This requires the creation of a clear regulatory state mechanism for the development of organic production and harmonization of Ukrainian legislation with European standards". The current state mechanism for regulating the production of organic products must meet the requirements of the international community. That is why the legislation of Ukraine on organic production should harmonize with the international one.

In addition, Granovska (2017) also determines that "The development of organic sector enterprises requires continuous improvement of their management and production activities to ensure competitiveness. Competitive development and the formation of sustainable competitive advantages help maximize management's positive economic effect, the disclosure of aggregate production potential, and economic growth of agricultural formations. The process of providing competitive advantage has several stages of development. Competitive advantages of the first level are formed due to the excess of basic resources, the second - due to the intensification of investment policy

and increased investment, and the third level is determined by innovation; such competitive advantages are considered the highest". The competitive development of organic production is impossible without an active investment policy and the search for essential resources that will ensure the implementation of innovations.

Tkachuk (2015) emphasizes that "Given the world experience, it can be argued that without the organization of the organic market it is impossible to spread organic farming, so it is necessary to support and stimulate its development, promote information about the benefits of organic products, create appropriate information and consultation structures. It protects the rights of consumers of organic products, research, educational centers, etc. All this will increase the number of organic enterprises and increase employment. In addition, the intensification of organic production will improve the biological activity of the soil, restore the balance of nutrients and, as a result, increase crop yields and increase producers' income". A compulsory component for developing organic production is the activation of all participants in the process. This will provide incentives from different sides to organize the production of organic products.

Food and Agriculture Organization of the United Nations (FAO) (2006) "Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences in order to lead a healthy and active life." This definition gives greater emphasis to the multidimensional nature of food security and includes: "the availability of food, access to food, biological utilization of food, and stability".

Given the significant potential for developing organic production and expanding the market for organic products in Ukraine, specific mechanisms have been launched to stimulate this area of agriculture. In particular, according to the Ministry of Agrarian Policy and Food, in 2021, the government has allocated UAH 50 million for state support of producers of organic agricultural products, which will be directed as follows:

1) Budget subsidy per unit of cultivated land (1 hectare) - for UAH 5,000, but not more than UAH 100,000. Per one operator (total amount UAH 30 million);
2) Budget subsidy for the maintenance of cattle, identified and registered by the law as of August 1 of this year - in the amount of 5 thousand UAH. Per 1 head of livestock (total amount UAH 15 million);
3) Partial reimbursement of the cost of certification of organic products - in the amount of 30% (excluding value-added tax), but not more than 20 thousand UAH per business entity (total amount of 5 million UAH) (Ministry Agricultural Policy and Food, 2021).

The purpose of the article is to assessing the potential of regions in the field of organic production.

Materials and methods

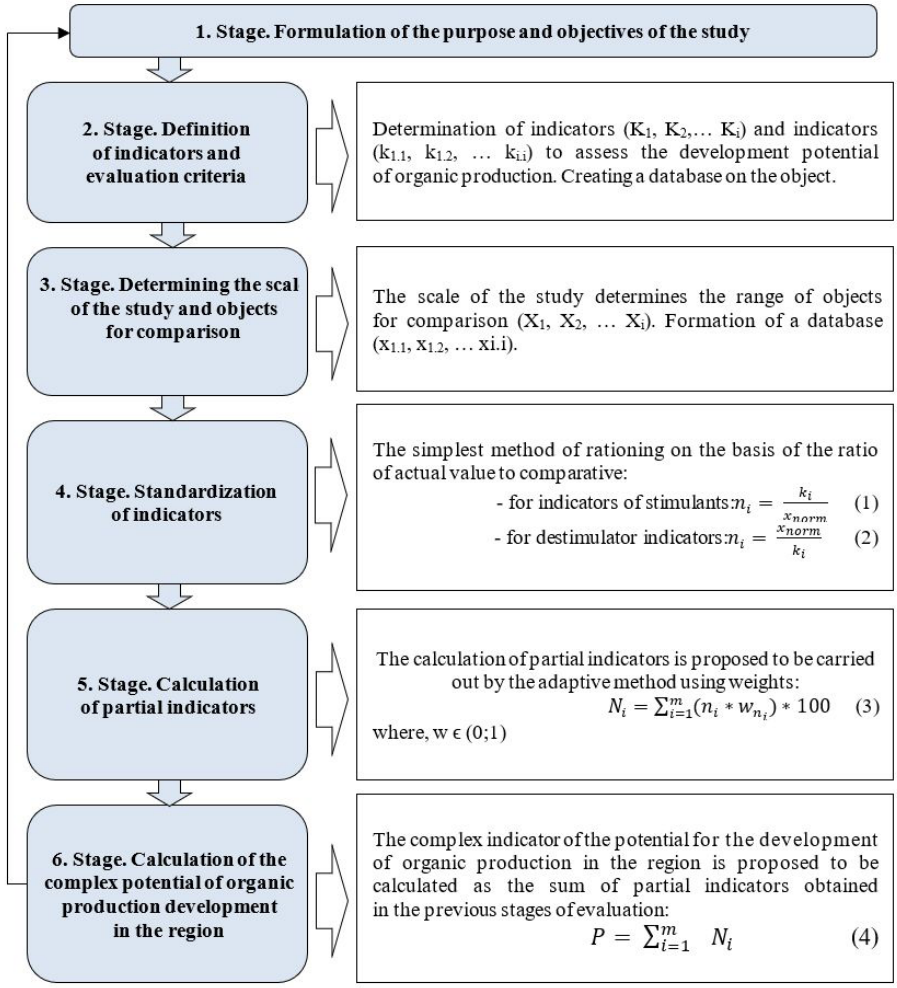
The formation and implementation of a strategy for developing organic production in the context of decentralization for OTG in which the rural population. Stimulating the development of the organic output and creating appropriate clusters, cooperatives, and other integration entities will help consolidate the people. Develop human potential, strengthen the economic base and infrastructure, and develop related economic activities: green tourism, green energy, and more.

In this context, we agree with Golyan et al. (2021) that "the creation of united territorial communities based on urban and rural settlements creates additional demand for organic agricultural products and enables local self-government to coordinate the activities of the subjects of organic farm production through the transfer of agricultural land and the provision of various financial preferences at the expense of local budgets. That is, decentralization has created additional opportunities for the accelerated development of organic agricultural production, which, provided the formation of appropriate institutional and financial support, will give new impetus to the socio-economic prosperity of united territorial communities.

The proposed method is based on the use of cluster and rating analysis tools and involves the following steps, shown in the Figure 1.

The first stage of assessing the potential of the region (territory) from the standpoint of organic production is to determine the purpose and objectives of such assessment. This will affect the selection of relevant indicators, indicators, and their ranking.

The next step is to select the most relevant indicators and evaluation indicators. In connection



Source: processed by the authors

Figure 1: Stages of assessing the potential of regions in the field of organic production.

with the features and conditions necessary for the development of the agricultural output, as well as the availability of statistical data available for evaluation, we have proposed indicators grouped into three groups:

1) Resources (resource potential) - a set of resources necessary for developing agricultural production and production of organic products. In particular, these are the area of agricultural land suitable for growing crops and humus content as an essential characteristic of their quality, rural populations that can potentially be involved in organic production processes. And the market value of agricultural land, which characterizes its value and potential productivity for crop development. This group of indicators in work is attributed to the stimulators of organic production.
2) Ecology (ecological potential) - the environmental condition of territories, which is an essential condition for growing organic products: waste of different safety classes, incineration and disposal of waste in the region, the level of wastewater treatment, and the concentration of emissions into the air. The indicators used to assess the environmental friendliness of the area with their content are disincentives that should be taken into account in the rationing process.
3) Experience (business potential) - indicators that characterize the region's

specific achievements in agribusiness and organic production in particular, as well as the level of support for producers at the level of local governments. All indicators used to assess this group are stimulants. The third stage determines the scope of the study (global market, country, region, territory) and identifies the object for comparison.

Table 1 shows the leading indicators and indicators proposed to assess the potential of regions in the field of organic production.

Resources (R)	
Area of agricultural land, thousand hectares	r_1
Humus content in the soil, t/ha	r_2
Availability of tractors at agricultural enterprises, units	r_3
Rural population, thousand people	r_4
Normative monetary valuation of agricultural land, UAH/1 ha	r_5
Ecology (E)	
Waste generation of I-III hazard classes, t/km²	e_1
Generation of hazard class IV waste, t/km²	e_2
Waste incineration, thousand tons	e_3
Emissions of pollutants into the atmosphere from stationary sources of pollution, thousand tons	e_4
Discharge of contaminated return water into surface objects, million m³	e_5
Experience (P)	
Number of certified organic market operators, units	p_1
Area of agricultural lands with organic status, ha	p_2
The share of the region in the gross output of agriculture, %	p_3
The share of investment in agriculture in the structure of gross investment in the region, %	p_4
Regional support for the development of organic production (availability of existing regional programs or projects) (1-yes, 0-no)	p_5

Source: systematized by the authors

Table 1: Indicators and indicators for assessing regional potential in the field of organic production.

Objects for comparison can be:

- similar (adjacent, competing, alternative) regions, economic entities, or territories;
- the most perfect in terms of organization of production and market activities, regions, businesses, or territories;
- a system of normative values of selected evaluation criteria.

In the context of our study, the object of comparison is the regions of Ukraine, and as benchmarks - the best values achieved in the areas at the time of the assessment. That is the maximum values of indicators of stimulants and the minimum values of indicators of disincentives for the development of organic farming. The system of actual indicators for assessing the potential of regions in terms of hands is given in the appendices.

It is proposed to use weights to determine the selected indicators in certain numerical intervals and ranking of hands for the evaluation of needles depending on the purpose of assessment. In the context of our study, the weights of all indicators are set at 0.2.

Results and discussion

Standardization of indicators for assessing the development potential of organic agriculture in the regions was carried out, and partial indicators were calculated. The results of the calculations are shown in Tables 2 – 5.

The results of the calculations showed that Odesa (86.7), Kharkiv (85.2), Dnipropetrovsk (84.6), Poltava (80), Vinnytsia (77.2), and Kirovohrad (77.3) regions are in the lead in terms of resource provision. This is because these are the regions with the largest areas of agricultural land, a significant rural population, and relatively high quality of agricultural land. On the contrary, the lowest level of resource potential is concentrated in Zakarpattia, Volyn, Chernivtsi, and Rivne regions.

In general, the assessment of resource potential at this level is relevant for determining the development potential of agriculture in general. However, it is more appropriate for organic production to supplement the analysis with an assessment of the ecological potential of the regions, as one of the necessary conditions for growing organic products is the level of environmental safety of the territories. In addition, organic farming, in essence, contributes to the preservation of the environment and ecosystems and has a positive impact on the development of other ecologically oriented economic activities: livestock, hunting, tourism and recreation, and alternative energy.

The indicators of ecological potential of the regions calculated in Table 3 allowed us to determine the group of leaders in which the most optimal conditions from the point of view of the ecological situation are formed both for growing organic products and for determining this type of management as a priority in agricultural production. First of all, these are regions with a low concentration of heavy industry and a relatively

Regions	Normalized indicators					Resource potential, R
	r_1	r_2	r_3	r_4	r_5	
Vinnytsia	0.78	0.57	0.93	0.77	0.81	**77.2**
Volyn	0.40	0.15	0.23	0.50	0.65	**38.7**
Dnipropetrovsk	0.97	0.92	0.91	0.52	0.90	**84.6**
Donetsk	0.79	0.64	0.41	0.63	0.92	**67.9**
Zhytomyr	0.58	0.36	0.30	0.51	0.64	**47.8**
Zakarpattia	0.17	0.06	0.05	0.80	0.81	**38.0**
Zaporizhzhia	0.86	0.64	0.80	0.39	0.74	**68.8**
Ivano-Frankivsk	0.24	0.24	0.11	0.78	0.78	**43.0**
Kyiv	0.62	0.49	0.80	0.68	0.79	**67.7**
Kirovohrad	0.79	0.81	0.97	0.35	0.95	**77.3**
Luhansk	0.74	0.49	0.55	0.59	0.81	**63.6**
Lviv	0.48	0.24	0.23	1.00	0.64	**51.7**
Mykolayiv	0.77	0.80	0.64	0.36	0.80	**67.6**
Odesa	1.00	0.74	0.88	0.80	0.92	**86.7**
Poltava	0.84	0.77	1.00	0.54	0.90	**80.9**
Rivne	0.36	0.17	0.15	0.62	0.65	**39.0**
Sumy	0.65	0.57	0.50	0.34	0.80	**57.2**
Ternopil	0.40	0.39	0.30	0.58	0.86	**50.6**
Kharkiv	0.92	1.00	0.87	0.52	0.96	**85.2**
Kherson	0.76	0.47	0.57	0.41	0.73	**58.6**
Khmelnytsky	0.60	0.44	0.46	0.55	0.91	**59.3**
Cherkasy	0.56	0.58	0.66	0.53	1.00	**66.6**
Chernivtsi	0.18	0.12	0.11	0.52	0.99	**38.3**
Chernihiv	0.80	0.45	0.54	0.36	0.72	**57.1**

Source: authors´ calculation

Table 2: Standardized indicators and indicators for assessing the potential of organic farming in the regions of Ukraine by resource component.

Regions	Normalized indicators					Business potential, P
	p_1	p_2	p_3	p_4	p_5	
Vinnytsia	0.77	0.04	1.00	0.52	1.00	**66.7**
Volyn	0.23	0.07	0.29	0.21	0.00	**16.1**
Dnipropetrovsk	0.27	0.27	0.74	0.08	1.00	**47.0**
Donetsk	0.01	0.00	0.36	0.06	0.00	**8.6**
Zhytomyr	0.41	0.56	0.48	0.44	1.00	**57.6**
Zakarpattia	0.22	0.02	0.15	0.04	0.00	**8.6**
Zaporizhzhia	0.22	0.27	0.48	0.24	0.00	**24.2**
Ivano-Frankivsk	0.13	0.01	0.24	0.17	0.00	**11.0**
Kyiv	1.00	1.00	0.71	0.28	1.00	**79.8**
Kirovohrad	0.14	0.24	0.63	0.82	0.00	**36.8**
Luhansk	0.14	0.00	0.25	0.66	0.00	**21.1**
Lviv	0.39	0.24	0.40	0.11	1.00	**42.9**
Mykolayiv	0.54	0.15	0.45	0.34	0.00	**29.7**
Odesa	0.48	0.70	0.49	0.19	1.00	**57.2**
Poltava	0.33	0.40	0.76	0.34	1.00	**56.6**
Rivne	0.27	0.17	0.30	0.26	1.00	**39.9**
Sumy	0.08	0.00	0.52	0.82	0.00	**28.6**
Ternopil	0.12	0.17	0.43	0.69	0.00	**28.2**
Kharkiv	0.30	0.07	0.67	0.27	0.00	**26.1**
Kherson	0.65	0.98	0.50	0.39	0.00	**50.4**
Khmelnytsky	0.30	0.21	0.63	0.48	0.00	**32.4**
Cherkasy	0.19	0.69	0.70	0.65	1.00	**64.8**
Chernivtsi	0.05	0.00	0.18	0.09	0.00	**6.4**
Chernihiv	0.19	0.19	0.55	1.00	1.00	**58.6**

Source: authors´ calculation

Table 3: Standardized indicators and indicators for assessing the development potential of organic farming in the regions of Ukraine by environmental component.

low level of demographic load of the territories, namely: Zakarpattia (65.2%), Volyn (59.1%), Chernivtsi (51.7), Zhytomyr (40.6%) and Rivne (36%).

Dnipropetrovsk (3.9), Zaporizhia (5.8), Kharkiv (6.8), Poltava (3.9), and Ivano-Frankivsk regions are the least suitable from the ecological point of view for the development of organic agriculture.

Business potential or the potential of experience characterizes specific achievements of regional farmers in the field of organic production, the level of support of local governments in this type of management, and the path of certification of land and products. As shown by the results of calculations (Table 4), the highest level of business potential at the end of 2019 demonstrates Kyiv (79.8), Vinnytsia (66.7), Cherkasy (64.8), and Zhytomyr regions. On the contrary, the worst indicators are in Zakarpattia, Donetsk, Chernivtsi, and Ivano-Frankivsk regions.

The complex indicator of the potential of each region is calculated, and the corresponding rating. Odesa (179), Kyiv (176), Vinnytsia (170), Cherkasy (152), and Chernihiv oblasts lead the ranking with the highest total potential of 140 points. The business potential gives these regions the highest scores in the evaluation process. In particular, the Odesa region leads in the production of organic oilseeds; the Vinnytsia region grows organic wheat and oats, Kyiv region, in particular the city of Kyiv, uses the high potential of the domestic market as a competitive advantage in Zhytomyr, Chernihiv and Poltava regions - a high level of administrative support for organic production.

It should be emphasized that an essential characteristic of the potential is the balance of its components, the use of which will provide a synergistic effect in the production of organic products.

Comparing the three components of the assessment based on the results of our calculations, the most balanced are the components of the potential of the Zhytomyr, Rivne, and Ternopil regions.

In other regions, the potential is not balanced by the main components. An approach based on determining the region vector on a matrix

Regions	Normalized indicators					Business potential, P
	p_1	p_2	p_3	p_4	p_5	
Vinnytsia	0.77	0.04	1.00	0.52	1.00	**66.7**
Volyn	0.23	0.07	0.29	0.21	0.00	**16.1**
Dnipropetrovsk	0.27	0.27	0.74	0.08	1.00	**47.0**
Donetsk	0.01	0.00	0.36	0.06	0.00	**8.6**
Zhytomyr	0.41	0.56	0.48	0.44	1.00	**57.6**
Zakarpattia	0.22	0.02	0.15	0.04	0.00	**8.6**
Zaporizhzhia	0.22	0.27	0.48	0.24	0.00	**24.2**
Ivano-Frankivsk	0.13	0.01	0.24	0.17	0.00	**11.0**
Kyiv	1.00	1.00	0.71	0.28	1.00	**79.8**
Kirovohrad	0.14	0.24	0.63	0.82	0.00	**36.8**
Luhansk	0.14	0.00	0.25	0.66	0.00	**21.1**
Lviv	0.39	0.24	0.40	0.11	1.00	**42.9**
Mykolayiv	0.54	0.15	0.45	0.34	0.00	**29.7**
Odesa	0.48	0.70	0.49	0.19	1.00	**57.2**
Poltava	0.33	0.40	0.76	0.34	1.00	**56.6**
Rivne	0.27	0.17	0.30	0.26	1.00	**39.9**
Sumy	0.08	0.00	0.52	0.82	0.00	**28.6**
Ternopil	0.12	0.17	0.43	0.69	0.00	**28.2**
Kharkiv	0.30	0.07	0.67	0.27	0.00	**26.1**
Kherson	0.65	0.98	0.50	0.39	0.00	**50.4**
Khmelnytsky	0.30	0.21	0.63	0.48	0.00	**32.4**
Cherkasy	0.19	0.69	0.70	0.65	1.00	**64.8**
Chernivtsi	0.05	0.00	0.18	0.09	0.00	**6.4**
Chernihiv	0.19	0.19	0.55	1.00	1.00	**58.6**

Source: authors´ calculation

Table 4: Standardized indicators and indicators for assessing the potential of organic farming in the regions of Ukraine according to the component of experience.

with coordinates (0; x; y; z) is proposed to determine the main strategies for developing organic production in regions. Three components of estimating their potential depends on the degree of balance and predominance of one or another part. The resulting vector begins at the zero point of the y-axis, and its orientation to a particular sector of the multidimensional plane will determine the primary strategy for developing organic production in the region.

Determination of the vector (A of each region in the field of organic production is proposed to be carried out according to the formulas:

$$\vec{A}\begin{Bmatrix} X = Ri - \bar{R} \\ Y = Pi - \bar{P} \\ Z = Ei - \bar{E} \end{Bmatrix} \quad (5)$$

where, P, R, E - integrated assessments of the potential of the i-th region in terms of resource, environmental, and business potential;

$\bar{P}, \bar{R}, \bar{E}$ – average values of integrated capacity assessment achieved in all regions of the sample.

SECTOR (R; P; E) - Relatively high level of all components of potential. Strategy for the formation of a regional model of organic-oriented multidisciplinary agriculture. Creating conditions for the potential transition of agricultural enterprises to organic technologies. This will complete the preconditions for organic food production, organic livestock, and related sectors of environmentally oriented economic activities. It is possible to develop an innovative component for implementing SMART specialization projects.

SECTOR (R; P; -E) - Characterized by a relatively high level of resource and business potential development with reasonably low environmental performance. A strategy focused on the most efficient use of the region's limited environmentally friendly resources for the cultivation and processing of organic products for the domestic market is proposed for interregional cooperation and development of the processing industry.

SECTOR (-R; P; E) - A sector that combines relatively high business potential and environmental benefits with a relatively low level of resources, including a shortage of suitable arable land for organic production. Proposed to grow crops that do not require significant areas of cultivation: vegetables, berries, fruits, and spices: Eco-oriented positioning in the domestic and foreign markets, multidisciplinary specialization, and interpectoral cooperation.

SECTOR (-R; - P; -E) - Relatively low competitive advantages in organic farming development. It is proposed to give preference to traditional approaches to agricultural activities.

Sectors with one advantage need further research to develop another advantage. For example, suppose there is a purely environmental advantage. In that case, it is advisable to research the development of business preferences in the region (financial, administrative, and informational support at the local government level, search for niches in the domestic market, attract investment) or focus on other economic activities in the region. If there is a purely business advantage - research the development of resource potential in certain areas - narrower territorial specialization, and internal market development. If there is only a resource advantage - to conduct additional analysis of environmental suitability of land resources and (or) to develop inner potential in the field of traditional management.

The proposed strategies are a logical generalization of the situation about a specific ratio of components of the potential for developing organic farming in a given region. The development of more detailed production, financial and market strategies requires additional analysis of the conditions for the development of organic agriculture at the level of districts or individual united territorial communities and the impact of such products on the economic situation and food security of certain administrative-territorial entities. They are using the proposed approaches the coordinates of the vector of the organic production development strategy for the Ukraine regions are calculated. The results of the calculations are shown in Table 5.

According to the results of the calculations, the sector with the most optimal conditions for developing organic production can include Kyiv, Odesa, and Cherkasy regions. On the other hand, the industry with the least favorable in the context of the analysis combines Sumy and Ivano-Frankivsk regions. Therefore, in the different areas, combined strategies should be used.

Russia's war against Ukraine led to the execution of the most extensive territories, characterized by agricultural product cultivation. Kharkiv, Luhansk, Donetsk, Kherson, Mykolaiv, and Zaporizhia oblasts, where hostilities are taking place and victims of occupation are potential for organic production and have significant areas for agricultural production. We emphasize that

Regions of Ukraine	R	P	E	Strategy sector
Vinnytsia	16	29	-1	SECTOR (-R; P; -E)
Volyn	-23	-21	33	SECTOR (-R; - P; E)
Dnipropetrovsk	23	10	-22	SECTOR (R; P; -E)
Donetsk	7	-29	-11	SECTOR (R; - P; -E)
Zhytomyr	-14	20	14	SECTOR (-R; P; E)
Zakarpattia	-23	-29	39	SECTOR (-R; - P; E)
Zaporizhzhia	8	-13	-20	SECTOR (R; - P; -E)
Ivano-Frankivsk	-18	-26	-18	SECTOR (-R; - P; -E)
Kyiv	6	42	3	SECTOR (R; P; E)
Kirovohrad	16	-1	-11	SECTOR (R; - P; -E)
Luhansk	2	-16	2	SECTOR (R; - P; E)
Lviv	-10	5	-12	SECTOR (-R; P; -E)
Mykolayiv	6	-8	-16	SECTOR (R; - P; -E)
Odesa	25	20	9	SECTOR (R; P; E)
Poltava	20	19	-22	SECTOR (R; P; -E)
Rivne	-22	2	13	SECTOR (-R; P; E)
Sumy	-4	-9	-14	SECTOR (-R; - P; -E)
Ternopil	-11	-9	5	SECTOR (-R; - P; E)
Kharkiv	24	-11	-19	SECTOR (R; - P; -E)
Kherson	-3	13	1	SECTOR -R; P; E)
Khmelnytsky	-2	-5	10	SECTOR (-R; - P; E)
Cherkasy	5	27	2	SECTOR (R; P; E)
Chernivtsi	-23	-31	26	SECTOR (-R; - P; E)
Chernihiv	-4	21	10	SECTOR (-R; P; E)

Source: authors´ calculation

Table 5: Coordinates the vector strategy of the development of organic production in the context of the regions of Ukraine.

in the other war in Ukraine, there will be a reduction in agricultural production, including organic, which will lead to a violation of food security in most countries.

It should be emphasized that the representative data obtained during the study are due to the subjective choice of the author of the evaluation criteria, the scale of the compared sample, weights, and optimality criteria. However, in general, the proposed methodological approaches are pretty universal. Therefore, they can be used as analytical tools for developing strategies and programs for developing organic production in the regions and individual OTG, justification of business projects, and business plans for the organization or transition of business entities in the organic segment. Presentation at the micro-level optimization of structural models of the region's economy, taking into account the principles of sustainable development. The authors' team considers combining territories into clusters for their socio-economic development (Nadtochiy et al., 2022). The authors discuss the advantages of forming clusters in agriculture while determining the growth of employment of the population of the respective territories. They point out that wages in clusters are usually higher than in non-clustered firms or average wages in the region. Transaction costs are reduced in the division of labor and subcontracting (Zheliazkov et al., 2015).

Shcherbina et al., (2020) consequently the model of rural region territorial cluster is useful in making guidelines for land-use planning for sustainable development of rural settlement system. Directions for future research are in making recommendations for integrated rural development, taking into account local resources and characteristics.

The clusters in question produce several social and environmental benefits as an integral part of their business strategies. This should be clear by their contributions to the education and training of the local workforce, the creation of new jobs, the improvement of local incomes, the production of sustainable energy, and the production of healthy, sustainable, and additive-free food, etc (Martinidis et al., 2021).

Most of the robust clusters relating to the modern branches of the economy are concentrated in the larger urban areas of Sweden, though in some

cases, also in other larger regional urban centres. The most surprising result was perhaps that clusters of employment within such modern branches are relatively over-represented in certain parts of some lagging areas, a fact that may reflect the effects of regional policy measures on the decentralisation of R&D and post secondary education (Ceccato et al., 2002).

Therefore, the clustering of territories according to rural-Boyarsky purposes can become a tool for ensuring road safety in the conditions of Russia's war against Ukraine. Many of today's food crises are linked to war and violent conflicts. This paper elaborates four logics of war that have an impact on food insecurity: a) destruction; b) conflict-induced displacement; c) food control; d) hunger as a "weapon of war". These logics explain why governments or belligerents are often unable or unwilling to respond to food crises, and why humanitarian assistance faces challenges in reaching people in need, while simultaneously avoiding exacerbating conflict (Birgit et al., 2022).

Despite USDA's optimistic 2022-2023 forecast for increased wheat production "World wheat production in 2022/2023 is estimated at 783.92 million metric tons, about 4.32 million tons more than forecast of the previous month" (US Department of Agriculture, 2022), it can be confidently stated that further military actions on the territory of Ukraine will lead to its decrease. In fact, Ukraine occupies a significant share of world food: about 27% of sunflower seeds, 5% of barley, 3% each of wheat and rapeseed, and 2% of corn (Gordiychuk, 2022).

In 2020, Ukraine exported 217,210 tons of organic products to the EU. The key product categories are cereals and oilseeds (the largest exporter to the EU), soybeans, honey, fruit and vegetables and the products of their processing. Russia and Ukraine mostly supplied wheat (pdf) to countries in eastern Europe, the Middle East, and Africa, but their crops also traveled as far as Nicaragua (World Economic Forum, 2022). The total organic export from Ukraine in 2020 amounted to 332 thous. tons and USD 204 mln1. Since 24 February 2022 (the beginning of Russia's full-scale invasion of Ukraine) the organic sector as well as the entire agrarian industry has been suffering from aggression (Organicinfo, 2022). Many regions, such as the Middle East and North Africa, are heavily dependent on wheat and other exports, including maize, barley, and sunflower oil, from Russia and Ukraine. Together, the two countries represent 12 percent of the global market share in calories. Our research shows that the current crisis is disproportionally affecting the poor in developing countries (Glauber et al., 2022)

On May 24 2018, the United Nations (UN) Security Council unanimously passed a resolution condemning the use of food insecurity and starvation as a tactic of war. It was the first time the Council had ever addressed the issue, acknowledging a threat to the lives of tens of millions of people. Aimed at countries currently engaged in international or civil wars, the resolution implores all parties to leave food stocks, farms, markets, and other distribution mechanisms intact. It demands parties in conflict permit humanitarian aid workers unimpeded access to populations in dire need and states that "using starvation of civilians as a method of warfare may constitute a war crime." (National Geographic, 2022).

At the time of war in Ukraine the EU is introducing new measures to strengthen food security. In particular, on 23 March the European Commission presented a range of short-term and medium-term actions to enhance global food security and to support farmers and consumers in the EU in light of rising food prices and input costs, such as energy and fertilisers, accelerated by Russia's invasion of Ukraine. The proposed measures are aimed at the agricultural supply chains becoming more resilient and sustainable in line with the Farm to Fork strategy. Support to organic production in Ukraine and implementation of the measures provided for in the Farm to Fork and Biodiversity strategies may ensure sustainability in general productivity of agriculture.

Despite international law and accepted international conventions to ensure global food security, the mechanism of exporting agricultural products from Ukraine during the war remains an unresolved issue. That is why developing a strategy for the further development of organic production in Ukraine in war conditions is a prospect for further research.

Conclusion

The authors proposed methodical approaches for assessing the potential of the regions of Ukraine in the field of organic production. The proposed methodological approaches make it possible to form clusters of regions based on the prospects

for developing organic production in the conditions of war in Ukraine, where appropriate specific strategies will operate. So, for example, according to the results of calculations in the industry, the most optimal conditions for developing organic production as of 2019 were Kyiv, Odesa, and Cherkasy regions. That is why the authors proposed for these regions the use of the strategy of forming a regional model of organically oriented multidisciplinary agriculture. This will create prerequisites for producing organic food products, organic animal husbandry, and related branches of ecologically oriented economic activity. The opposite is the results of the analysis where Sumy and Ivano-Frankivsk regions are combined, where the development of organic production with insignificant favorable conditions, the existing potential and structure do not allow farms to be completely converted to organic technologies for the production of agricultural products. The regions of Ukraine most affected by hostilities and occupation (Kharkiv, Luhansk, Donetsk, Kherson, Mykolaiv, and Zaporizhzhya) are potential for organic production. It has been determined that the additional economic losses of the industry from the war in 2022 alone are expected in the amount of about 22 billion dollars, and a decrease in the income of agriculture and related sectors - from 10 to 30%. According to the results of 2021, the share of the agro-industrial complex was 10.6% of the national GDP. However, the assessment of the consequences of hostilities for the agricultural industry is complicated by the lack of an analogy, when a country with such a large-scale and important for the world market agricultural sector as Ukraine would be involved in the war.

They have significant areas for the production of agricultural products, which is why it is suggested to use combined strategies. It is predicted that the war in Ukraine will lead to a reduction in the production of agricultural products, including organic ones, and this will lead to food security in most countries. The article's authors emphasize the non-fulfillment of international law and accepted international conventions by the aggressor country, which will increase global food security. It is proposed to develop a mechanism for exporting Ukrainian organic products and to develop relevant production strategies at the regional level and the level of individual united territorial communities in wartime conditions.

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Developing an Efficient System with Mask R-CNN for Agricultural Applications

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Abstract

In order to meet the world's demand for food production, farmers and producers have improved and increased their agricultural production capabilities, leading to a profit acceleration in the field. However, this growth has also caused significant environmental damage due to the widespread use of herbicides. Weeds competing with crops result in lower crop yields and a 30% increase in losses. To rationalize the use of these herbicides, it would be more effective to detect the presence of weeds before application, allowing for the selection of the appropriate herbicide and application only in areas where weeds are present. The focus of this paper is to define a pipeline for detecting weeds in images through the use of a Mask R-CNN-based weed classification and segmentation module. The model was initially trained locally on our machine, but limitations and issues with training time prompted the team to switch to cloud solutions for training.

Keywords

Deep learning, CNN, Mask R-CNN, precision agriculture, weed detection.

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Introduction

Agriculture is a crucial sector in Morocco, providing livelihoods for millions of people, especially in rural areas with limited industrial activity. Sustainable agriculture practices, including soil conservation, environmental resource management, and biodiversity protection, are essential for overall rural development. With over 4 million jobs, agriculture is one of the most important drivers of Morocco's economy (Jabir et al., 2021).

Precision Agriculture is an innovative approach that leverages technologies and data to optimize crop management strategies, such as fertilizer inputs, irrigation, and pesticide use. It involves collecting field data, analyzing the information, and making informed decisions to improve crop yields and reduce costs (Tiwari and Jaga, 2012). Site-specific weed management is a key component of Precision Agriculture that aims to reduce herbicide usage, improve weed control, and minimize environmental pollution (Fernández-Quintanilla et al., 2018). Weeds are a major challenge for farmers, as they compete with crops for resources and can lead to reduced yields. Chemical weed control is the most common approach, but the use of herbicides is increasingly being scrutinized due to environmental concerns. Therefore, it is important for farmers to inspect their fields and apply only the necessary amount of herbicides. This manual process is time-consuming, and an automated solution is needed to streamline the workflow.

In this study, we propose a pipeline for detecting and masking weeds in images. The images undergo preprocessing and are fed into a Mask R-CNN model. The training stage involves exploring two approaches: local training using local resources on our machine, and cloud-based training using remote resources. Finally, both approaches are compared and evaluated based on time and memory allocation. The framework acts as a feature extractor, capable of discovering complex patterns in the data that are then inputted into a multi-class classifier for classification and instance segmentation.

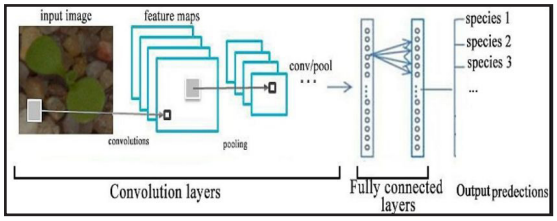
The structure of this paper is organized as follows: we start by discussing the basics of Convolutional Neural Network (CNN) and the algorithms used in our study. Then, we present the datasets and tools used in our implementation of the Mask R-CNN algorithm. After that, we describe the implementation process and the two approaches to training our model - local training using

local resources and cloud-based training using remote resources. Next, we present the results and discussion, evaluating the performance of our model and comparing the results obtained from both training approaches. Finally, we conclude our study by summarizing our findings and offering insights into the potential of this approach for future work in precision agriculture.

Materials and methods

The Convolutional Neural Network (CNN) is a widely used Deep Learning algorithm, particularly in image classification. CNNs work by attributing significance (weights and learnable biases) to objects in an input image, enabling their differentiation from one another (Sewak et al., 2020). The structure of the CNN is modeled after the human brain's neuron connectivity and is inspired by the regulation of the visual cortex. Just like in the human brain, individual neurons in a CNN only respond to stimuli within a restricted area of the visual field, known as the receptive field. The combination of these fields covers the entire visible area. In computer vision, a grayscale image is represented as a two-dimensional array of pixel values, with brightness ranging from 0 to 255. 0 indicates black, 255 indicates white, and all other values are shades of gray. Color images are represented by a third dimension of depth, with 3 values representing the fundamental colors Red, Green, and Blue (Jabir et al., 2021). Simply put, what a CNN does is extract features from an image and convert it into a lower dimension representation, while preserving its characteristics, by passing the image through a set of layers that define the algorithm's architecture.

As Figure 1 shows, an input image is passed into the input layer. The image will be handled by the Convolutional layer to extract the features of the image, but you are probably wondering how this convolution operation actually relates to feature extraction. First of all, a part of the image is connected to the Convolutional layer to perform convolution operation and calculates the dot product between the receptive field (it is a local region of the input image that has the same size as that of filter) and the filter which is formed from a set of weights. The output of the process is a one-number integer of the volume of the output. Then, we slide the filter to the following receptive field of the same entry image by one pitch and do the same operation again. We will repeat the same process repeatedly until we have traversed the entire image. The result called the convolution maps will be the input to the subsequent layer.



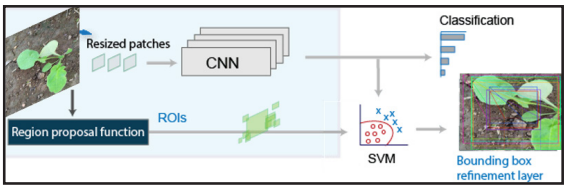
Source: (Jabir et al., 2021).

Figure 1: Standard architecture of a CNN.

After the feature extraction, an activation function called ReLU (y = max(x, 0)) is applied on the convolution map to handle highly non-linear data. The ReLU function inputs any real number and sets all values less than zero to zero, while keeping values greater than zero unchanged (Zhu et al., 2020). The pooling layer is then used to reduce the size of the input image after convolution. Multiple convolutional layers and one pooling layer may be used before the fully connected layer performs classification. The last layer of the CNN is either the Softmax or the Logistic layer, which is located at the end of the fully connected layer. Logistic is used for binary classification and Softmax is used for multi-classification (Khachnaoui et al., 2020). Transfer learning is a machine learning technique where a model trained for one task is reused as the basis for a model in a different task. This is a popular method in deep learning, where pre-trained models can serve as starting points for computer vision and natural language processing tasks due to the vast computing resources and time required to build neural network models (Hoo-Chang et al., 2016).

R-CNN

The R-CNN merges the region proposal with the CNN, based on the principle that a single object of interest would dominate in a particular region. This is achieved by using a selective search algorithm to generate category-independent region proposals, which retrieves approximately 2000 proposals. Each proposal is then warped and passed to a large convolutional neural network that acts as a feature extractor, producing a fixed-length feature vector from each region. The R-CNN extracts a 4096-dimensional feature vector from each region proposal, as shown in Figure 2. Subsequently, a Support Vector Machine (SVM) is applied to the features extracted from the CNN to rank the objects in each region. Finally, regression is used to predict the four bounding box values necessary for object detection (Hoeser and Kuenzer, 2020).



Source: Author's illustration

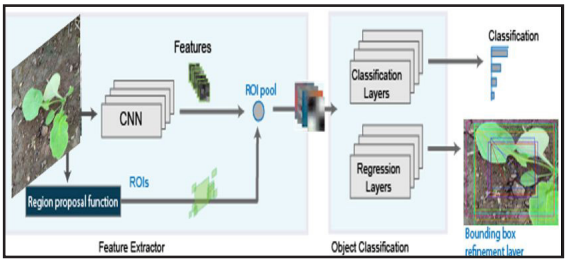
Figure 2: R-CNN: Regions with CNN features.

Fast R-CNN

Fast R-CNN is an improved version of R-CNN with a few changes. It replaces the resizing operation with a RoI pooling layer to obtain a fixed-size feature map. Secondly, it replaces the SVM with fully connected layers responsible for classification and bounding-box regression, while the region proposal is still based on selective search. Fast R-CNN takes as input an image and a set of object proposals and uses convolutional and max pooling to produce a convolutional feature map. For each object proposal, Fast R-CNN extracts a fixed-length feature vector from the feature map using a region of interest (RoI). Each feature vector is fed into a fully connected network with two sibling output layers: the first one produces softmax probability estimates over K object classes plus a catch-all "background" class, while the second one gives the four real values for the bounding-box positions for the K classes (Han et al., 2022).

Faster R-CNN

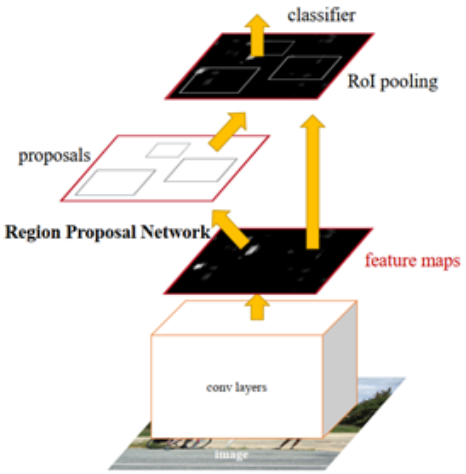
Faster R-CNN is an object detection system that consists of two modules: the first is a fully convolutional network responsible for proposing regions, and the second is a Fast R-CNN detector that uses the image and region proposals to give object classification and bounding-box positions (as shown in Figure 3). Faster R-CNN is a single, unified network for object detection.



Source: Author's illustration

Figure 3: Fast R-CNN architecture.

With the addition of the Region Proposal Network (RPN) module, Faster R-CNN is able to determine precisely where to look, which is a key advantage of Faster R-CNN (as shown in Figure 4).

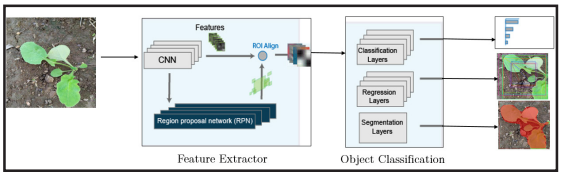


Source: (Rajeshwari g et al., 2019).

Figure 4: Faster R-CNN (single, unified network for object detection).

Mask R-CNN

Mask R-CNN is a state-of-the-art object detection and instance segmentation model developed by Facebook using Python. It extends Faster R-CNN by adding a mask prediction branch to its final stage (Liu et al., 2022). As shown in Figure 5, Mask R-CNN has three outputs: class label, bounding-box offset, and an object mask. The ROI pooling layer in Faster R-CNN has been replaced with the ROI Align layer, which performs better in mask prediction. Mask R-CNN is divided into two parts: the backbone, responsible for feature extraction, and the head of the network, which performs classification, regression, and mask prediction. Mask R-CNN is built on the Feature Pyramid Network (FPN) and uses RestNet101 as its backbone. Unlike traditional models that use a single feature map, FPN architecture utilizes features from multiple convolution layers to provide a better prediction (Lin et al., 2021). The network head classifies the proposed RPN bounding box and generates the segmentation mask. In the training stage, Mask R-CNN employs transfer learning by using pre-trained weights from the MS COCO dataset, which has 80 classes and 115,000 training images (Lin et al., 2018).



Source: Author's illustration

Figure 5: The architecture of the Mask R-CNN.

Dataset

The main dataset used by Mask R-CNN is an MS COCO dataset, which has 80 classes and one hundred fifteen thousand training images. Evaluation metrics for bounding boxes and segmentation mask is based on Intersection over Union. The pretend weights learned on MS COCO dataset are used such as pre-trained weights to train our model with our own datasets. The dataset we use is composed of 150 images, after the augmentation it became a 300 images. We divided our dataset used in this study to three sets, the first one consisting of 200 image for treating our model, the second one include 20 images for he validation and the last one be composed of 80 images for testing. All the images that are used in the study are pictures of weeds found in the fields and the corps in Morocco (Timpanaro et al., 2021).

Data augmentation

After the step of collecting images for our study. We need to ensure we have a wide variation in angles, brightness, scale, etc. and to make sure, there are a several data augmentation techniques, In our case we increase the amount of images by adding slightly modified copies of already existing images by adjusting the capture angles and brightness. This process used mostly in the case we have only small data sets to train our Deep learning models. The objective behind feeding the model with varied data is to improve the overall training procedure and performance generalization purposes (Shorten and Khoshgoftaar, 2019).

Data pre-processing

Our study involved some image pre-processing steps, before the image or particular characteristics / features / statistics of the image were fed as an input to the DL model. Our pre-processing procedure was creating pixel level mask annotations to define the boundaries of the objects in the dataset (Huang et al., 2021). Among various available tools, we choose an intuitive and well-done tool: VGG Image Annotator (VIA) (see the Figure 6). This tool does not need any installation; we lunch it via html file with a modern browser. The output of pre-processing step will be an annotated dataset and a JSON files include the annotation's metadata for the annotation for both training and validation datasets. This operation take approximately 420 min to manually annotate all image, by the average of a minute and a half for each image separately.

Source: Author's illustration

Figure 6: Image annotation.

The model architecture

The Mask R-CNN framework consists of two stages. In the first stage, the framework inputs an image and uses a Region Proposal Network (RPN) to identify potential object regions. The second stage then predicts the classes, refines the bounding boxes, and generates segmentation masks for each object. In the Mask R-CNN system, the convolutional backbone is composed of the backbone network, region proposal network, and object classification module. The network head includes the boundary box regression module and the mask segmentation module. An input image is transformed into a feature map through the backbone network, a standardized convolutional neural network (CNN) that extracts features. The feature map is then used as input for the RPN to detect potential object areas. The feature extraction step is based on the original implementation of Faster R-CNN with ResNet-101 (Lei and Sui, 2019).

```
Configurations:
BACKBONE                        resnet101
BACKBONE_STRIDES                [4, 8, 16, 32, 64]
BATCH_SIZE                      1
BBOX_STD_DEV                    [0.1 0.1 0.2 0.2]
COMPUTE_BACKBONE_SHAPE          None
DETECTION_MAX_INSTANCES         100
DETECTION_MIN_CONFIDENCE        0.9
DETECTION_NMS_THRESHOLD         0.3
FPN_CLASSIF_FC_LAYERS_SIZE      1024
```

Source: Author's compilation

Figure 7: Backbone of Mask R-CNN.

The ResNet-101 architecture, as shown in Figure 8, includes a total of 104 convolutional layers. It is comprised of 33 blocks of layers, with 29 of these blocks utilizing the output of the previous block as a direct input via residual connections. The remaining 4 blocks perform an additional operation of a 1x1 convolution layer with a stride of 1 followed by batch normalization before being added to the output of the previous block. The Mask R-CNN framework extends the Faster R-CNN box heads from ResNet and FPN by adding a fully convolutional mask prediction branch as part of its network head (Hafiz and Bhat, 2020).

```
Selecting layers to train
fpn_c5p5                (Conv2D)
fpn_c4p4                (Conv2D)
fpn_c3p3                (Conv2D)
fpn_c2p2                (Conv2D)
fpn_p5                  (Conv2D)
fpn_p2                  (Conv2D)
fpn_p3                  (Conv2D)
fpn_p4                  (Conv2D)
In model:  rpn_model
    rpn_conv_shared         (Conv2D)
    rpn_class_raw           (Conv2D)
    rpn_bbox_pred           (Conv2D)
mrcnn_mask_conv1        (TimeDistributed)
mrcnn_mask_bn1          (TimeDistributed)
mrcnn_mask_conv2        (TimeDistributed)
mrcnn_mask_bn2          (TimeDistributed)
mrcnn_class_conv1       (TimeDistributed)
mrcnn_class_bn1         (TimeDistributed)
mrcnn_mask_conv3        (TimeDistributed)
mrcnn_mask_bn3          (TimeDistributed)
mrcnn_class_conv2       (TimeDistributed)
mrcnn_class_bn2         (TimeDistributed)
mrcnn_mask_conv4        (TimeDistributed)
mrcnn_mask_bn4          (TimeDistributed)
mrcnn_bbox_fc           (TimeDistributed)
mrcnn_mask_deconv       (TimeDistributed)
mrcnn_class_logits      (TimeDistributed)
mrcnn_mask              (TimeDistributed)
```

Source: Author's compilation

Figure 8: The head's layers.

Implementation

This section defines the environment requirements for implementing Mask R-CNN in this study. We use Python 3.6 as the programming language and the TensorFlow and Keras libraries for learning and classification (Yang et al., 2020). To enhance the model's performance, we employ simple and effective techniques such as data augmentation and use Tensorboard for log visualization.

TensorFlow

TensorFlow is an open-source machine learning library developed by Google for developing and running machine learning and deep learning applications. Its name is derived from the fact that operations in neural networks are primarily performed on multi-dimensional data tables, called tensors. A two-dimensional tensor is equivalent to a matrix. In this study, we use TensorFlow 1.15 for local training on our machine and Tensorflow-GPU 1.5 for cloud training.

Keras

Keras is an open-source library written in Python (under the MIT license) based on the work of Google developer François Chollet as part of the ONEIROS (Open-ended Neuro-Electronic Intelligent Robot Operating System) project. The library's goal is to allow the rapid constitution of neural networks, serving as an application programming interface (API) for accessing and programming various machine learning frameworks (Wäldchen and Mäder, 2018). In this study, we use Keras 2.2.5.

Tensorboard

Tensorboard is a visualization tool for understanding, debugging, and optimizing TensorFlow programs. It visualizes the TensorFlow graph, plots quantitative metrics about the execution of the graph, and displays additional data.

Training

The training can be carried out at two levels. At the first level, only the heads can be trained by freezing all the backbone layers and training only the newly initialized layers, not using pre-trained weights from MS COCO. The second level involves training all layers of the entire model.

For this study, it is not necessary to train the model fully since the starting point is COCO-trained weights. Moreover, with a small dataset of 300 images, consisting of 200 for training and 20 for validation, it is not necessary to train

all layers, as it would consume a lot of time. Just training the heads should suffice.

CPU vs GPU

The central processing unit (CPU) is the main component that performs arithmetic, logic, and control for every computer. Its main function is to execute instructions stored in the computer's memory in a sequential manner. The CPU plays a critical role in neural network computation because it handles general arithmetic calculations during the learning phase. CPUs are usually built with several powerful processing cores that are clocked between 2 and 3 GHz, making them ideal for performing sequential tasks (Padilha and Lucena, 2020). Additionally, the CPU independently of the GPU's computation role (Pang et al., 2020), such as loading training data, handles all input/output operations during the learning phase. Due to these tasks, training a large model using the CPU can be risky and time-consuming, which is why using the GPU instead of the CPU in the training stage is seen as beneficial.

The graphics processing unit (GPU), like the CPU, is a component of a computer used to process instructions, but the GPU can run multiple instructions simultaneously through parallelization. A GPU typically consists of multiple weak processing cores with a much lower clock speed compared to the CPU. This multiple processing core system was developed to parallelize computations through the use of threads, thus speeding up computations that would normally take a longer time on the CPU.

Since the GPU has the ability to run many processes simultaneously, it is useful for training neural networks that involve computationally intensive matrix multiplications. Training a neural network requires a large number of computations, and the GPU optimizes these computations using multiple memory channels and streaming processors (Thao et al., 2021).

Originally, GPUs were designed for rendering graphics. As a result, executing custom code on the GPU requires APIs that provide a higher level of abstraction, from low-level to high-level programming languages. CUDA was developed to utilize the GPU architecture's parallelism capabilities, such as multithreading, MIMD, SIMD, and instruction level, through low-level instructions (Carneiro Pessoa et al., 2018). TensorFlow, in conjunction with CUDA, can use the entire GPU architecture to further optimize computation time.

Train the algorithm locally on our machine

In our study, we trained the model using a machine with the following configuration: an Intel Core i5-2520M CPU @2.50 GHz and 8GB of RAM. The training took approximately 7 hours for 10 epochs, with an average of 2100 seconds per epoch (Figure 9). Each epoch consisted of 60 training batches and a prediction threshold of 0.9. The training loss was 0.6350 and the validation loss was 0.9447. Despite having a small training dataset, the model still achieved a decent level of accuracy.

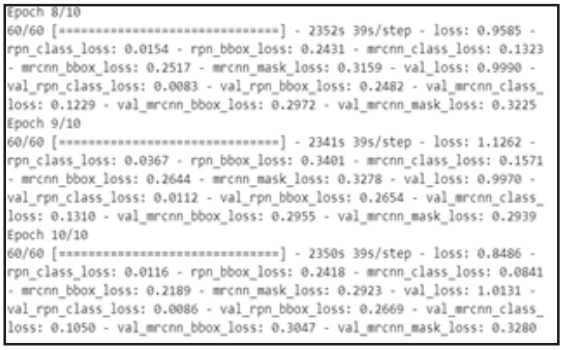
```
Epoch 1/10
60/60 [==============================] - 2314s
loss: 0.4575 - val_loss: 1.2266 - val_rpn_class
WARNING:tensorflow:From C:\Users\El-Mehdi\anacc

Epoch 2/10
60/60 [==============================] - 2271s
loss: 0.3390 - val_loss: 1.1620 - val_rpn_class
Epoch 3/10
60/60 [==============================] - 2202s
loss: 0.3405 - val_loss: 1.0426 - val_rpn_class
Epoch 4/10
60/60 [==============================] - 2165s
loss: 0.3377 - val_loss: 0.9638 - val_rpn_class
Epoch 5/10
60/60 [==============================] - 2133s
loss: 0.2975 - val_loss: 0.9637 - val_rpn_class
Epoch 6/10
60/60 [==============================] - 2138s
loss: 0.3003 - val_loss: 0.9113 - val_rpn_class
Epoch 7/10
60/60 [==============================] - 2128s
loss: 0.2577 - val_loss: 0.9187 - val_rpn_class
Epoch 8/10
60/60 [==============================] - 2107s
loss: 0.3122 - val_loss: 0.9027 - val_rpn_class
Epoch 9/10
60/60 [==============================] - 2131s
loss: 0.2805 - val_loss: 0.9736 - val_rpn_class
Epoch 10/10
60/60 [==============================] - 2107s
loss: 0.2495 - val_loss: 0.9447 - val_rpn_class
```

Source: Author's compilation

Figure 9: Train the algorithm locally on a machine.

In our dataset, we found various species of weeds with different sizes and shapes. The images in the dataset were of different sizes, so we resized them to 512 X 512 pixels. Then, we created two paths, one for the test dataset and another for the validation dataset. After that, we set up our model by extending the Dataset class and the Config class, which exist in the mrcnn folder, and configured it. Finally, we started the training. In the above model shown in Figure 9,

we trained a model for binary classification. However, to differentiate between weeds and crops with more precision, we decided to make the model larger and give it more classes. Therefore, we expanded our dataset by adding new weed species and crop types, such as sugar beet and wheat, which comprised almost 620 images. After preparing the new dataset, we re-trained the model with it.



Source: Author's compilation

Figure 10: The model is being retrained locally on our machine.

This time, the model took longer to train, approximately two hours more than the previous training. It took approximately 9 hours for 10 epochs, with an average of 2400 seconds per epoch (as shown in Figure 10). Each epoch consisted of 60 training batches and had a prediction threshold of 0.9. The training loss was 0.6350 and the validation loss was 0.9447. Training the model on our machine requires more resources and performance optimization to improve accuracy and reduce the training time.

Training the model on the cloud

Using cloud computing for deep learning simplifies the integration and management of large datasets for training algorithms. Deep learning models can then be efficiently and cost-effectively scaled using the processing power of GPUs. The cloud optimizes network distribution, enabling faster design, development, and training of deep learning applications. The use of the cloud offers several advantages, such as:

Speed: Deep learning algorithms are designed for fast learning. By utilizing GPU and CPU clusters for complex matrix operations, users can speed up the training of deep learning models. These models can handle large amounts of data and provide increasingly relevant results.

Scalability: Deep learning neural networks are ideal for running on multiple processors and distributing workloads across different types and amounts of processors. The cloud provides a wide range of on-demand resources, enabling the deployment of virtually unlimited resources to build deep learning models of any size.

Flexibility: Deep learning frameworks such as Apache MXNet, TensorFlow, Microsoft's Cognitive Toolkit, Caffe, Caffe2, Theano, Torch, and Keras can be run in the cloud, allowing you to choose the set of deep learning algorithm libraries that best fit your use case, whether it involves web, mobile, or connected devices.

There are several platforms and servers available for training remote models, including:

Amazon Web Services (AWS): AWS offers over a hundred services that fall into categories such as compute, storage, database, developer tools, security and identity, analytics, artificial intelligence, and more. New customers are eligible for 12 months of free use with certain restrictions and limitations. Any usage beyond these limitations must be purchased. For example, they offer a Remote Desktop Protocol with 30 GB of storage, 2 GB of RAM, and 1 CPU for free. Additional resources, such as GPUs, must be purchased.

Google Colab: In recent years, Google Colab has become a popular choice for an end-to-end machine learning platform. It provides free GPU, CPU, storage, and RAM, but also has limitations. Some of the downsides of Google Colab include service interruptions, slow storage, unconfigured environments, and limited functionality (12 hours of interactive use).

Kaggle: Kaggle, another Google product, is a web-based platform that hosts data science contests. It offers an end-to-end machine learning platform with features similar to Colab, including free Jupyter notebooks and GPUs. Kaggle also provides many pre-installed Python packages, making it easier for some users to start.

Paperspace Gradient: Gradient is the solution we utilized in this study. An end-to-end platform offers a free-hosted Jupyter notebook cloud service with several options for pre-configured environments and free access to GPUs and CPUs. Gradient makes it easy to build, train, and deploy deep learning models, with a web-based user interface, a CLI, and an SDK. It appeals to both beginners and experts alike, with a user-friendly interface and low entry barrier. Some of the benefits of Gradient over other solutions are:

Faster, persistent storage, eliminating the need

to re-install libraries and re-download files each time you start your notebook.

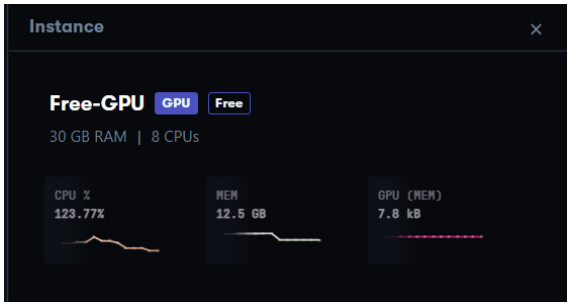
Guaranteed sessions, reducing the risk of having your instance shut down mid-work. You can log out and come back later to find your session unchanged.

Pre-configured containers and templates, including popular environments with pre-installed dependencies (such as PyTorch, TensorFlow, or the Data Science Stack) or the option to use a custom container. There is also an ML showcase with sample projects that you can create and run free on your account.

A public dataset repository with a wide range of popular datasets available for free use and mounted on every notebook.

The ability to easily scale up and add more storage and high-end dedicated GPUs for the same environment as needed.

In this study, we will use the free environment offered by Gradient. It provides two options: the first offers access to 2 GB of RAM, 2 CPUs, and no GPU (Figure 11), with a runtime of 12 hours without interruption. The second option provides access to 30 GB of RAM, 8 CPUs, an Nvidia Quadro M4000 GPU, and a runtime of 6 hours without interruption. We have chosen to work with the second option.



Source: AWS Cloud (2022)

Figure 11: The training environment (Cloud).

We will start by taking the same dataset and model used in the second local training and re-run the training on the cloud. This time, it took around 28 minutes for 10 epochs, with an average of 170 seconds per epoch, 60 training batches, and a threshold of 0.9 for prediction. The training loss was 0.8406, and the validation loss was 0.964.

To decrease the loss, we increased the number of training batches to 100 and retrained the model. This time, the model took 45 minutes for 10 epochs, with an average of 280 seconds per epoch and 100 training batches, with a prediction threshold of 0.9. The training loss was 0.6896 and the validation loss was 0.9113. However, as the loss was still high, we retrained the model again, this time with 40 epochs, 100 training batches per epoch, and a prediction threshold of 0.9. The training loss reached 0.2871, while the validation loss was 0.9663 (Figure 12). This time, the model took almost 3 hour.

```
Epoch 36/40
100/100 [==============================] - 255s 3s/step - loss: 0.273
9 - rpn_class_loss: 0.0044 - rpn_bbox_loss: 0.0452 - mrcnn_class_los
s: 0.0314 - mrcnn_bbox_loss: 0.0373 - mrcnn_mask_loss: 0.1556 - val_l
oss: 0.9307 - val_rpn_class_loss: 0.0078 - val_rpn_bbox_loss: 0.3262
- val_mrcnn_class_loss: 0.0848 - val_mrcnn_bbox_loss: 0.2101 - val_mr
cnn_mask_loss: 0.3018
Epoch 37/40
100/100 [==============================] - 259s 3s/step - loss: 0.295
4 - rpn_class_loss: 0.0045 - rpn_bbox_loss: 0.0508 - mrcnn_class_los
s: 0.0355 - mrcnn_bbox_loss: 0.0437 - mrcnn_mask_loss: 0.1609 - val_l
oss: 0.9927 - val_rpn_class_loss: 0.0072 - val_rpn_bbox_loss: 0.4082
- val_mrcnn_class_loss: 0.0675 - val_mrcnn_bbox_loss: 0.2174 - val_mr
cnn_mask_loss: 0.2922
```

Source: Author's compilation

Figure 12: Training the model on a Gradient server (in the cloud).

Results and discussion

In this section, we will examine the results obtained during the training of our model, evaluate its performance, and demonstrate its prediction on sample data from the test dataset in the inference stage. Evaluating a deep learning model is a crucial step in any project process as it allows us to assess the accuracy and performance of the model. There are various parameters and metrics that can be used for evaluation. In our study, we will use logarithmic loss as our evaluation parameter.

Logarithmic loss, also known as log loss, is a suitable metric for multi-class classification. It penalizes false classifications by requiring the model to attribute a probability to each class for all samples. If we have N samples belonging to M classes, the log loss is calculated as follows:

$$Logarithmic\ Loss = \frac{-1}{N}\sum_{i=1}^{N}\sum_{j=1}^{M} y_{ij} \times log\ (p_{ij})$$

Where,

y_{ij}, indicates whether sample i belongs to class j or not

p_{ij}, indicates the probability of sample i belonging to class j

The log loss has no upper limit and exists in the range [0, ∞). A log loss closer to 0 would indicate higher accuracy, while if the log loss is away from 0, it will indicate less accuracy.

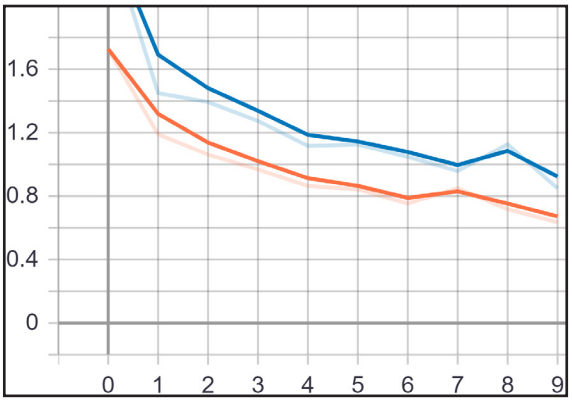
In general, decreasing the log loss will give a better accuracy for the classifier.

The goal of training a model is to find a set of weights and biases that have low Loss, on average, across all examples.

In Mask R-CNN we have 5 small principle losses, each one has a specific signification, and the figures below Losses obtained as a result of training, it can be accessed through the use of Tensorboard:

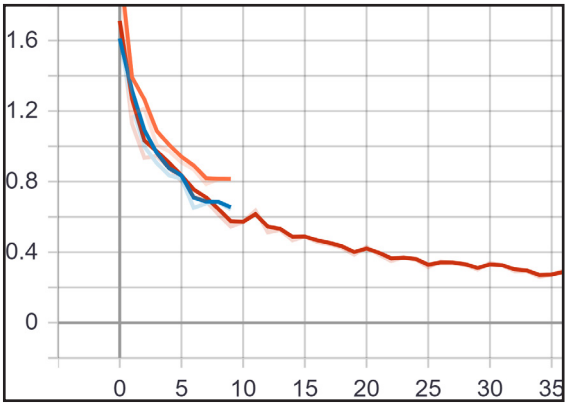
- **rpn_class_loss:** How well the Region Proposal Network separates background with objetcs.
- **mrcnn_bbox_loss:** How well the Mask RCNN localize objects.
- **mrcnn_class_loss:** How well the Mask RCNN recognize each class of object.
- **mrcnn_mask_loss:** How well the Mask RCNN segment objects.

We use thus losses to calculate a big Loss: A combination (surely an addition) of all the smaller losses.



Source: Author's compilation

Figure 13: The model loss during cloud training.



Source: Author's compilation

Figure 14: The model loss during local training.

After training the model both locally and on the cloud, the results shown in Figures 13 and 14 indicate that cloud training is faster and better. The loss reaches 0.26 in the last epoch. However, it is evident that 10 epochs are not enough to train the model effectively, as seen in the reduction of the loss rate after epoch 13. This is because the model starts to memorize the input data rather than learn the underlying patterns, leading to overfitting. Hence, we will use the weights obtained after epoch 13 for inference.

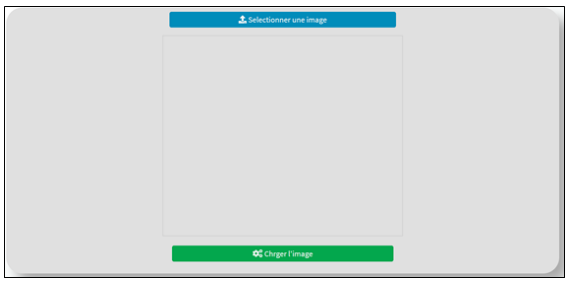
A comparison between local and cloud training is summarized in Table 1. The first local training, with a dataset of 300 images, 10 epochs, and 60 batches, took 7 hours and resulted in a loss of 0.848, indicating an inaccurate model. In the second local training, the number of images was increased to 620, and the training time increased to 9 hours. However, the model became more accurate. On the cloud, with an environment offering 30 GB of RAM, 8 CPU, and GPU, the same model was trained in 28 minutes with the parameters from the second local training. The accuracy was not suitable, so the number of epochs and batches was increased to 40 and 100 respectively, which took 3 hours to complete with a convincing precision.

	Epoch	Batches	Dataset	Duration	Duration / epoch	Duration / step	Loss
Local	10	60	300 images	7 hours	2100 seconds	36 second	0.8486
Local	10	60	620 images	9 hours	2300 seconds	39 second	0.635
Cloud	10	60	620 images	28 minutes	170 seconds	2 seconds	0.8406
Cloud	10	100	620 images	45 minutes	280 seconds	3 seconds	0.6896
Cloud	40	100	620 images	3 hours	280 seconds	3 seconds	0.26

Source: Compiled by the authors

Table 1: Comparison of local model training and cloud model training.

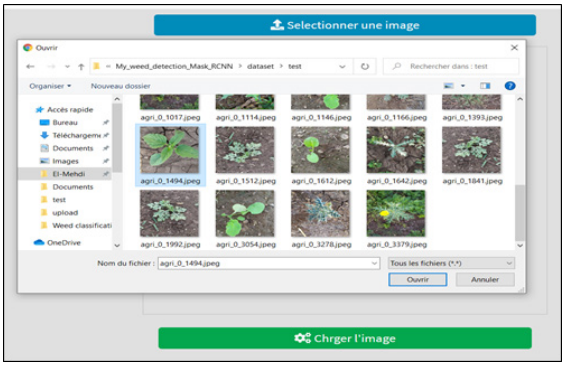
In this section, we will use the trained model on the test dataset to predict the presence of weeds or crops in images. We have integrated the trained model into a web application developed using Flask. The interface of the application includes two buttons and an image frame as displayed in Figure 15. The upper button enables users to select an image, while the lower button allows them to load the image onto the server.



Source: Author's illustration

Figure 15: Home page.

After clicking the "Select Image" button (as shown in Figure 16), a window will appear for selecting the specific image to be used in the prediction process.



Source: Author's illustration

Figure 16: Upload image

After selecting the image, it can be viewed in the frame. To start the prediction process, the image must be uploaded to the server by clicking the "Upload Image" button. Once the image has been uploaded, the prediction can be initiated by clicking the "launch Detection" button, as depicted in Figure 17.

Source: Author's illustration

Figure 17: Launch detection

At the end of the prediction process, the application provides the result of the initial image with a bounding box around the specific object (if it exists) along with the name of the class and the prediction probability. A mask is also applied to detect the object boundaries, as depicted in Figure 18. Users can start another prediction by clicking on the "New Prediction" button. The results shown in the images indicate that the application, using the trained model, can accurately detect and surround the grass in a short amount of time, and if run on the cloud, the results will be even faster.

Source: Author's illustration

Figure 18: Result

Conclusion

The objective of this study was to create, train, and optimize a Mask R-CNN model for weed detection in images by comparing two training approaches: local machine and cloud. The goal was to achieve the highest accuracy and lowest loss in predicting, segmenting, and identifying the presence of common weeds in pictures. The successful implementation of this model can aid in optimizing herbicide use and controlling the spread of weeds. However, this model is limited to the images it was trained on and may

not be applicable to all weed species or growing conditions. Future work will aim to improve the model by incorporating a hybrid approach, incorporating additional data and increasing the diversity of the training set. This has the potential to further improve the accuracy of the model and make it more applicable to a wider range of use cases. The results of this study and future work in this area could have important implications for the agricultural industry, reducing environmental damage and improving crop yields.

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Sensor Data Gathering for Innovative Climatic System for Effective Water and Nutrient Management

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Abstract

Climate change is having a major impact on various sectors such as agriculture and water management due to changes in the distribution of rainfall. Mitigation of climate change impacts can be achieved through early detection of these changes by monitoring systems and the adoption of appropriate adaptation measures. One of the main goals is to design and develop a next generation monitoring and alerting system to support the optimization of water and soil nutrient management in agricultural domain. Sensors and sensor data management play an important in this kind of monitoring systems. A complete sensor data chain was developed based on modern wireless sensor networks and IoT technologies that covers the data gathering up to the data publication by interoperable interfaces. The monitoring system was tested on vineyards in pilot localities in Czech Republic and in Argentina.

Keywords

Sensors, monitoring, alerting, water management, wireless sensor network, data processing.

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Introduction

Sensors and sensor data provide important methods on how to get current and up-to-date information about various phenomena in different domains. A very important role for data collection representing sensors in agriculture, fishery, and forestry (Rogotis et al., 2021). Especially, IoT technologies and communication protocols have provided a wide spectrum of different sensors with various applicability and connectivity. Decreasing hardware prices, lower energy demands, coverage of modern communication networks enabled spreading of sensor utilization. Agriculture as a domain has taken a lot of advantages of sensors and IoT. Utilization of sensor data and its analyzing with a combination of other datasets can improve the decision-making process and allow it to react to any events on farms. Modern IoT communication networks allow continuous monitoring with low power consumption data transmission to the Internet (Java et al., 2021). Agriculture is very dependent on environmental conditions and other external events therefore a monitoring and alerting system can support decision-making processes and prevent loss on crops and yield. Based on data from monitoring and alerting systems, effective optimization of water management and nutrient management can be implemented. Where the monitoring part depends on sensor data gathering in fields and effective processing of observed data. Typical crops where utilization of sensors in production is growing rapidly are high-cost crops – fruits, vegetables, wine, etc.

Wine production is a domain where sensors and IT technologies have been playing important roles already for more than 20 years. Incorporating of sensors and modern technologies provided a shift from traditional methods to precise viticulture and define challenges in production and management of vineyards (Arnó et al., 2009). Modern technologies like monitoring, modelling or remote sensing are involved in optimizing water management in vineyards (Mirás-Avalos and Araujo, 2021). Building wireless sensor networks on vineyards to monitor different phenomena is a task for incorporating different technologies and modern approaches to gather relevant data. Different sensor networks and computing technologies monitor maturity of grapes and influences of freeze on production (Burrell et al., 2004, Beckwith et al., 2004, Galmes, 2006). But not only in-situ sensors are used for monitoring, remote sensing and image processing improves methods to detect different

diseases and overall status of plants (Lloret et al., 2011). Monitoring networks are focusing on complex climate conditions in vineyards by monitoring air and soil conditions and incorporating weather forecasts (Togami et al., 2011, Catania et al., 2013) to increase quality of grapes and reduce operation costs. Monitoring of soil conditions in vineyards is important for detection of water stress during the whole season (Ginestar et al., 1998) as well as the spatial variability of the water stress in fields to optimize irrigation mechanisms based on need of water (Bellvert et al., 2014).

A modern monitoring and alerting system (AgriClima) of the new generation was designed to provide a monitoring and support system to optimize water and nutrition management in agriculture with pilot focus on viticulture. The system was designed to incorporate modern IoT technologies as well as interoperable interfaces. This paper is describing the monitoring sensor network and sensor data management part of the whole monitoring and alerting system AgriClima. The Materials and methods section describes components of the system from hardware and sensor part and data transmission as well as the sensor data flow from receiving on server to publication. The Results and discussion section describes new results as the alerting mechanism and data visualization and evaluates the operational status of the sensor network.

Materials and methods

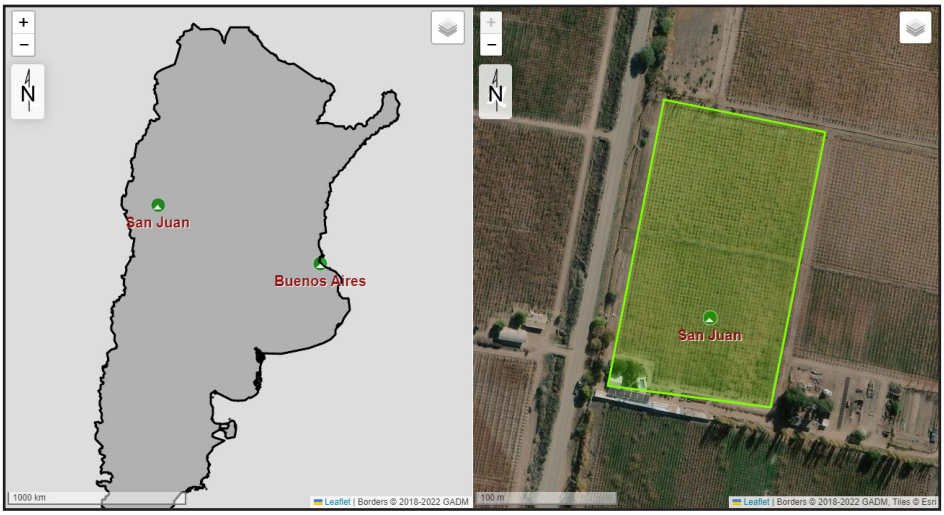
Pilot localities

Pilot localities for the monitoring use cases were selected based on used methods of production according to changing meteorological conditions, data availability, acceptance of proposed actions, level of technological support etc. While the research project was focused on cooperation in the Czech Republic and Argentina, localities were selected in both countries (Boukalová et al., 2019).

As the pilot locality in the Czech Republic, a vineyard was selected located in the north-west part of the country near to the city of Most (see Figure 1). The vineyard Most – Čepirohy is located on the Čepirohy spoil bank of the brown coal strip mine "Šmeral". Vineyards in the surroundings of the city of Most are situated on the area of 30 hectares and are part of the Litoměřická wine sub-region and they are the most northern vineyards in the Czech Republic. Grape vine (Vitis vinifera, L.) has been used as a revegetation plant during the mine reclamation process since 70's in the locality of the city of Most. The monitored part of the locality was the vineyard "Mariana" which was selected as experimental part with new planting of grape vine in 2020 using biochar (Hendrychová et al., 2021). Biochar applied with compost should provide support during taking of roots for young plants. There were both methods for planting – traditional one only with compost and experimental one using compost with biochar.

Source: Processed by the authors

Figure 1: Location of the Čepirohy pilot locality.



Source: Processed by the authors

Figure 2: Location of the San Juan pilot locality.

Sensors for monitoring soil moisture and soil temperature were deployed randomly to both types of planting.

The pilot locality in Argentina is located in San Juan province where agriculture and especially viticulture is an important part of the economy (Boukalová et al., 2019) (Figure 2). The local climate, characterized by a high level of sunshine, is very beneficial to the health of the vines, which generally have a very low risk of fungal or other diseases. The major challenge in the area is the lack of water for irrigation. The monitored pilot was vineyard "ECOHUMUS". The locality is characterized by water scarcity, the vineyard is irrigated by surface water from a remote reservoir through a system of canals. The water that comes to the locality by canals to irrigate the crops is not adequate. To prevent the vines from drying out, the lack of water from the canals needs to be replaced by groundwater from wells on the locality. Thus, the sensor monitoring system and experimental application of biochar was important for optimization of irrigation in the locality.

Used sensors in sensor network

The proposed system for data collection was based on Internet of Things (IoT) technology applied to wireless sensor networks. The data collection system was designed taking into account the local and regional conditions in pilot sites and the needs of individual end users (Křivánek et al., 2020). The individual sensor network measurement nodes transmit the current values of the measured phenomena, together with the identification of each individual sensor and a timestamp, to the respective IoT network, from which they are sent to a data server.

The sensor network for data collection in the pilot sites was aimed at acquiring data on current meteorological and soil conditions using modern IoT components and transmission technologies (Křivánek et al., 2020). The basic sensor component was a soil water content sensor, which was installed at the depth (or multiple depths) required by local conditions defined by:

- soil type,
- the expected precipitation,
- the existence of irrigation.

The main combination of sensors were the METER TEROS 11 and METER TEROS 21 (see Figure 3) which measure not only the humidity but also the soil temperature. The sensor measurement of the water content in the soil is based on the measurement of the dielectric permittivity of the soil at a frequency of 70 MHz. The permittivity is then converted to volumetric water content (VWC) using an empirical formula that can be adjusted to the specific soil type to refine the calculation of the water content itself.

Source: Processed by the authors

Figure 3: TEROS 21 sensor used in pilot localities.

The monitoring of basic meteorological parameters in the locality is carried out by a basic meteorological station METER ATMOS 14 (see Figure 4). The weather station monitors the following phenomena:

- air temperature,
- relative air humidity,
- atmospheric pressure,
- water vapor pressure.

Source: Processed by the authors

Figure 4: Installation of meteostation METER ATMOS 14 in pilot locality.

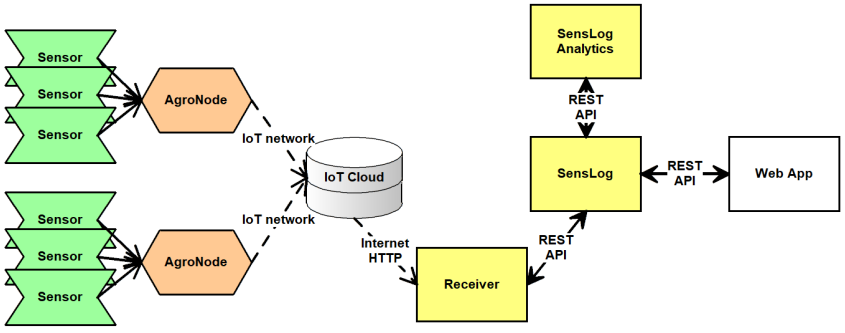
Dataloggers used in the system worked in semi-online mode. Harvesting of data is triggered by timeout defined by the user (most common 60 minutes for soil phenomena – moisture, temperature, and 15 minutes for meteorological phenomena) or value change of parameter (sensor of water in irrigation channel) or both. Measured value is then stored in internal nonvolatile memory in datalogger and simultaneously sent to server storage through several IoT radio technologies. Sigfox IoT network, that was used in dataloggers on pilot locality on vineyard "Ecohumus" in Argentina, used UNB (ultra-narrow band) radio modulation with very low power demands to achieve high range coverage (Křivánek et al., 2021). Local regulations allow the use of radio modules on free frequency 920 MHz - RC4 (Sigfox Radio Configuration) with duty cycle with frequency hopping, no emission during 20 seconds from last transmission. Used data protocols allowed to send up to three measured values during one radio session.

CRA LoRaWan IoT network was used for data transmission on pilot locality in vineyard Čepirohy in Czechia. LoRa is IoT radio network communication technology based on spread spectrum modulation with long range, low power consumption, low data rate. Local regulation on pilot locality allows the use of 868 MHz frequency band with maximum output power 25 mW and up to 1% duty cycle. In Czechia dataloggers are using the network of local LoRaWan provider České Radiokomunikace (CRA), which covers the whole country. In normal conditions, the uploaded message can be received at least by two base stations.

SensLog system

Measured data are collected and processed by the SensLog system in the proposed solution. SensLog is a web-based sensor data management and processing solution that is suitable for both static and mobile sensors (Kepka et al., 2017). SensLog receives data directly from AgroNode datalogger or from IoT network providers' repositories – using the Receiver component.

SensLog also provides storage and preprocessing of data in the repository in the SensLog Model data model, which is derived from the ISO 19156 (ISO, 2011) standard with an extension to store the metadata of the sensor network and its structure. The data model is implemented in a relational database with a spatial extension, which provides appropriate storage in the relational model as well as storage and processing of the spatial component of the collected sensor data. The relational database stores the original measured data, but also the processed results of analyses and other



Source: Processed by the authors

Figure 5: Schema of data flow from sensors to applications.

calculations. Measured and processed data are published for visualization and presentation applications, or for further processing by third-party applications using the web services system. Web services based on REST methods publish data in JSON or CSV format, but also in other text formats. Other modules of the solution – Receiver, SensLog Analytics – communicate with the main part of SensLog using the REST API system. The general overview of the data flow between sensors and SensLog component are shown in Figure 5.

Data analyses

The added value of the measured data is the information which can be retrieved from that. Such information is then important not only for an automatization and a trend monitoring, but also as a base for obtaining knowledge for a defined area. Due to these requirements, we developed an application SensLog Analytics performing following four types of calculations:

- calculations of statistical characteristics of measured values for different intervals (average, minimum, maximum for different time periods),
- calculations of cumulative values for defined variables over a given period,
- monitoring of exceeding the defined threshold value of the selected sensor,
- monitoring of a defined combination of values of different variables in a sliding time interval.

The application needs to be fed by raw observations that are further processed (see Figure 6). An approach of retrieving data directly from the SensLog database periodically was chosen, however with an awareness of extendibility with data-stream processing due to the advantage of modular design. Loaded observations go through modules (pipe and filters architecture), which each is responsible for a single task (e.g., threshold checker). The calculating methods represent separate modules as well and the calculation is done based on a type (i.e., calculation model) and its initial configuration, e.g., selected sensors of the required phenomena is the configuration, and a model is the logic for the calculations.

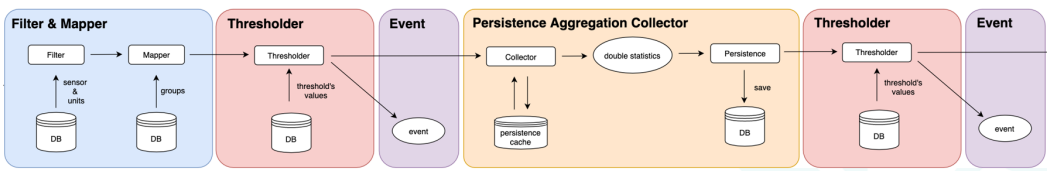
Alerting mechanism is also a crucial part of the application. It triggers an event if some threshold rules are violated. For instance, an advanced scenario can be configured as follows - raw values of a temperature must be in the interval <-10;50>, an average value on a defined interval must be higher than 0. In a case of violating some of the rules, the application sends an alert via email or uses the SensLog Alert mechanism, which can be integrated to other systems (e.g., for automatization). Calculated statistics are then stored back in the database and are accessed via web APIs.

Data visualization

Visualization of measured data and results of analytical functions are important functions for end users of the whole system. The proposed system was using the SensLog Client application. The application is available for web and responsive for smartphone interface. The SensLog Client application provides visualization of sensor data in the form of charts (see Figure 7) as well as a map window with location of sensors (see Figure 8). Visualization of sensor data in form of charts is using the Vega visualization grammar. Vega describes the interactive visualization in JSON format and then the final view is realized by Canvas or SVG graphics. This approach provides effective visualization of different combinations of time series of data and set of user-defined views of collected data.

Map visualization of sensor location provides additional functions for map compositions with other data layers. Map window contains different data layers:

- general base map,
- soil map of the locality with additional information from local samples,
- weather forecasts and meteo models for locality,
- locations of sensors,
- interpolated results of analyses.



Source: Processed by the authors

Figure 6: Structure of SensLog Analyst components.

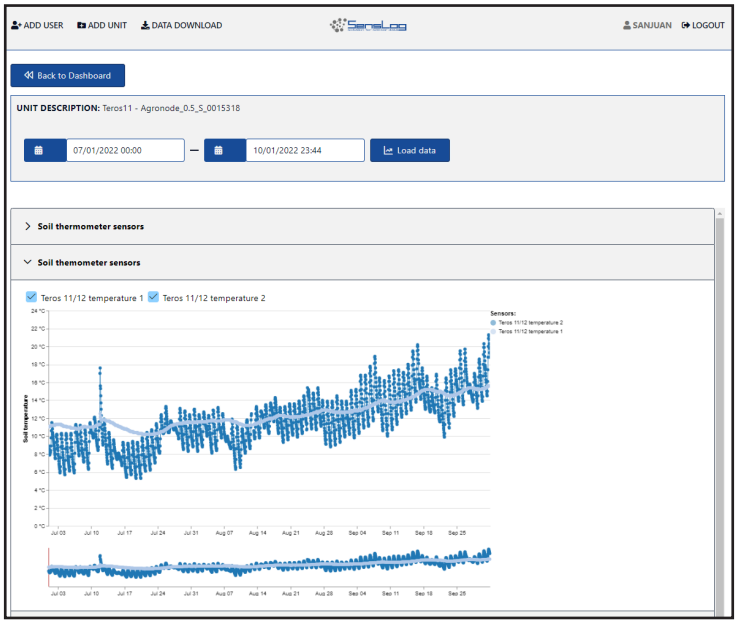


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Figure 7: Example of chart visualization.

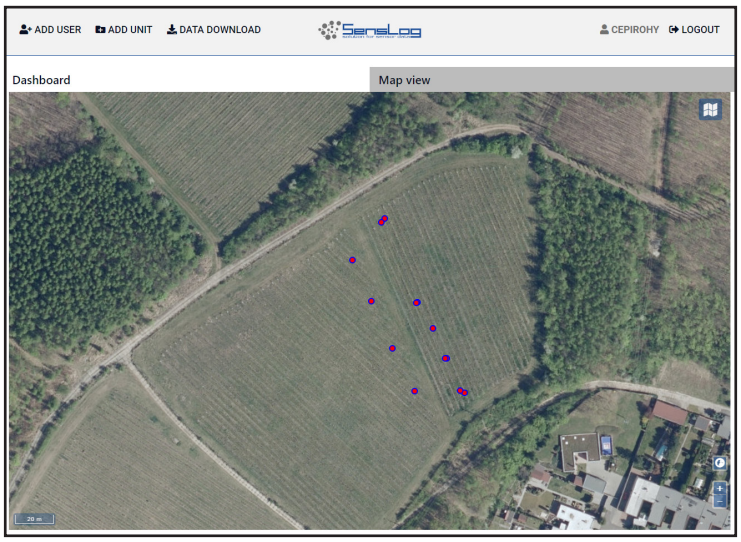

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Figure 8: Example of the map window with locations of sensors and orthophoto layer.

Results and discussion

The developed system provides monitoring and sensor data management part of the whole system for optimization of water and nutrient management. The monitoring system utilizes commercial sensors for monitoring of different phenomena and existing components of the SensLog system to collect, store and publish sensor data.

Monitoring campaign in pilot localities was prepared during spring 2020 in the Čepirohy locality respectively in winter 2020 in the San Juan locality. Data were collected with a frequency of an hour in both localities. Four sets of soil sensors, one meteostation and inundation detector were installed in San Juan locality where sensors collected about 8,000 resp. 17,000 observations during 24 months of installation. Twelve sets of soil sensors, two meteostations were deployed in Čepirohy locality where sensors collected about 13,000 resp. 19,000 observations during 32 months of installation. Sensors in both localities were operating for 65-100% of deployed time. The malfunction cases were generated

by different aspects - hardware malfunction, solar panels coverage by leaf, wild animals gnawing of cables especially in Čepirohy locality etc. The detection of non-operating states of monitoring units was improved during the monitoring time by development of a monitoring and alerting component – SensLog WatchDog.

SensLog WatchDog

The new component that was developed as a part of the alerting mechanism is the SensLog WatchDog component. Collecting observations is a complex task (see SensLog Data Flow), which consists of several nodes and technologies. And even if they are developed with a high availability by design, some unexpected conditions could appear (e.g., hardware damage by animals, radio jamming) and the fluent data flow is broken. This leads to some problems - a hardware unit (i.e., a sensor) has an issue and should be repaired as soon as possible; and the void of time-series observations cause a problem for the statistics calculation. To minimize such consequences, we developed WatchDog. The application periodically monitors the presence of observations and sends a report to the responsible people.

The core functionality is simple, but the power of this tool is given through its configuration ability. WatchDog is a stand-alone application and uses the REST API of the SensLog, which extends the usability of monitoring more SensLog instances (i.e., a data source) just via one WatchDog. This brings an advantage of summarizing more results to just one report, e.g., sending an email of the results from multiple data sources to a service support.

Sensors and units form a sensor network which then can be grouped and give a name that is usually chosen by the operating area. Due to a diversity of responsible people, not everyone is interested in everything, because such networks could be quite large, so WatchDog enables a detailed configuration of desired level - entire group, particular units, or selected sensors. To allow monitoring from different data sources, the configuration includes an option to merge multiple groups as well. Special functionality is monitoring a single sensor across multiple units or groups. This may be primarily useful for a technician who is interested only in one phenomenon (e.g., battery level) across all networks.

Such configurations of observable entities are further assigned to a message broker. The architecture and the configurations allow further extensibility of multiple message brokers (e.g., instant messages services), however current configuration allows reporting only by email with an option of specifying respondents for each observable entity.

The visible part of the application is the report. It is generated periodically every day at a specific time and contains a present of an observation during the previous day. The result is formatted into two separate tables. The first one contains all configured units where each row is under-colored by linear gradient visualizing an information of how many sensors either passed or not (e.g., 2/4 passed then the background of the row will contain half green and half red color). The second table contains only the failed sensors with timestamp information of the last observation.

Such a report is then sent to the recipients to have a status of their networks of sensors and respond to some issues that could eventually occur as soon as possible.

SensClient configuration & visualisation

Components of SensLog platform mainly operate without a user graphic interface and communication is done via web APIs or static start-up initialization. Nonetheless this approach may be inconvenient for some operators, so the SensClient aims to configure the components in featured oriented style by web application. Such various configurability among other components (e.g., a logged user can enable a monitoring for a specific sensor and the report is sent to his assigned email address) is an aim, however current version allows a management of sensor network.

Beside the configuration abilities, the SensClient visualizes the sensor network as well. The main overview is a dashboard placing all units onto a geographic map. Each unit can be opened, and all assigned sensors will be displayed, and a chosen sensor will then visualize its data in a chart. Some specific multi-sensors also allow multiple curves within one chart (e.g., groundwater measurement in various high levels). Such graphical data visualization is convenient for users due to easy and quick data correctness checking.

Conclusion

The main outcome of the whole activity was the development of a next-generation IoT-based alerting and monitoring system using interoperable interfaces to optimize water and nutrient management in agriculture. A crucial step for the alerting and monitoring system is

the design and establishment of a monitoring and sensor data management system. The monitoring and management part is producing sensor data that are stored, processed, and provided for other components for further processing and decision-making. Further components utilizing monitoring data by the set of SensLog services provided soil condition modelling and then evaluation for decision-making. The final product provides data support for decision-making to optimize water management or nutrient management in localities.

The presented monitoring solution provided a complex component of the whole system that provides interfaces by defined APIs to ensure interoperability between components of the system. Amount of collected sensor data and continuity of data time series has shown that selected technologies and processes of the monitoring system are suitable for the defined tasks of the complex alerting and monitoring system.

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What is Inside the Bottle? - Factors Influencing Pálinka Consumption

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Abstract

Pálinka is the national spirit of Hungary and is in possession of the geographical indication of the European Union, but it used to be listed as a poor-quality product for a long time. The turnaround in this field began in the early 2000s. The aim of this study is to analyse the behaviour and attitudes regarding the purchase and consumption of pálinka and, to assess the product-related awareness of Hungarian consumers who like this particular spirit. Based on the literature, the knowledge of Hungarian consumers about pálinka is rather low, which is confirmed by the results of our questionnaire survey of 1,000 people. Furthermore, based on the results obtained, participants in the pálinka sector are more likely to understand how important certain product attributes that are perceived by consumers when purchasing pálinka. In order to increase the awareness of the spirit, it is essential to get to know the consumers, which can be followed by a well-positioned marketing strategy from both the government and corporate side.

Keywords

Pálinka, spirit, Hungary, consumer survey, knowledge, geographical indication.

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Introduction

Almost every country has its own national drink, which is decisive from a cultural, social, and economic point of views. Which is whiskey in the former British Empire, tequila in Mexico, cognac in France, or grappa in Italy, is undoubtedly pálinka in Hungary. The name pálinka is probably derived from the Slovak word 'palenka' or 'pálit', which means to distil (László et al.; 2016, Török, 2013). Pálinka is a distillate made exclusively from fruit, which can only be produced in Hungary. The only exception to this is the one made from apricot, which can be delivered in four provinces of Austria (Lower Austria, Vienna, Burgenland, Styria). In Hungary, the pálinka culture, which includes the traditions, ceremonies of making and consuming fruit spirits, has a centuries-old history (see e.g., Békési and Pándi, 2005; Harcsa et al., 2014).

In the 1990s, pálinka was still considered to be an extremely poor-quality spirit, due to the low reputation received during the communism, when this product could be distilled from low quality materials with industrial scale (Török, 2013). The break-through in the field of quality took place at the beginning of the 21st century, and now pálinka, as a liquid food, and the consumption of pálinka is experiencing its renaissance (Géczi et al., 2018) due to changes in Hungarian and EU legislation, the establishment of the Pálinka National Council (PNC), the acquisition of the EU Geographical Indication (GI) and the distinguished Hungarian national product (Hungaricum) status. In the last decade, pálinka has come a long way, has left the 'peasant' drink classification, and become the favourite national drink and value of Hungarians (Harcsa, 2017b; Harcsa, 2017a).

Aim of the research

The main goal of the present research is to explore the preferences of Hungarian consumers interested in pálinka during the purchase of the drink along different attributes, considering the latest changes and trends related to it. The importance of the topic is justified by the fact that Hungary has placed great emphasis on improving the image of pálinka as a national drink, and that the government budget

receives significant revenue from the excise duty on this product. In addition, there is an increasing emphasis in the European Union on protected and quality products, including different kind of spirits. The novelty of the research is also given by the fact that several factors determining the purchase (e.g.: the result of spirit competition, consumer ethnocentrism, the knowledge of the pálinka seal) were included, which were not examined in previous studies. The results may be of interest from both a scientific and a marketing perspective.

Literature review

Major legislative changes of the recent years

In Hungary, for a very long time, three different types of drinks were purchasable under the same name 'pálinka' (Harcsa, 2018). This chaotic situation was clarified by the provisions of the Codex Alimentarius Hungaricus No. 1-3-1576 (Hungarian Food Codex Committee, 2002), which entered into force in 2002. It put an end to the decades-long struggle for the uniqueness, specialty, and quality of the spirit. The Act LXXIII of 2008, provides a base for the so-called 'Pálinka Act' on pálinka, törkölypálinka (made from grapes) and the establishment of the Pálinka National Council. According to the law, pálinka is a fruit distillate made from fruit grown in Hungary, which is also mashed, distilled, matured, and bottled within the country. As for fruit production, it essential for it to be in Hungary, since for example, imported distillates made from fruit or vegetables and honey cannot be considered as pálinka. In addition, the use of the pálinka seal, which later became mandatory, was possible for beverages marketed domestically, which is different in colour from other excisable alcoholic products.

According to the current regulations (Act LXVIII of 2016 on Excise Duties), an alcoholic product (distillate or pálinka) can currently be made from fruit in three ways: by private distilling, in contract distilleries and in commercial distilleries. We talk about private distillation when someone makes distillate from (typically) their own fruit, with their own distillation equipment, in their home. When someone uses the services of a contract distillery to make their own fruit, we are talking about a contract distillate. If a specialized company produces distillate for commercial purposes, typically from purchased raw materials, the product made here can only be called pálinka. It is important to point out that products from private and contract distillation can only be described as distillates (with a few exceptions), they cannot be officially called pálinka; and that only the drinks produced in commercial distilleries qualify as a Hungarikum and EU's protected drinks.

In recent years, many changes were introduced in the regulation of distillation regarding excise duty (Harcsa, 2016; Zsótér and Molnár, 2015). From 2021 onwards, the rules of production changed again in several respects (National Tax and Customs Office, 2021), as the production of distillates became duty-free up to a certain amount for both private distillation (up to 86 litres – maximum value) and contract distilleries (up to 50 litres).

Consumer habits for other international spirits

Examining the international competitors of pálinka, we can find some studies similar to this research that deal with consumer preferences (Table 1). Glenk et al. (2012) examined consumer preferences associated with Scotch whisky on sustainable production, consumption, and the purchase of environmentally friendly food. Based on their results, about half of the survey participants consider the proportion of Scotch-grown barley in their whisky at the time of purchase. Furthermore, it was proved that the demand for environmentally friendly production of Scotch malt whisky is rather low, suggesting that consumers are unlikely to be key players in promoting sustainable production.

The number of studies analysing the relationship between glassware (glass or bottle) and consumer preferences has increased over the past few years. Wan et al. (2015) examined red wine, white wine, beer, whiskey, and Chinese grain spirit (baijiu). It is worth noting that for consumers, it is important to serve a particular alcoholic beverage in a suitable glass, based on which they are willing to pay a higher price for it - so the type of glass or bottle affects the willingness to pay. All of this also affects product marketing as well as the design of bottles and glasses.

Prentice and Hadsjuk (2016) analysed consumer factors (brand, country of origin, packaging, social media) that arise during the purchase of vodka. Based on their results, similarly to Siegel et al. (2013), brand has a significant impact on consumer decision-making and purchasing preferences. Packaging has of relatively low importance when buying vodka, and many have found that this factor indicates to them the quality of the product they purchase. Social media has a greater effect on the frequency of purchases. For consumers in Italy, the choice of grappa was most related

Authors	Year of the survey	Examined alcoholic beverage	Target group and data collection technique	Key findings
Glenk et al., 2012	2012	Scotch malt whisky	Questionnaire survey (400) with Scottish respondents over the age of 18.	The presence of Scottish-grown barley is not a decisive factor. Demand for more environmentally friendly whisky production is quite low.
Marinelli et al., 2014	2014	Alcoholic drinks	Questionnaire survey (430) with Tuscan respondents aged between 18 to 35 years.	Young consumers prefer to see alcohol as a means of socializing and getting out of everyday life. The time of consumption and the place of purchase differ for different drinks.
Wan et al., 2015	2015	Red wine, white wine, beer, whiskey, Chinese grain spirit	Questionnaire survey (120) with Chinese students between the ages of 18 and 23 + questionnaires (100) with American respondents between the ages of 19 and 75.	The type of glass or bottle affects the willingness to pay. Proper serving of the drink is essential.
Prentice and Handsjuk, 2016	2016	Vodka	Questionnaire survey (454) with Australian respondents over 18 years of age.	The brand has a significant impact on consumer preference. Packaging is of relatively low importance when purchasing vodka.
Merlino et al., 2019	2019	Grappa	Interviews and questionnaire survey (667) with Italian respondents over 18 years of age.	The most key factors in making a choice are experience, product knowledge and origin. Less crucial factors are alcohol content and packaging.
Cravero et al., 2020	2020	14 alcoholic and non-alcoholic beverages	Questionnaire survey (2388) with Italian respondents aged between 18 to 60 years.	Similar preferences were found for both sexes. Consumption of alcoholic beverages has decreased with aging, with the sole exception of wine.

Source: own editing

Table 1: Key studies examining international alcohol consumption patterns.

to previous experience, product knowledge and origin. In contrast, consumers considered alcohol content and packaging to be the two least crucial factors when making a purchase (Merlino et al., 2019).

Cravero et al. (2020) examined taste sensitivity among 14 alcoholic and non-alcoholic beverages (including beer, wine, spirits, cocktails). Despite strong gender differences, because women tend to like and consume less alcohol than men, similar patterns of liking and interest were found for both sexes. Consumption of alcoholic beverages decreased with age, apart from wine. It should be emphasized that people see moderate wine consumption as part of the Mediterranean diet. In Italy, older people associate alcohol with relaxation and everyday life (Bastian et al., 2019), while young consumers see alcohol more as a means of socializing and getting out of everyday life (Marinelli et al., 2014). Young people consume wine mostly during meals, while beer and spirits are mostly consumed outdoors, in the evening and on weekends. As for the preferred places to shop, the wines are mostly in restaurants, pizzerias, and supermarkets; beers, especially in bars, pubs, distilleries, supermarkets, and pizzerias; and spirits are usually purchased at discos and clubs.

Alcoholic beverages are produced all over EUs, both for domestic consumption and for export, but the number of studies on the subject is rather limited. It should also be emphasized that the number of studies examining the competitiveness and market share of fruit spirits in Central and Eastern Europe is limited (Torok and Jambor, 2013). However, in the case of wines and beers, several publications can be found. Mtimet and Albisu (2006) found that the consumption of PDO and PGI wines is increasing in Spain. During the consumer choice, the age of the wine and the protection of its origin stand out the most. Perrouty et al. (2006) concluded that brand and origin are very important decision-making aspect for those who do not have adequate

information about the quality of the wines. In Japanese wine purchasing decisions, such as taste, style, colour, price and the recommendations of friends are considered outstanding (Bruwer and Buller, 2012). Men prefer beverages from Old World wine countries, while women prefer beverages from the New World wine countries. In Poland (Schaefer et al., 2018), consumers are more likely to buy wines produced outside the country.

Meanwhile, during the selection of beers, also several product attributes appear as a decision criterion (Betancur et al., 2020). In the Czech Republic, consumers' choices are mostly influenced by taste, quality brand and Czech production. Price was not found to be an influencing factor in the selection of beer, but this is due to consumers being interviewed on the street (Svatošová et al., 2021). Another tendency is that with the increase of consumer ethnocentrism, Czech consumers are less likely to choose foreign beer brands (Wanninayake and Chovancová, 2012). In Poland, beer consumers are more attached to national and regional symbols. In Siemieniako et al.'s (2011) research, respondents felt it was their moral duty to buy local beers, thereby supporting the local community by expressing their local identity. All this plays a significant role in the purchase and selection of beer. Hajdu et al. (2007) examined beer consumers in Hungary, it was found that those with a higher education consume new types of beers more often than those with less education, who are more likely to consume traditional beverages (e.g., homemade distillate).

Consumer preferences in the Hungarian pálinka sector

Several studies have examined the pálinka consumption habits of Hungarians, the transformation of consumer habits and the change in attitudes related to pálinka (Table 2). The report of the GFK Hungária Market Research Institute (2008), commissioned by the Agrármarketing Centrum, highlighted the poor information of consumers about the pálinka, and the remarkably high proportion of non-commercial purchases. Consumers' attitudes towards pálinka were mostly related to nostalgia, the rural atmosphere (although pálinka consumers typically live in the larger cities) and Hungarianness, so they found that the name pálinka had become obsolete. Traditions determine the consumption habits and occasions of pálinka (e.g., slaughter of pigs, weddings).

A researches on the topic in the early 2010s have come to the conclusion that positive associations (group of friends, family event, good mood, cheerfulness) are tied to pálinka; and the negative stereotypes associated with the drink (e.g., poor quality, "old-fashioned" drink) are disappearing (Totth et al., 2011a; Totth et al., 2011b). When buying pálinka, the following aspects are decisive for consumers: taste, packaging (especially design) and price, followed by alcohol content and brand. In the case of a gifting, it is much more common to pay a higher price than in the case of a purchase for one's own purposes; and in the case of gifting, special flavors are the determinants, while for gatherings of friends and home consumption, traditional, more popular flavors are dominant. The role of the brand and the region is less important for the respondents, only a few of the brands/distilleries are better known (e.g., Zwack, Rézangyal). For all types different consumption occasions, 'homemade pálinka' has appeared, mainly due to its origin (self-made, they know what it is made of) and its price (cheaper). Consumers also mix pálinka and pálinka-like drinks in terms of name.

The authors repeated the research later. Based on their results, it can be stated that a significant part of the respondents, between the ages of 18 and 39, used to buy pálinka for various occasions (e.g., home consumption, ceremonies, meetings). The authors highlighted that young people prefer and consume this spirit besides whiskey and vodka - this can contribute to increasing the image of the drink and thus its competitiveness (Totth et al., 2017). In their research, published in 2018, the authors already reported an increase in consumer awareness, as most respondents were aware that only distillate made from 100% domestic fruit could be considered to pálinka. Consumption of pálinka is still mainly associated with celebrations (christening, name days, birthdays, Christmas, funerals) and social events (meeting of friends, family events). Men prefer whiskey and pálinka, while women prefer vodka. Classic flavours (such as plum, apricot, pear) are the most popular, however, in terms of flavour preferences, it should be mentioned that the majority of respondents prefer 'homemade pálinka' regardless of taste. Overall, therefore, there were no significant changes compared to the survey conducted in 2010, which results in a slowdown and stagnation in the improvement and change of the pálinka' image (Totth et al., 2018a; Totth et al., 2018b).

The study of Szegedyné et al. (2017) concluded that (basically) the occasional drinking is

the nature of pálinka consumption (e.g., weddings, house parties, illness). Men, as well as those over 50 and 18-24 years of age, consume pálinka more frequently and more often. The main factor influencing purchasing, in addition to the type of fruit, is the recommendations of friends, and the price, followed by protection of origin. According to the respondents, it is possible to make pálinka from cereals, citrus fruits and potatoes by mistake.

Mucha et al. (2020a) examined the image of pálinka based on different product properties. The 626 respondents considered quality to be the most important purchasing criteria, followed by price, Hungarian origin, prestige, and fashion. Two particularly important conclusions were drawn: (1) the image of homemade distillate is more positive than that of store pálinka; (2) knowledge about pálinka is still extremely incomplete among Hungarian consumers. In a later publication, Mucha et al. (2020b) concluded that in the case of purchases, price has the greatest influence

Authors	Year of the survey	Target group and data collection technique	Key findings
Totth et al., 2011a	2010	Questionnaire survey (1487) among economically active consumers of pálinka aged 23–60, who consume pálinka at least occasionally.	The pálinka got rid of its negative image. Pálinka consumption is associated with social events and holidays.
Totth et al., 2011b	2010	Interviews (80) with people over the age of 23 who have consumed pálinka in the last 3 months.	Positive associations can be connected with pálinka consumption. Purchasing aspects: taste, packaging, price, alcohol content, brand.
Totth et al., 2017	2016	Questionnaire survey (1550) among consumers over the age of 18, who purchase alcoholic beverages at least occasionally.	A significant proportion of respondents between the ages of 18 and 39 tend to buy pálinka for various occasions. In addition to whiskey and vodka, young people mostly consume pálinka.
Totth et al., 2018b	2016	Questionnaire survey (1500) among economically active consumers of pálinka aged 23-60, who consume the spirit at least occasionally.	Within the spirits, the popularity of three products stood out: vodka, whiskey, pálinka. Men prefer whiskey and pálinka, while women prefer vodka.
Szegedyné Fricz et al., 2017	2017	Questionnaire survey (1014) with respondents over 18 years of age.	Men, as well as those over 50 and 18-24 years of age, consume pálinka more frequently and more often. The main purchase aspects are the type of fruit, the recommendations of friends, the price, and the protection of origin.
Totth et al., 2018a	2018	Interviews (67) with people over 23 who have consumed pálinka in the last 3 months.	Increasing consumer awareness. Among the not preferred flavours, pálinka-like drinks appear. Consumption of pálinka is mainly associated with festive occasions.
(Mucha et al., 2020a)	2019-2020	Questionnaire survey (626) of respondents over 18 years of age who have consumed pálinka in the last 3 months.	Knowledge about pálinka is extremely incomplete. The most important aspect is quality, followed by price, Hungarian origin, prestige, and fashion criteria.
(Mucha et al., 2020b)	2019-2020	Questionnaire survey (626) of respondents over 18 years of age who have consumed pálinka in the last 3 months.	Price is the most crucial factor when buying pálinka or distillate. The purpose of the purchase determines the role of the price, the type of fruit, and the origin in the purchase.
(Mucha et al., 2021)	2019-2020	Questionnaire survey (626) of respondents over 18 years of age who have consumed pálinka in the last 3 months.	The image of homemade distillate and whiskey is better than that of store pálinka. Consumers mistakenly consider homemade distillate to be a Hungarikum product.
Maró et al., 2022	2021	Questionnaire survey (760) with Hungarian pálinka consumers over the age of 18.	The geographical indication, the Bestillo brand and the small-pot distillation method are associated with a higher sense of utility. People living in big cities are characterized by the consumption of pálinkas, while in the countryside homemade distillate still dominates.

Source: own editing

Table 2: Key studies examining pálinka consumption patterns.

on the decision, which is followed by the type of fruit used and the origin. A significant proportion of consumers prefer homemade distillate, considering the origin, which is explained by differences in image and price. Mucha et al. (2021) also examined the image of store-bought pálinka, homemade distillate and whiskey, which is popular in Hungary. Emotional attachment is highest for homemade distillate, followed by whisky and store-bought pálinka. This is also since homemade spirits were considered by the respondents to be of a more reliable quality than in-store pálinkas. The latter can be explained not only by emotional and behavioural differences, but also by knowledge and knowledge gaps, which is also confirmed by the fact that the majority of the respondents consider homemade distillate to be a Hungarikum product. In Hungary, the consumption of whiskey is clearly a status symbol.

The latest consumer survey by Maró et al. (2022) who examined Hungarian pálinka consumers with the help of a discrete choice experiment. Based on their findings, the Gönc geographical indication, the Bestillo brand and small-pot (in Hungarian kisüsti) distillation method in increase the sense of utility of the customers. Branded pálinka is most preferred by those living in big cities, who typically buy pálinka in commercial units, and who are more informed about alcoholic beverages than the average consumer. Because pálinka specialties are associated with higher quality, they are willing to pay a higher price for these products. The popularity of homemade distillate is still dominant in the Hungarian countryside and in smaller towns, so branded pálinka is less likely to be consumed there.

Materials and methods

During our research, the data collection of the online questionnaire was carried out by a professional market research company (InnoFood Marketing Ltd.). The data collection took place between April and July 2021. Due to restrictions related to COVID-19, data collection was done online only using the research software of Qualtrics. The questionnaire was aimed at analysing the behaviour related to the purchase and consumption of pálinka and assessing the respondents' proficiency in the topic, with a special focus on collecting the sociodemographic characteristics of the respondents.

To establish the questionnaire, we prepared a wide-ranging literature review and expert interviews in advance. Subsequently, a pilot survey (n = 73) was conducted, based on which the questions were finalized. From the data of the final survey of 1,000 Hungarian people, representative for the Hungarian alcohol consumer population, 760 responses were evaluated after data cleaning (e.g., exclusion of incomplete or incorrectly completed questionnaires). The most important characteristics of the sample is summarized in Table 3. In the case of gender, (older) men predominate in the sample, which is not surprising, as several studies (e.g., Szegedyné Fricz et al., 2017; Totth et al., 2018b) have found that older men can be considered typical pálinka consumers. In terms of place of residence and the number of people living in one household, the sample is close to the national average (compared to the 2011 HSCO census). In the case of education, those with lower education were under-represented, while those with higher education were over-represented in the sample. All this is mostly explained by the online nature of the query (Bethlehem, 2010). The obtained results can be evaluated further in the light of these representativeness characteristics.

	Survey	HSCO census
Total respondents / Population	1,000	9,937,628
Respondent involved	760	-
Gender		
Female (%)	36.45	52.52
Male (%)	63.55	47.48
Average age (years)	54.73	41.39
Residence		
Village (%)	26.45	30.52
City (%)	40.92	34.35
Large city (%)	32.63	35.13
Education		
Basic education	2.37	31.72
Secondary education	43.42	51.31
Higher education	54.21	16.97
Average number of people living in a household (person)	2.77	2.60

Source: own editing based on survey and HSCO (2013) data

Table 3. Presentation of the sample.

In addition to the descriptive statistical and non-parametric correlation (Spearman's rank correlation) analyses, we performed a regression (o-logit) analysis to understand the factors influencing the preferences of Hungarian consumers regarding pálinka. In the case of our dependent variables (measured on, importance from 1 to 5, Likert scale) to be modelled, we could build

and estimate an ordinal logit (OL) regression model at the ordinal measurement level. The approach often appears when analysing data from research that uses rating-scale-based statements in the context of a questionnaire survey (see, e.g., Bellizzi et al., 2018; Eygu and Gulluce, 2017).

Prerequisites for estimating the model include aspects that appear when other types of regression are used (e.g., lack of multicollinearity), while some are procedure-specific (the level of measurement of the dependent variable should be ordinal, the proportional probabilities of threshold parameters).

The fulfilment of the 'proportional odds' condition can be examined by applying the parallel lines test. This tests whether there is a significant difference between the models estimating common and unique coefficients according to the independent variables for the threshold parameters. If the test is not significant, it can be concluded that the model estimating individual coefficients does not show a significant improvement, so the proportional odds model can be used (McCullagh, 1980; Brant, 1990; Erkan and Yildiz, 2014). The transformed form of the model into a linear formula (taking the natural logarithm of the odds ratios) can be written according to Equation 1 (Ananth and Kleinbaum, 1997):

$$Y = \alpha_t - \sum_{k=1}^{K} \beta_k X_k, \quad (1)$$

where Y is the dependent variable, α_t is the threshold parameter for the t-th category (t = 1, 2, … , t-1), X_k is the k-th explanatory variable, β_k denotes the estimated coefficient for the k-th explanatory variable.

Based on all this, the study seeks to answer the following questions:

- How important for the respondents the pálinka purchasing aspects we have discovered (production in Hungary, colour of pálinka, bottle capacity, colour of the bottle, alcohol content, results of the pálinka competition)? How do consumers prioritize these aspects?
- What is the share of those who use private or contract distillation?
- Are consumers aware of the difference between pálinka and distillate?
- Do the respondents know the pálinka seal? If so, can it be distinguished from the seals of the distillate and other spirits?
- Where do consumers buy and how often do they consume pálinka?
- What factors affect consumer preferences during shopping?

Results and discussion

Typical characteristics

In our research, several aspects of the purchase of pálinka, which were also examined by the literature, analysed. The aspects (quality and price) analysed by most studies (Szegedyné Fricz et al., 2017; Mucha et al., 2020a) observed using a discrete choice experiment (DCE), so these aspects were not explored in the present research. The most important aspect that arises during the purchase of pálinka (Table 4) is that the drink should be made in Hungary (average value of 4.11 on the 5-point Likert scale) - this is consistent with the research of Mucha et al. (2020a). It also follows that the respondents are not aware that, except for apricot pálinka, pálinka can only be of Hungarian origin, so it is likely that people often buy different spirits instead of pálinka. The importance of the origin of the drink is becoming increasingly emphasized in other alcoholic beverages as well (Siemieniako et al., 2011; Perrouty et al., 2006; Merlino et al., 2019). Production in Hungary was followed by alcohol content (3.80), to which applies strict rules during pálinka production (Codex Alimentarius Hungaricus, 1-3-1576).

The aspects concerning the appearance of the drink, i.e., the colour of the bottle (3.09) and the capacity of the bottle (3.02), had equivalent results. Respondents on average do not really consider it important for the drink to have colour (2.74) when purchasing. Overall, the appearance of the pálinka was not considered as important by consumers as the aspects presented earlier. In the early 2010s, consumers placed even more emphasis on the appearance of the beverage (Totth et al., 2011b), however, in a recent study (Mucha et al., 2020a) we can already see results similar to our research. Moreover, it is clear that the appearance of pálinka is not such an important decision criterion, similar to the case of vodka (Prentice and Handsjuk, 2016), in contrast to the experiences of other competitors (Wan et al., 2015).

According to the respondents, the least decisive factor when buying pálinka is whether the pálinka has a result in a competition (2.53). However,

those who still found the results of the competition important mentioned the National Pálinka and Törkölypálinka Competition spontaneously.

Aspects of purchasing pálinka	Average	Standard deviation
Production in Hungary	4.11	1.12
Alcohol content	3.80	1.02
Colour of the bottle	3.09	1.33
Capacity of the bottles	3.02	1.25
Colour of the pálinka	2.74	1.25
Place in pálinka competition	2.53	1.11

Note: the answer was possible on a Likert scale from 1 to 5, where 1 meant that the aspect was not important at all to the respondent, while 5 meant that it was of paramount importance
Source: own editing based on survey

Table 4: Respondents' views on the purchase of pálinka.

During the examination of the correlation among the aspects presented in Table 4, we came to the conclusion that there is mostly a weak relationship or no relationship among the aspects. There is a moderate strength correlation with positive direction ($r_S > 0.3$) between the importance of the capacity of the bottle and the colour of the bottle, which indicates that as the importance of the former aspect (capacity of the bottle) increases, the importance of the latter aspect (colour of the bottle) also increases. A similar conclusion is true for the pairing of colour of the bottle and alcohol content as well as for the pairing of colour of the pálinka and the capacity of the bottle.

More than half (460 people) of the 760 respondents (or one of their families) use the services of a contract distillery. If we look at private distillation, it is less common than contract distillation, as only 29% of respondents said that someone in the family distillates at home. The changes in legislation in 2021 (e.g., the production of distillates is duty-free up to 86 litres for private distillation and up to 50 litres for contract distillation) may bring the distilleries to the forefront again, as from 2015 to 2021 was a taxable activity under the 92/83/EGK directive.

It is important to highlight opposing judgement of private distillation, since on the one hand it increases the popularity of the drink, but on the other hand quality issues arise. A similar situation can be seen in several countries of Europe or Asia, where various regulations (e.g., restrictions on opening hours) prioritized homemade spirits over their shop counterparts (Skorobogatov, 2014; Manthey et al., 2020; Probst et al., 2021). As in the case of home-distilled pálinka, the quantity and quality of homemade drinks also causes problems in other countries of the word and of the European Union. In 5 member states (Croatia, Finland, Greece, Hungary, Portugal) of the European Union, homemade, unrecorded alcohol made a significant contribution to total consumption (Manthey et al., 2019; Manthey et al., 2020). It is clear from the literature (Manthey et al., 2019, Probst et al., 2021) that consumers of homemade distillates (as well as wines and beers) are usually from the lower social classes. In contrast, the consumers of store-bought spirits

	Production in Hungary	Alcohol content	Colour of the bottle	Capacity of the bottles	Colour of the pálinka	Place in pálinka competition
Production in Hungary	1.00					
Alcohol content	0.23***	1.00				
Colour of the bottle	0.19***	0.35***	1.00			
Capacity of the bottles	0.16***	0.27***	0.36***	1.00		
Colour of the pálinka	0.17***	0.12***	0.26***	0.31***	1.00	
Place in pálinka competition	0.27***	0.16***	0.27***	0.17***	0.25***	1.00

Note: The matrix contains Spearman's rank correlation coefficients (r_S). The results (strength of correlation coefficients) were interpreted based on the categorization of Dancey and Reidy (2007). *** significant at 1%.
Source: own editing based on survey

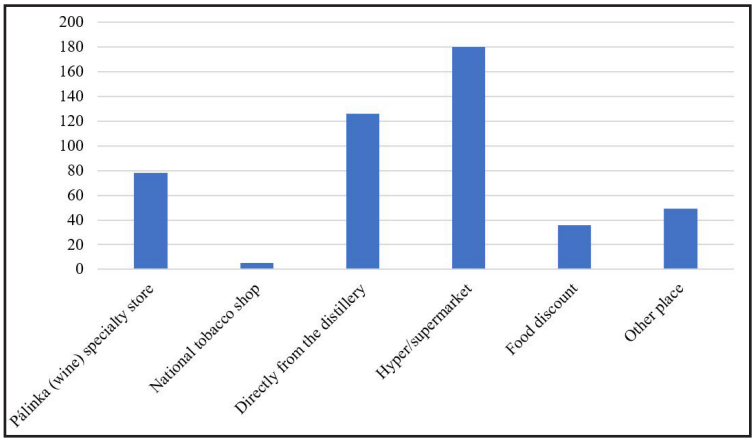
Table 5: Spearman's correlation analysis between the examined aspects.

(e.g., pálinka) come from the higher social classes, and it can be concluded from this that the consumers must be properly targeted by companies.

541 people (71%) stated that they knew the difference between pálinka and distillate, but less than one in two respondents (only 31% of all respondents) knew the difference between distillate and pálinka. Although some studies (Totth et al., 2018a) have reported an increase in awareness, the most recent publications on the subject (Mucha et al., 2020a; Mucha et al., 2020b) found a similar result to this study. Pálinka, distillate and other spirits (e.g., vodka, whiskey) have different seals (Act LXVIII of 2016 on Excise Duties). The seal represents a guarantee of quality and certifies that the alcoholic drinks has been placed on market in accordance with the law, thus excluding the possibility of counterfeiting. The seal is reddish-brown on the pálinka, green on the distillate and blue on the other spirits. 60% of the respondents stated that they are aware that the pálinka, that can be bought commercially in Hungary, has a unique seal that is different from all other alcoholic products. However, when these respondents had to choose between the three different seal types, only 41% (165 people) correctly marked the reddish-brown seal.

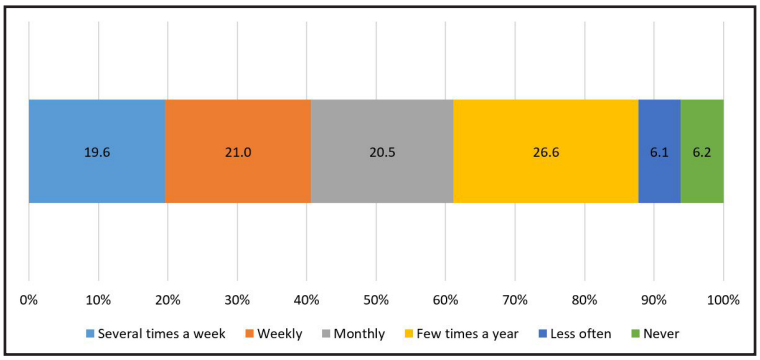
Most respondents purchase pálinka in a hypermarket or supermarket (38%) or directly from the distillery (27%). The least common place of purchase was the national tobacco shop (less than 1%) (Figure 1). Shopping goals include consumption with friends (33%), consumption within the family (27%), shopping for gift (23%), and personal consumption (17%). As the knowledge of Hungarian consumers about pálinka is still extremely incomplete, in many cases pálinka-like drinks (e.g., Fütyülős) may be purchased in hypermarkets or supermarkets. In contrast, in the case of purchases directly from the distillery, the chances of this are much lower, as only a few contract distilleries can market their product after paying the excise duty and affixing the pálinka seal. Pálinka consumption is tied to various occasions (e.g., family events, meetings of friends), which has been confirmed by several previous studies (Totth et al., 2011b; Totth et al., 2018a).

Most respondents (202 people) consume pálinka a few times a year, followed by weekly



Source: own editing based on the questionnaire

Figure 1: Respondents' most common place to purchase pálinka.



Source: own editing based on the questionnaire

Figure 2: Frequency of respondents' pálinka consumption.

(160 people), monthly (156 people) and several times a week (149 people) consumptions with almost the same values (Figure 2). The least common of the fillers is that they never (47 people) or less than a year (46 people) consume pálinka. Such frequent consumption of the drink is not surprising, as alcohol is considered by many to be a means of socialization (Marinelli et al., 2014).

Factors affecting certain product properties

Following the descriptive statistics, Table 6 shows the results of the estimated regression models. The columns contain the examined dependent variables, while the rows contain the explanatory variables of the models. It is necessary to mention that the modelling of our independent variables was done simultaneously, without any algorithms, in order to avoid the often-mentioned disadvantages of stepwise methods (Harrel, 2015). The fit of the models was first examined using the Deviance and Pearson χ^2 tests, the results of which were not significant in either case, suggesting that our models fit well - the predicted values do not differ significantly from those observed. Henceforth, the result of the likelihood ratio test shows significant results for five models (the only exception being model 3), which leads to the conclusion that we obtained significantly better fitting models compared to the base model without explanatory variables (Field, 2009). Finally, the parallel lines test did not show a significant difference at the level of 1% for any of the models. The results of additional indicators related to the fit of the models can be found in the notes of Table 6.

Based on the significant coefficients of the 1st model, we can conclude that the chances of higher importance values for pálinka made in Hungary were 1.51 times higher for those respondents who claimed to be aware of the existence of a unique seal for commercially available pálinkas in Hungary, compared to respondents who have no knowledge of it. In comparison to respondents who buy directly from the pálinka distillery, respondents who purchase from the national tobacco shop, grocery discount, hypermarkets and supermarkets, and other places (e.g., nightclubs) are also less likely to place more importance on homemade products. Compared to buying for own consumption, those who buy pálinka as a gift or for consumption with friends are more likely (2.20 times and 1.84 times, respectively) to consider the product made in Hungary to be essential. Respondents who consume pálinka weekly are more likely; while those who drink pálinka less than a few times a year are less likely to give priority to domestically produced products, compared to those who consume such a product several times a week. Along with the increase in the level of ethnocentrism, the chances that respondents fill in the Hungarian origin more important when buying are increasing. If the goal is to increase the turnover of Hungarian drinks, especially pálinka, it may be a good strategy to introduce Hungarian consumers to the difference between the seals (e.g., colour).

In the case of the 2nd model, respondents who claimed to know the difference between pálinka and distillate were less likely to associate a higher importance value with the colour of the pálinka than those who claimed not to know what the difference between the two types of drinks. In contrast to those who drink pálinka several times a week, both respondents who drink pálinka a few times a year and those who never drink pálinka are more likely to prioritize the colour of pálinka when choosing a drink. The higher the value of ethnocentrism for a pálinka consumer on the CETSCALE, the greater their chances of prioritizing the colour of the drink. Only natural, fruit-coloured alcoholic beverages can be considered pálinka. If Hungarian consumers are aware of this, they do not consider it a primary priority whether a given pálinka is matured on a fruit bed.

Based on the significant coefficients of the 3rd and 4th models, we can see that those in whose family distillate drinks at home are 0.72 times more likely to have a higher importance value in terms of the capacity and the colour of the bottle than those who do not have private distillery in their family. Furthermore, the colour of the bottle (4th model) is much more likely to be a priority for those who have claimed to know what the difference is between pálinka and distillate; and those with a higher level of ethnocentrism. The 5th model (for alcohol content) shows similar significant values and coefficients (home distillation; difference between pálinka and distillate; ethnocentrism) as for the colour of the bottle. However, compared to those who drink pálinka several times a week, those who drink pálinka once or less a week are less likely to find alcohol content important.

Based on the 6th model, it can be stated that the chances of higher importance values for receiving a place in a pálinka competition were 1.70 times higher for those who claimed to be aware of the existence of a unique seal for commercially available pálinkas in Hungary, compared to respondents who are unaware of this. Those respondents who actually knew about the legislation had a 1.48 higher chance

Explanatory variables	**Production in Hungary** (1st model)	**Colour of the pálinka** (2nd model)	**Capacity of the battle** (3rd model)	**Colour of the bottle** (4th model)	**Alcohol content** (5th model)	**Place in pálinka competition** (6th model)
Coefficient (β) exp (β)						
Does anyone in your family uses the services of a contract distillery? (base category: No)						
Yes	0.022 (1.022)	0.007 (1.007)	-0.151 (0.860)	-0.082 (0.921)	-0.056 (0.945)	0.075 (1.078)
Does anyone in your family make pálinka (distillate) at home? (base category: No)						
Yes	-0.176 (0.838)	-0.215 (0.806)	-0.325* (0.723)	-0.323* (0.724)	-0.554*** (0.575)	-0.121 (0.886)
Do you know the difference between pálinka and distillate? (base category: Do not know)						
Knows	-0.013 (0.987)	-0.333* (0.717)	-0.196 (0.822)	0.592*** (1.808)	0.455** (1.577)	0.152 (1.164)
What is the difference between pálinka and distillate? (base category: Do not know)						
Actually knows	-0.138 (0.871)	-0.006 (0.994)	0.047 (1.048)	-0.323 (0.724)	0.063 (1.065)	0.048 (1.049)
Did you know that pálinka, that can be bought commercially in Hungary, has a unique seal different from all other alcoholic products? (base category: Did not know)						
Knew	0.414* (1.512)	0.291 (1.338)	-0.002 (0.998)	0.165 (1.179)	0.091 (1.095)	0.532*** (1.702)
Which of the following is the pálinka seal? (base category: Do not know)						
Actually knows	0.226 (1.254)	-0.092 (0.912)	-0.086 (0.917)	-0.027 (0.974)	-0.103 (0.902)	0.393* (1.482)
Where do you usually purchase pálinka? (base category: Directly from the distillery)						
From a pálinka (wine) specialty store	-0.259 (0.772)	0.162 (1.176)	0.162 (1.176)	-0.133 (0.875)	-0.329 (0.720)	0.542** (1.719)
From a national tobacco shop	-1.528* (0.217)	-0.315 (0.730)	0.778 (2.178)	-1.132 (0.323)	-0.704 (0.495)	-0.942 (0.390)
From hypermarket/ supermarket	-0.786*** (0.456)	0.164 (1.178)	0.166 (1.180)	-0.201 (0.818)	-0.174 (0.840)	-0.070 (0.932)
Food discount store	-1.117*** (0.327)	0.535 (1.708)	-0.202 (0.817)	0.026 (1.026)	0.007 (1.007)	0.330 (1.391)
Elsewhere	-0.734** (0.480)	0.032 (1.032)	-0.177 (0.838)	-0.119 (0.887)	0.019 (1.019)	0.033 (1.034)
For what purpose do you usually purchase pálinka? (base category: For own consumption)						
For consumption within the family	0.370 (1.448)	0.236 (1.266)	0.337 (1.401)	-0.043 (0.958)	-0.047 (0.954)	0.077 (1.080)
For consumption with friends	0.612** (1.844)	0.023 (1.024)	0.211 (1.235)	-0.159 (0.853)	-0.057 (0.945)	0.129 (1.138)
As a gift	0.786** (2.195)	-0.131 (0.877)	0.061 (1.063)	0.084 (1.088)	-0.016 (0.985)	0.219 (1.245)
How often do you consume pálinka? (base category: Several times a week)						
Weekly	0.552* (1.736)	0.058 (1.060)	0.344 (1.410)	0.275 (1.316)	-0.692** (0.501)	0.296 (1.345)
Monthly	0.312 (1.366)	-0.058 (0.944)	0.227 (1.255)	-0.173 (0.841)	-0.949*** (0.387)	-0.028 (0.973)
A few times a year	0.124 (1.132)	0.489* (1.630)	0.249 (1.282)	0.224 (1.250)	-0.941*** (0.390)	0.191 (1.210)
Less often than a year	-1.007* (0.365)	0.005 (1.005)	0.649 (1.914)	0.736 (2.087)	-0.041 (0.960)	-0.039 (0.962)
Never	0.196 (1.216)	1.195** (3.304)	0.623 (1.864)	0.238 (1.269)	-0.389 (0.678)	1.440** (4.222)
Ethnocentrism						
Ethnocentrism	0.043*** (1.044)	0.025*** (1.026)	0.009 (1.009)	0.024*** (1.024)	0.026*** (1.026)	0.017*** (1.017)

Note: *1st model:* Akaike's information criteria: 1071.226; Bayesian information criteria: 1171.095; Likelihood ratio test: $\chi^2 = 89.581$, df = 20, $p < 0.01$; *2nd model:* Akaike's information criteria: 1484.350; Bayesian information criteria: 1584.219; Likelihood ratio test: $\chi^2 = 39.054$, df =20, $p < 0.01$; *3rd model:* Akaike's information criteria: 1467.294; Bayesian information criteria: 1567.163; Likelihood ratio test: $\chi^2 = 18.988$, df = 20, $p = 0.523$; *4th model:* Akaike's information criteria: 1482.809; Bayesian information criteria: 1582.678; Likelihood ratio test: $\chi^2 = 41.908$, df = 20, $p < 0.01$; *5th model:* Akaike's information criteria: 1194.060; Bayesian information criteria: 1293.929; Likelihood ratio test: $\chi^2 = 51.856$, df = 20, $p < 0.01$; *6th model*: Akaike's information criteria: 1386.102; Bayesian information criteria: 1485.971; Likelihood ratio test: $\chi^2 = 50.632$, df = 20, $p < 0.01$. *** significant at 1%, ** significant at 5%, * significant at 10%.

Source: own editing

Table 6: Results of the estimated ordinal logistic regression models.

of showing a greater importance value assigned to the result achieved in the pálinka competition. Compared to those who buy directly from the pálinka distillery, buyers from the pálinka (wine) specialty store are more likely to have a priority to the places the drink achieved in any pálinka competition. Contrasted to fillers who consume pálinka several times a week, those who never consume pálinka are more likely (4.22) to prefer whether a given pálinka has a result in a pálinka competition. Similar to all models where ethnocentrism was significant, simultaneously with the increase in the level of ethnocentrism, there is a higher chance that a respondent considers the result achieved in the pálinka competition to be important.

Conclusion

About a quarter of the respondents (or their families) make distillaties at home (private distillation), while more than half of them use the services of a distillery. The perception of private distillation in Hungary is twofold, as on the one hand it increases the consumption of distillates and makes the product better known; on the other hand, only constant quality can be guaranteed for drinks produced in contract distilleries as well as in commercial distilleries

The conceptual confusion between pálinka and distillate continues to exist according to the research. Seal can help to distinguish pálinkas from other alcoholic beverages, as pálinkas, that can be purchased commercially in Hungary, have a different (reddish-brown) seal. Knowledge of the seal, which has not been previously examined in any study, is considered to be similarly low, than knowledge of the actual difference between pálinka and distillate. Respondents most often purchase pálinka in a hypermarket or supermarket, as well as directly from the distillery and a sizeable proportion of respondents (approximately 61%) consume pálinka monthly. It is important to emphasize the moderate consumption of the drink, as Hungary is at the forefront of per capita alcohol consumption both in the European Union and in the world.

For Hungarian pálinka consumers, the most important decision-making aspect when purchasing is the Hungarian origin of the drink, followed by the alcohol content and the appearance of the drink. The Hungarian origin of pálinka is clearly defined by laws, which also shows the low proficiency of Hungarian consumers in the subject. Furthermore, there is a close relationship between alcohol content and price, so we can conclude that price is also a decisive factor for Hungarian consumers.

Finally, several conclusions can be drawn from the ordinal regression models. One of the most important is that by increasing the knowledge of the seal, the turnover of quality, commercial pálinkas can clearly increase. The spread of real pálinkas could also be helped by more and more consumers purchasing the product directly from pálinka distilleries. The more a consumer knows the rules and regulations for pálinka (for example, because it is consumed many times), the more likely he or she is to choose the product in a purchasing situation, and the appearance of the drink (e.g., colour of the drink) is less and less important to such consumers. Furthermore, it is also clear from the results that those who have already chosen homemade distillate (e.g., makes pálinka at home) are less likely to buy pálinka more regularly. They cannot be considered as a consumer group to be targeted by companies.

Overall, it can be concluded that the knowledge of Hungarian consumers about pálinka can still be considered low (e.g., the differentation between pálinka and distillate, the knowledge of the seal), the increase of which is an important task at both the governmental and corporate level. To do this, it is essential to launch further (marketing) campaigns and a well-positioned marketing strategy, which can help to make the drink more widely known. Based on the presented results, the pálinka distilleries and the companies selling the spirit can even better understand how important certain product attributes are considered by the consumers. However, it is worth emphasizing that the results cannot be considered representative of the entire Hungarian population (due to, among other things, the limitations of online research), we conducted our survey among consumers interested in pálinka. Further examination of this target group of consumers (e.g., the role of prices, the effect of the existence of the geographical indication) would also be important, since it would give us an even more accurate picture of the Hungarian pálinka sector.

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The Context Relevance of ICT, Freshwater Management Activity and Sustainability Goal: A Proposed Encapsulated Conceptual Framework

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Abstract

This study proposes an Encapsulated Conceptual Framework (ECF) for understanding the links between Information and Communication Technologies (ICTs), water resource management activities, and Sustainable Development Goals (SDGs). The study aims to contribute to national, regional, and global debates on the potential of ICTs in achieving sustainability goals. A combination of two socio-technical theories - Relevance Theory (RT) and Technology Acceptance Model (TAM) was adopted to inform the study. The literature review further informed the construction of the ECF. The framework testing involved sampling participants and collecting and analyzing the data. A sample of 251 (n = 251) individuals from formal and informal water user groups on the Tanzanian side of the Lake Victoria Basin participated in testing the framework. The study adopted the cross-sectional design to a mixed research approach. Furthermore, it used three quantitative and qualitative data collection techniques: Focus Group Discussions (FGDs), Key Informant Interviews (KIIs), and Questionnaire Administration (QA). Each FGDs session accommodated a group of participants with 9 – 12 members across the selected sites. KIIs targeted groups network leaders, water resource managers at various levels, and other individuals with potential information. Gathered dataset was cleaned, summarized, and analyzed using descriptive, correlation, and content analytical methods. The study capitalized on the strength of Tableau and R statistics to produce the visualizations that support the descriptive analysis of the data. Furthermore, the study used R and MS Excel software to establish the relationships among the variables. Results indicated the prominent use of mobile as ICTs for freshwater management activities. Furthermore, mobile-based tools such as SMS, voice call, image and video supported these activities to attain some indicators of SDGs related to water resource management. The study concludes that the framework contributes to understanding the contextual issues on ICT, freshwater management and SDGs.

Keywords

Sustainability goals, conceptual framework, freshwater resource, encapsulation.

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Introduction

General introduction

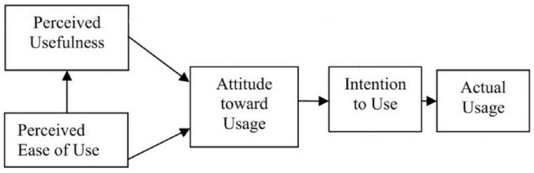
Water resources were among the priority areas for the Millennium Development Goals (MDGs) and now are for the Sustainable Development Goals (SDGs). SDG number 6 addresses the sustainability of freshwater resources. It calls for urgent action to combat climate change and its impacts (United Nations, 2021). Among sectors impacted by climate change is agriculture, which utilizes vast freshwater resources. The Bank Group (2014) indicates that, of the 6,122m^3 of international freshwater per capita worldwide, agricultural production consumes 70%. Therefore, freshwater is among the most wanted resources, especially in developing countries where the economies depend heavily on agriculture. Despite the importance, both traditional and contemporary factors challenge water resources. The evidence of the declining trends of freshwater amid increasing demand, not only for irrigated agriculture but also for industry and households, fuels present-day debates (UN, 2009; UN, 2013; UNEP, 2010; UN-FAO, 2005; WHO/UNICEF, 2010). This evidence calls for adaptation and mitigation

measures leading to the sustainable governance and management of freshwater resources. Information and Communication Technologies (ICTs) are considered valuable inputs for the sustainability of irrigation water resources. They are a "diverse set of technological tools and resources used to communicate and create, disseminate, store, and manage information" (Blurton, 1999). Modern ICTs contribute to the management and development aspects of irrigation in a variety of ways. Glória et al. (2020) show how the Internet of Things (IoT) can improve the sustainable management of irrigation water systems. Theimplementation context of a developed nation, showed that the system significantly reduced over 30% of the wastage of critical freshwater resources." A similar management scenario by Yasin et al. (2021) indicates an increasing trend toward integrating IoT with ICT-based intelligent water monitoring systems for a more efficient, resilient, and sustainable availability and use.

The International Telecommunication Union (ITU), contends that ICT is a potential tool for enhancing the management of freshwater resources (ITU, 2016). It further contributes to various functions of the water sector at multiple scales (Jéquier and Constant, 2010; Ellert et al., 2013; Garriga and Foguet, 2013; Kalitsi, 2003; Baron et al., 2002; World Bank, 2014; UNESCO, 2016). The water resources sector considers ICT a critical asset for promoting, coordinating, enhancing, and enabling participation and control (Georgakakos, 2004). These activities are vital to strengthening water resources institutions and organizations. ICT tools support stakeholders' participation by reducing the power distance that results from several disparities related to demographical characteristics. They also provide crucial infrastructure and tools for knowledge creation, sharing and diffusion; and boost the innovation capacity (Mas et al., 2012). Against this background, the links between ICT tools, water resource management activities they support, and development goals have remained a debatable subject at national, regional, and global levels from the era of MDGs and now SDGs (Kaino, 2012; Siriginidi, 2009; Ono et al., 2017; Odongtoo et al., 2019; Wu et al., 2018). Optimists and pessimists have emerged, taking the roles of proposers and opposers of the motion 'ICTs contributes to sustainability". As a result, findings from some of the studies above have identified linkage as the potential area for further exploration. This paper suggests an encapsulated conceptual framework as an option to study the contextual relevance of activity, and water resources sustainability.

Theoretical framework and literature review

A theoretical framework is the composition of inter-related concepts derived from a theory or a combination of theories (Imenda, 2014). Studies often use theoretical frameworks to explain a particular phenomenon or phenomena. The theoretical framework justifies carrying out the research. It is usually presented early enough before the methodology section of the proposal. Theoretical frameworks provide the lens and scope for studying a particular phenomenon. Two theoretical models have guided this work: Technology Acceptance Model (TAM) and Relevance Theory (RT). TAM which came in the late 1980s, has provided a framework for understanding the technology adoption among users (Davis, 1989). Figure 1 shows a schematic representation of the final version of TAM.



Source: Davis (1989)

Figure 1: The original version of the Technology Acceptance Model (TAM).

The goal of TAM was "to explain the determinants of technology acceptance that in general is capable of explaining user behavior across a broad range of end-user computing technologies and user populations" (Davis et al., 1989). These authors suggest that technology acceptance depends on two fundamental constructs: perceived usefulness (PU) and perceived ease of use (PeoU). Despite the fact that TAM has been revised several times since its formulation, its two constructs - PU and PeoU - have remained the same. PU means "the degree to which a person believes that using a particular system would enhance his or her job performance." In contrast, PeoU means "the degree to which a person believes that using a particular system would be free from effort" (Davis, et al, 1989). In this study, RT complements TAM.

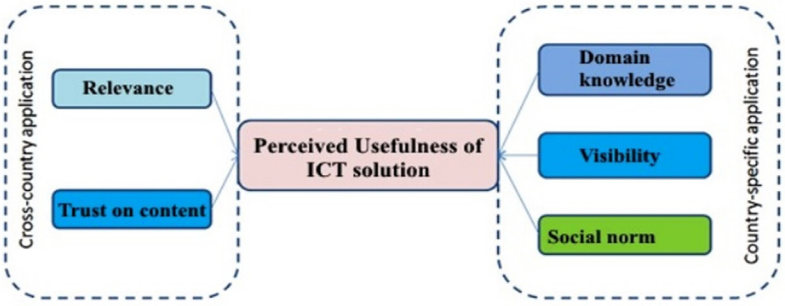
Relevance Theory (RT) authored by Sperber and Wilson came between 1986 and 1995 (Wilson and Sperber, 1986). It is a cognitive theory of human communication that has been used within the discipline of information science. The

theory builds upon the definition of relevance and two principles. According to Wilson and Sperber (1986), the two principles are the cognitive and communicative principles of relevance. The former states that "human cognition tends to be geared towards maximization of relevance". In so doing, human cognition allocates attention and processing resources to the most relevant information; in other words, information that guarantees an optimal balance between cognitive effects and processing effort. The latter principle states that "every ostensive stimulus conveys a presumption of its optimal relevance". In simplifying the meaning of the words in this principle, the authors argue that the term optimal relevance is a key to relevance theory in pragmatism. Furthermore, for the ostensive stimulus to be optimally relevant to an audience, it must have the following characteristics: be relevant enough to be worth the audience's processing effort and be the most relevant one compatible with the communicator's abilities and preferences.

Miller and Khera (2010) introduced relevance into TAM. They confirmed a cross-country application of TAM and identified factors that determined PU within and across countries. Five PU factors likely to influence a technology's intent to use were relevance, trust on content, visibility, social norm, and knowledge domain (Figure 2).

Hypotheses for each of these factors predicted the perceived usefulness across countries. The authors also found that relevance was the most vital factor, followed by the trust in the content in influencing the cross-country usefulness of ICT solutions. Social norm and knowledge do-main had a significant relationship at the country level, while visibility was insignificant within and across countries. Further analysis revealed that, among cross-country factors, relevance was the most crucial determinant of PU. The authors conducted this research within the context of information management/information science, comparing two countries: USA and Kenya. Despite this fact, the relevance component of the extension would be appropriate in this study for three reasons: The first reason is that IS, particularly its fields such as green-IS, are still growing, thus borrowing its justified concepts and theories from other disciplines or fields. The second reason is that TAM and its many extensions have been used widely in IS research. Third, water resources, in the context of this study, are largely transboundary. Therefore, adopting tested concepts like relevance from a cross-boundary context is appropriate.

Hjørland and Christensen (2002) proposed a different interpretation of determinants of relevance using logically connected concepts. They proposed that in viewing relevance should consider the logical relationship among thing (T), activity (A), and goal (G). Some Researchers contend that users can own and sustain 'things" (T) that they are involved in designing, focused on their actual needs, and resolve cost and related technical barriers (Millett and Estrin, 2012; Cobb, 2011; Aubert, 2004; Maldonado et al., 2010). Furthermore, the authors argue that regardless of their context, the three parameters should align so someone can track a meaningful contribution to the goal. Such consideration helps most information scientists to use relevance as a basis for system design and evaluation while at the same time dealing with theoretical issues related to it. Despite their potential, their conceptualizations have limited use in information systems and related fields. The systematic review study by Mongi and Meinhardt (2016) in Southern Africa regarding trends of measuring relevance within the water resources sector revealed linkages between tools, activities, or/and goals. This nexus could be tracked from several publications, though by extra effort of the reader. This study used



Source: Created from Miller and Khera (2010)

Figure 2: Factors influencing usefulness at national and international scales.

the three concepts as determinants of the relevance of ICT for public engagement activities in the water sector. The concepts were linked in the two theories which were then combined to build a proposed conceptual framework. Theory combination is common in research whereby they normally complement each other in various fashions to guide the study. The term "integration" has been used in studies employing TAM and other models. Integration means a combination of two or more elements to increase efficiency by optimizing their strengths and minimizing their weaknesses. A distinction be-tween hybridization and integration is that the latter does not necessarily result in a new individual. In the IT/IS theories, integration is combining two or more theories to develop a new superior theory from two different ones. In a set theory, this combination usually takes only features applicable in both and leaves the rest.

A. J. Chen et al. (2009) propose an integrated model developed using three theories, namely, TAM, Theory of Planned Behaviour (TPB), and Technological Readiness (TR). The new architecture explains the users' adoption of self-service technologies. Cheng (2014) proposed an integrated model composing Expectation-Confirmation Model (ECM), TAM, and updated IS Success Model (ISSM) to examine whether the quality factors as the antecedents to user beliefs affected users' continuance intention toward the digital library. The author argues that the proposed model was an excellent explanatory tool for the user's intention to use the digital library. Furthermore, the authors added that information relevance, system accessibility, and technical support played an important role in users' continuance intention of digital library use via their beliefs. Klopping and Mckinney (2004) combined their modified TAM with TFF models to study the consumers' e-commerce behaviour. In modifying the TAM, they argued that PU de-linked from PeoU. Nabavi et al. (2016) enumerate more examples of authors who have used TAM in integrated fashions (Nabavi et al., 2016). The set of information shows that authors who used TAM with other models adopted hybrid models much earlier than integrated ones (Nabavi et al., 2016; Chen et al., 2008; Liu et al., 2012; Cheng, 2014; Klopping and Mckinney, 2004). In contemporary trends, however, both fashions are used probably because of proposed new directions in IS research. Therefore, this paper proposes another combination of two models to inform IS research in the water resource sector.

This study introduces the concept of Theory Encapsulation (TE), hence contributing in both conceptualization and related debates. ET is a proposed form of combined architecture for theories. “Encapsulation” is a common technical term in computer networks and information systems. Collin (2004, p. 88) defines encapsulation in a computer network as “a system of sending a frame of data in one format within a frame of another”. In Information Systems (IS) development, especially with Java programming language, encapsulation refers to “wrapping data and methods within classes in combination with implementation hiding” (Eckel, 2006, p.228). In Chemistry, the term "encapsulation" relates to "technologies which enable to formulate one active compound (or more), inside individualized particles with a specific geometry and properties" (Capsulae.com, 2015). In the social realm, encapsulation applies especially regarding to “the friendship cohesion between internal and external friends” (Stark and Bainbridge, 1980, p.3). In this case, more cohesion tends to develop among friendship groups that share many in the same socio-cultural environment (internal) than among those who share just a few (external). The scholarships indicate wide and contextual use of the term "encapsulation" for tangibles and intangibles as well as materials and non-material things. This study proposes the application of the term "encapsulation” in theories combination.

Materials and methods

Overview of research design and approach

The study adopted a mixed research approach that combines qualitative and quantitative socio-technical methods. This combination allows for collecting qualitative and quantitative data and dynamics in analysis. On time-based design, the research adopted a longitudinal approach to data collection. This approach allows sequential implementation of the mixed methods. In this approach, the quantitative (QUAN) is followed by the qualitative (QUAL) paradigm, whereby the sequence does not necessarily attach equal weight to methods from each of the QUAL and QUAN paradigms. The literature review informed the construction of Encapsulated Conceptual Framework (ECF). The construction involved the review of constructs from the two guiding theories, and mapping them to augment the ECF in an encapsulated way. The literature review further informed the potential elements

of ICT as a tool, management activities for water resources, and sustainability goals.

The study area was the Mwanza region which is part of the Lake Victoria Basin (LVB). Mwanza region lies in the extreme northern part of Tanzania Mainland, bordering the Southern shore of Lake Victoria. Geographically, it lies between latitudes 1° 30' and 3° 0' South of the Equator and the longitudes 31° 45' and 34° 10' East of Greenwich (United Republic of Tanzania (URT), 1998). Currently, the region has seven administrative districts: Nyamagana, Ile-mela, Magu, Kwimba, Sengerema, Ukerewe, and Misungwi. Mwanza is among the fast-growing cities along Lake Victoria. As for other parts of LVB, the water resources in Mwanza have been facing severe pollution challenges and declining levels due to the increasing demand, population growth, and climate change. The study selected three administrative districts: Ilemela, Nyamagana, and Kwimba, representing urban, metropolitan, and rural areas, respectively (Figure 3).

The criteria for selection of the districts were the presence of water resources of significant size, formal institutions for water utilization for agriculture at small and medium scales, and challenges amounting to classifying such sites as "hotspots." The institutions, their members, and the associated technical and managerial support at meso and macro levels became the core target group in the study. One ward from each district was selected purposively based on the same criteria. In addition, the readiness of communities to collaborate with the researcher informed the selection process. The selected wards from Ilemela, Nyamagana, and Kwimba districts with formal irrigation organizations were Buswelu, Lwanhima, and Mwanghalanga, respectively.

Selecting participants for testing the framework

The sample was produced from the study area's three geographic contexts: urban, peri-urban, and rural areas. The sampling frame was small-scale irrigators of the selected wards in the three districts, with the population estimated at 720. The population size was used to estimate the sample size. Israel (2013) argues when estimating the sample size have to consider five factors: the purpose of study, the population size, the level of precision, the level of confidence or risk, and the degree of variability in the measured attributes. Estimation of the sample size adopted the formula suggested by Chen and Popovich (2002), Krzanowski (2007), Kothari (2010), and Ryan (2013) (Equation 1):

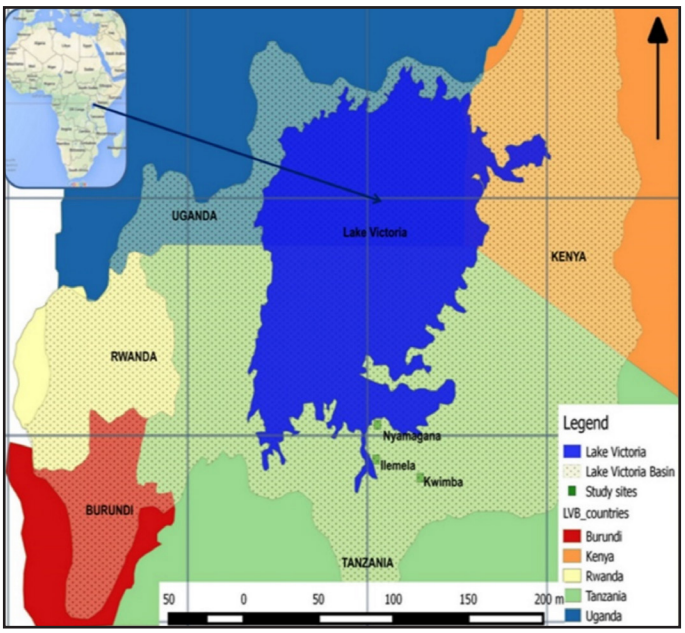
$$n = \frac{pZ^2}{Z^2 - 4e^2(1-p)} \quad (1)$$

Whereby:

n = estimated sample size.

z = a number relating to the confidence wished to be envisaged in the result.

e = the desired level of precision (standard error).



Source: Authors' creation with Google Maps

Figure 3: Map of LVB showing the location of study sites in Tanzania.

p = population that produced the sample.

Normally, 95% is considered a safe confidence interval associated with a Z-value of 1.96. The desired level of precision is therefore 5% (e = 0.05). The results of substituting these two values into Equation 1, is shown in Equation 2:

$$n = \frac{3.8416p}{3.8416 - 0.01(1-p)} \quad (2)$$

Substitution of the value of the estimated population size (p = 720) of members in the formal irrigation institutions and technical supporting individuals at micro and meso levels into into Equation 2 gives the sample size (n) = 251 respondents.

The study adopted purposive sampling, a non-probabilistic sampling procedure suggested by Trochim and Donnelly (2006) and Kothari (2010). In this study, purposive sampling served as the only appropriate method available, bearing in mind that formal irrigation associations and their members were limited in number. Dudovskiy (2013) indicates that this technique suits exploratory studies where the discovery of meaning can benefit from an intuitive approach. Since the researcher was aware of its disadvantages, he undertook necessary measures to minimize their effects. Purposive sampling targeted respondents who used smartphones to send and receive water resources information. The study, therefore, involved 251 participants drawn purposely and randomly from urban, peri-urban, and rural areas. Among them, 36.21% were females, and 63.79% were males.

Testing data collection and analysis

The collection of primary quantitative data used a closed-ended survey questionnaire. In contrast, primary qualitative data collection used open-ended survey questionnaires, focus-group discussions, key informant interviews, and observations. Secondary data collection used a systematic literature review of documents, reports, and other sources. Descriptive qualitative data analysis was coded and analyzed using descriptive statistics. Among the descriptive statistics employed were frequencies, means, and percentages. The study adopted correlation analysis to compare the system-oriented and user-oriented views to establish a significant relationship between the two.

Furthermore, it employed correlation analysis in testing the significance of relationships among the components of the system, public engagement, and sustainability indicators of water resources. The Spearman rank-order correlation or simply Spearman's correlation as denoted by ρ or "rho" was used to calculate the coefficients of association of pairs of ordinal variables. The requirements for Spearman's correlation test were observed, including that it does not make any assumptions about the distribution and that at least ordinal data and scores on one variable must be monotonically related to the other variable. The contextualization and usage of effect sizes were done. Several authors have suggested the effect sizes for interpreting the practical significance of correlation coefficients in statistics and behavioural studies. Among them are Hinkle et al. (2003) and Kotrlik et al. (2011). They suggested effect sizes' rule of thumb with intervals and five levels from negligible (±0.00 to ±30), low (±30 to ±50), medium (±0.50 to ±0.70), high (±0.70 to ±0.90) to very high (±0.90 to ±1.00). However, the most common is Cohen's rule of thumb (Cohen, 1988; 1990). It suggests three levels of interpretation of Spearman's correlation from small (± 0.10), medium (±0.30), to large (±0.50). Based on the three levels of relevance (low, medium, and high) adopted in this study, Cohen's rule is used with slight modification, as shown in Table 1.

High and very high levels are merged into high levels to confirm the context requirements. In this case, associations with Spearman's correlation below |0.30| were considered negligible.

Positive correlation		Negative correlation	
Size	Interpretation	Size	Interpretation
0.70 to 1.00	High (Strong)	-0.70 to -1.00	High (Strong)
0.50 to 0.70	Moderate (Medium)	-0.50 to -0.70	Moderate (Medium)
0.30 to 0.50	Low	-0.30 to -0.50	Low
0.00 to 0.30	Negligible	-0.00 to -0.30	Negligible

Source: Adopted with slight modification from Cohen (1988)

Table 1: Rule of thumb for interpretation of the effect sizes in correlation analyses

Results and discussion

Proposed Encapsulated Conceptual Framework

Encapsulated Conceptual Framework (ECF) is proposed as a gateway to linked ICTs, water resource management activities, and sustainable development goals. ECF is a conceptual stage toward the Encapsulated Theoretical Framework. ECF, in this context, extends the relationships but in the context of two theories, TAM and RT. Since extended TAM incorporated relevance as one of the criteria for PU of technology, it can combine with RT in a way that TAM "encloses" or "contains" the RT. Conceptualization in Miller and Khera (2010) for TAM and Hjørland and Christensen (2002) for RT formed a basis for the suggested conceptual encapsulation (Figure 4). Further, it operationalized each of the three encapsulated components of relevance (i.e., thing, activity, and goal) into variables in the context of water resource sustainability.

The Digital "Thing"

This study views the digital "Thing" or ICT solutions as having two interrelated and self-supporting parts: the social and technology sub-systems. The social sub-systems comprise the users, their activities in supporting the water resources, and their goals to ensure that the sustainability of the resources is enhanced. The technology sub-systems comprise ICT solutions for supporting various public engaging activities in water resource management. The ICT tools (T) can be operationalized into one or more variables as shown in Equation3:

$$T = \{T1, T2 \dots Tn\} \quad (3)$$

Where n = number of elements making a set of ICT tools

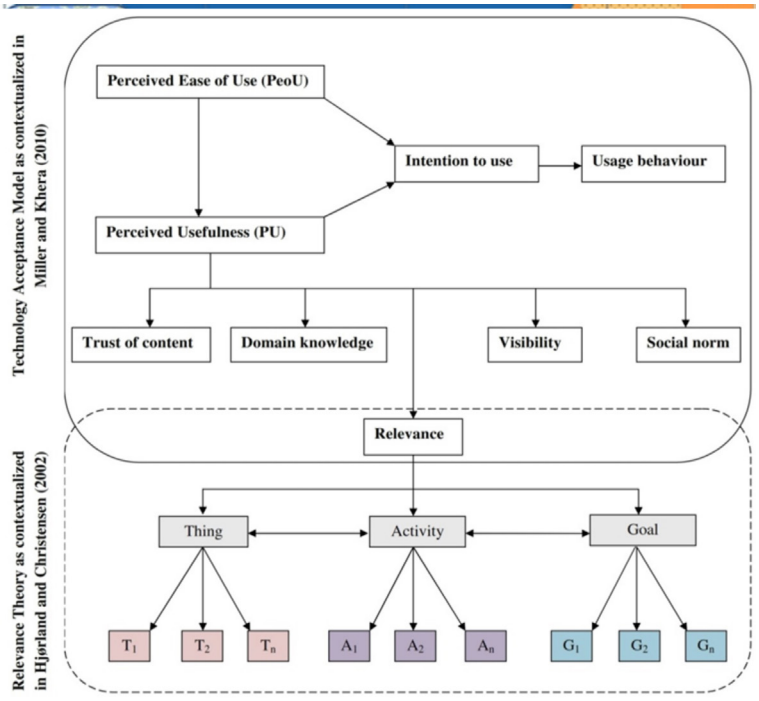
Some studies have indicated that ICT tools may vary with main and sub-tools. Using a case of a Water Resource Governance System (WaGoSy) that was developed in the study area (Faustine et al., 2014) exemplified and tested four (n = 4) ICT tools that were perceived to be basic applications at the community level. For mobile phones, for example, there were tools like SMS, voice, image, and video, while for web-based tools, the focus could be on social media.

The Digital-based Activity

The digital activities (A) identified within the context of the application of the framework can be operationalized into one or more variables as shown in Equation 4:

$$A = \{A1, A2 \dots An\} . \quad (4)$$

Where n = number of elements making a set of digital activities.



Source: Authors' processing

Figure 4: Encapsulated Conceptual Framework showing at the bottom the set of essential variables explored.

Each of these variables can represent a specific digital activity. For example, Mongi (2016) identified public engagement activities by members of small-scale irrigation organizations were from policy, strategies, and action plans. Public engaging activities from literature and confirmation during the first field visits. The author included eight (n = 8) categories of activities in his study.

The Goal

The Goal (G) can also be operationalized into one or more variables as shown in Equation 5:

$$G = \{G1, G2 \ldots Gn\} \quad (5)$$

Where n = number of elements contributing to an overall goal.

Different goals can be factored in depending on the context of the framework. To exemplify the applications of the goal (see Mongi (2016)) adopted the indicators of sustainable development goals entrenched in goal number 6. The United Nations (UN) suggests the following global indicators for Goal 6: (i) Ensure availability and sustainable management of water and sanitation for all; (ii) Proportion of population using safely managed drinking water services; (iii) Proportion of population using (a) safely managed sanitation services, and (b) a handwashing facility with soap and water; (iv) Level of water stress: freshwater withdrawal as a proportion of available freshwater resources; (v) Proportion of transboundary basin area with an operational arrangement for water cooperation; (vii) Amount of water and sanitation-related official development assistance that is part of a government-coordinated spending plan; and (viii) Proportion of local administrative units with established and operational policies and procedures for participation of local communities in water and sanitation management. Furthermore, the indicators were domesticated to Tanzania and validated in the context of smallholder FFG through local experiences.

Test Results of Encapsulated Conceptual Framework

Overview of participants' characteristics

Encapsulated Conceptual Framework (ECF) was tested by finding the actual ICT tools, water management activities, and locally perceived sustainability indicators for SDG number 6. The demographic characteristics of the sample selected for testing the framework were 36.21% and 63.79% for females and males, respectively. Except for rural areas where middle-aged persons seemed to dominate by 46.48% (N = 33), the rest of the geographical areas were dominated by youths by 62.64% (N = 57) and by 42.70% (N = 38) for urban and peri-urban areas, respectively. Participation by age categories showed that youth (20-35 years) were the majority with 49%, followed by middle age (36-50 years) with 35.06% and Elder (above 50 years) with 15.94%. Usually, the longer they stay in the same place, the more experience accumulated about the environment, including water and related resources. Participants with such experience (16 and more years) were 75.5% (N = 288) compared with less experience (less than 16 years) who were 24.5% (N = 94).

The Digital "Thing" in context

This study has indicated that ICT tools may vary with main and sub-tools. Using a case of Water Resource Governance System (WaGoSy) (Mongi, 2016) exemplified and tested three (N = 3) ICT tools that were perceived to be basic applications at the community level. In addition to that, some sub-tools were considered for each primary tool. For mobile phones, for example, there were tools like SMS, voice, image, and video, while for web-based tools, the focus was on social media tools. Table 2 shows the existing ownership of ICTs in the study area.

ICTs items owned (Mobile phone, Radio, TV, Computer)	**Study location**			**Average (N=251)**
	Ilemela (N=91)	*Nyamagana (N=89)*	*Kwimba (N=71)*	
Mobile phone	89	76	60	75
Radio	78	69	45	64
Television	29	24	5	19
Computer	19	17	0	12
None	2	5	2	3

Source: Authors' processing

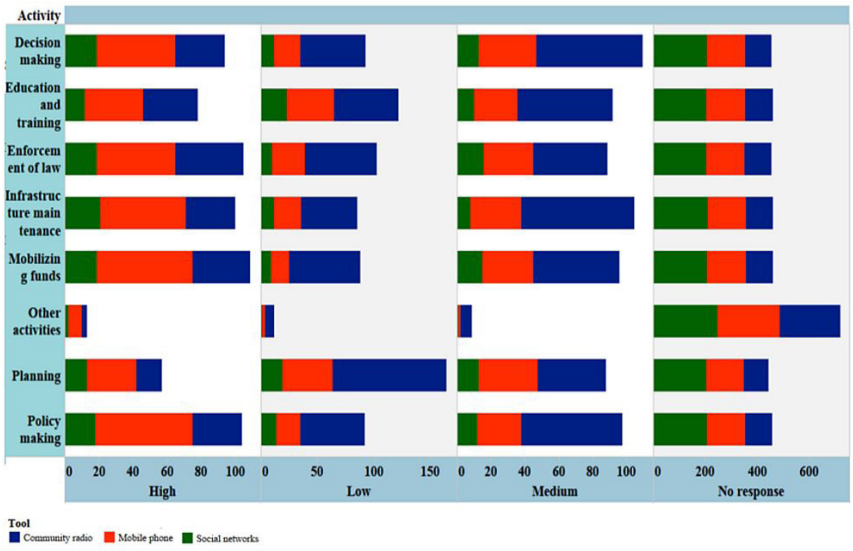
Table 2: Common ICT items (Things) owned in the study area.

The Digital-based Activity in context

There were several activities related to water resources management. These included decision-making, educating and training, enforcing the laws, maintaining the infrastructure, mobilizing the funds, planning, and policy marking. Figure 5 shows the perceived importance of ICTs in supporting various activities. Again, mobile phones became a prominent tool across activities.

The Goal in context

The perceived sustainability indicators for water resource management at the local level were mapped with standard SDG indicators for goal number 6. The purpose was to domesticate the indicators to gain context relevance for Tanzania, particularly for water resources management in LVB. Figure 6 shows the process of identifying the perceived indicators of water resource sustainability.



Source: Authors' processing

Figure 5: Perceived levels of contribution of selected ICTs to public engaging WRM activities.

Source: Authors' processing

Figure 6: Respondents in strategic action research to identify local indicators of water resources sustainability.

The following local indicators were rated for their importance in water resource sustainability: Controlled livestock population, controlled illegal fishing within the resources, Regular training and advisory services, Reduced income poverty, regularly maintained infrastructures, Con-trolled Siltation of water reservoirs, controlled human population, Controlled water pollution, controlled drought and floods, Mapped water resources and surroundings and Enforced rules and regulations. Table 3 summarizes the contextualized indicators for SDG 6 using the perceived sustainable indicators for freshwater management at the study area.

The relevance between T-A-G in context

Testing extended to the contextual relationship between "Thing," "Activity," and "Goal" showed the same trend. None of the selected ICT tools was perceived to have a strong correlation along the ICT tool – Activity – sustainability continuum. Although there were cases where ICT tools had strongly significant correlations, the complete relationship ended with non-significant correlations between activities and sustainability thus dropped. Table 4 shows the relationships along the continuum which have significant correlation as well as their associated effect powers (i.e., Cohon's RoT).

As an exploratory study, these relationships did not mean a waste but a message that there was something wrong with the end link that needed to be addressed. Cases like this one may equally attract the attention of researchers, innovators, decision-makers, and policymakers.

Table 4 further shows that despite the medium

Priority local perceived indicator	Total Scores (n, %)	Remarks	Nearly equivalent Corresponding SDGs 6 indicators
Controlled human population	109 (43.4%)	Medium	Ensure availability and sustainable management of water and sanitation for all.
Controlled water pollution	142 (56.6%)		The proportion of the population using safely managed drinking water services.
Controlled drought and floods	146 (58.2%)		Level of water stress: freshwater withdrawal as a proportion of available freshwater resources.
Mapped water resources and surroundings	149 (59.4%)	Strong	The proportion of transboundary basin area with an operational arrangement for water cooperation.
Enforced rules and regulations	163 (64.9%)		The proportion of local units with policies and procedures for local communities' participation in water and sanitation management
Average	141.8 (56.5%)		

Source: Authors' processing

Table 3: Fitting the top-ranked perceived indicators of water resources sustainability into their SDG equivalents.

ICT tool	Cohon's RoT	Activity	Cohon's RoT	Sustainability Indicator
Mobile SMS	Medium	Planning	Medium	Human population
Mobile Voice	Medium	Planning	Medium	Water sanitation
Mobile Image	Medium	Planning	Medium	Controlled GHG
Mobile Video	Medium	Planning	Medium	Encroachment of water sources
Mobile Voice	Medium	Decision making	Medium	Encroachment of water sources
Mobile SMS	Medium	Decision making	Low	Water sanitation
Mobile Image	Medium	Decision making	Medium	Controlled GHG
Mobile Video	Medium	Decision making	Low	Encroachment of water sources
Mobile SMS	Medium	Law enforcement	Medium	Water sanitation
Mobile Voice	Medium	Law enforcement	Low	Controlled GHG
Mobile Image	Medium	Law enforcement	High	Encroachment of water sources
Mobile SMS	Medium	Capacity building	Low	Encroachment of water sources

Source: Authors' processing

Table 4: Activities as a bridge between ICT tools and sustainability goals.

level that images contribute to enhancing law enforcement, it ended with high contribution in addressing challenges of encroachment into water resources. A few cases where medium linkages corresponded with high or low linkages were also observed. The findings support evidence in developing countries of a potential combination of ICT tools in engaging a wide array of the public in promoting sustainability of water resources. Low relevance, according to Cohen's RoT, was perceived for some cases of ICT tools and public engagement activity. As for the previous case, the contribution of activities that were supported by those ICT tools to sustainability was mainly low. The study adopted a mixed research approach that combines qualitative and quantitative socio-technical methods.

Conclusion

This paper describes the theoretical consideration within IS research, especially when more than one theory has to be used. This paper has described various combinations with which theories have been applied in information systems (IS) research. Problems with traditional combinations, especially with the popular TAM were described with examples of the nature of their use. A unique combination of two theories, TAM and RT, was proposed for future applications in IS research. Given the background of the two theories and the need to advance theoretical contribution to information systems, this study proposes an ECF. The architecture is neither integration nor hybridization. In this framework, the relevance of a cross-country usefulness of technology as one of TAM's constructs is strongly determined. ECF, therefore, zooms at relevance as a contextualized construct of TAM in developing countries as well as three factors that determine relevance: "thing," activity, and goal. Operationalizing these factors into variables with consideration of the context was exemplified based on an actual study that tested them in small-scale irrigation schemes. This study, therefore, proposes the ECF for use in studying the context-specific relevance where information systems mediate between activity and development goals.

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Factors Influencing the Prices of Rice, Maize and Wheat Prices in Nigeria

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Abstract

This study examines the impact of agricultural Gross Domestic Product (GDP) and imports on Nigeria's food commodity prices using annual data from 1981 to 2018. Data obtained were analysed using the unit root test, cointegration test and Autoregressive Distributed Lag (ARDL) model to evaluate the long-run and short-run effects of the hypothesized variables on the food commodity prices. The results reveal that maize import value and exchange rate significantly affect the price of maize in the short-run. In contrast, the lagged price of maize, maize output and the past value of maize imports are the factors that influenced the current price of maize within the review period. Also, the lagged price of rice, rice output and the lagged value of rice imported in the immediate year exerted significant influences on the price of rice in Nigeria. Furthermore, the study indicates that the lagged price of wheat, the import value of wheat and the lagged wheat import value were statistically significant in influencing wheat price in Nigeria. Hence, policies for flexibility in the harmonization of exchange rate movements strengthen domestic agricultural performance.

Keywords

ARDL, demand, exchange rate, food commodity price, import, supply.

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Introduction

The global food commodity price is a crucial variable in a market-oriented economy characterized by perfect information. Strategic and critical decisions are mostly taken based on the expected price at harvest, and farmers will be opened to better information opportunities to make the right decisions on future planting (Robert and Bergez, 2016). The volatile nature of agricultural commodity prices can be attributed to the low responsiveness of short term production and consumption (Haile et al., 2016; Brümmer et al., 2016). Planting decisions made by agricultural stakeholders before introducing new crop prices have caused a low production response to annual crop commodities output. However, these decisions are dependent on expected prices and not price realizations (FAO et al., 2020).

Albeit practically all the agricultural products experienced increased nominal prices, the pace of their increment from one commodity to another differed vehemently. Thus, there is a high surge in international prices of essential foods more than tropical commodities and raw materials. This relegates developing countries to be dependent on exports of major food commodities since their export earnings will be increasing sluggishly than the cost of food importations (Patel, 2012; Verter et al., 2020).

The selected food commodities for this study are maize, rice and wheat. These are Nigeria's essential food crops (staples) since they are known for high yield potential, storage value and wide range of use. Also, there is an increasing demand for these grains due to their importance as a raw material in producing animal feed for human consumption as food and beverage industries. First, however, some definite features give a general description of market price formation or these commodities. For example, there are annual production; long term

storage; movement from farm to market in bulk form; and trading on commodity futures exchanges that facilitate hedging and forward contracting. In addition, they compete for the same cropland in production, resulting in the indirect linkage of their prices across markets (Schnepf, 2006; Chen et al., 2020).

Increased food production in Nigeria has not satisfied the demand owing to the population growth. This has led to food imports and low food self-sufficiency levels (Fasanya et al., 2018). As a result of the heavy importation of food, the increasing food prices are traceable to the influence of international food market prices. The recent surge in food prices experienced in 2020 due to twice the increase in petrol price led to food price inconsistency and volatility among commodity markets. This has wreaked substantive havoc on agribusiness, marketing system and environment, as well as the entire economy. Also, Nigeria categorized as a net food importer, reflecting on the recent increase in food price in 2019 – 2020 due to depreciation in Naira to USD

Considerable studies have been carried out on the factors influencing food commodity prices. For example, Ajibade et al. (2018) modelled the maize price and determinants using the Error Correction Model (ECM) approach. The study found that both short-run and long-run relationships exist between the significant variables and maize prices in Nigeria. In addition, some academic research (Gilbert, 2010; Wang et al., 2018) suggests an impact on price volatility from speculative activity, increasing demand, economic growth, countries' aggressive stockpiling policies, exchange rate, and trade restrictions.

This study looks at some macroeconomic factors that may have influenced food commodity prices in Nigeria. The study adopted an autoregressive distributive lag (ARDL) bound test (Pesaran et al., 2001; Narayan, 2005) to know if a long-run relationship exists between the variable of observations to circumvent the likelihood of biased and spurious estimations. Techniques like the two-step procedure (Engle-Granger, 1987) and completely modified OLS estimators (Phillips-Hansen, 1990) are responsible for committing when data utilization of restricted or limited for instance, when a sample is less than 80 (Pesaran et al., 2001; Narayan, 2005).

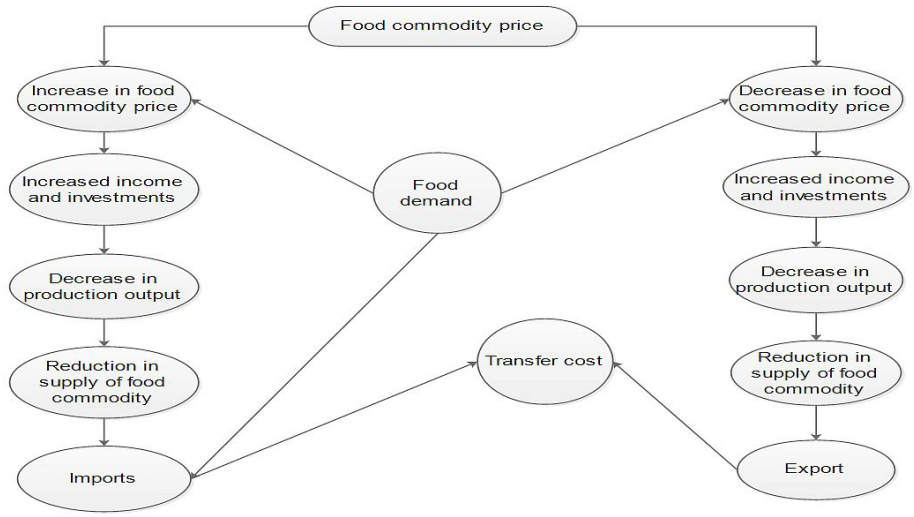
Conceptual framework

This section presents the conceptual linkages of the factors responsible for the price behaviour of agricultural commodities, as illustrated in Figure 1. Price is the fulcrum of agreement between buyers (demand) and sellers (supply) in the marketplace. The adjustments of different prices to their speed and efficiency rely on the market structure where the commodities are traded (Schnepf, 2006). Various market forces have compromised the global price level of food commodities and can alter both the current or future balances between supply and demand. These factors are food demand for human consumption, feed demand for animal use and industrial-use market demand for industries. Others include; government policies, factors influencing production processes; products' storage and transportation factors; and relative prices of substitute crops for production or consumption.

Also, the intensity of counties' engagement in international trade is a crucial factor. The differential outcome in the prices globally has a significant ripple effect on the differences in local supply and demand conditions. A complex web of local supply and demand situations (transfer cost) decides how and when commodities move through this network in international trade interaction. Price changes at any point along the chain can shift to alternate transport modes or routes as marketers search for the lowest-cost method of moving the food commodities between buyer and seller (Figure 1).

Food importation is predominant among many developing economies, and this phenomenon never ceases to decline at any instance. These countries majorly depend on huge supplies of agricultural commodities at lower costs in the global markets due to the intervention of developed economies/countries in providing subventions for production and trade. At any reduction in this support, commodity prices are expected to spike, thereby presenting exorbitant import bills for the vulnerable economies that heavily depend on food importations (FAO et al., 2019).

Some countries have abundant natural resources, but their agriculture sectors are unable to satisfy domestic food demand. Most of these countries adopt tariffs and border protection measures targeted at increasing domestic agricultural prices and providing subventions for agricultural growth and development (FAO et al., 2020). However, these countries have enacted policies that protect their producers while investing in improving productivity and technologies. A portion of these cost increments can be attributed to the depreciation of the US dollar



Source: Authors' Illustration

Figure 1: Conceptual framework for agricultural commodity price.

(USD), which dominates international prices. It has, therefore, complicated to relate the currency and commodity prices when assessing spikes in prices of agricultural commodities (Ogunmola et al., 2017). Likewise, it can be linked to the implications of how the changes influence various nations. In most developing countries, the gravity of increment in global market prices mirrors how dependent the local consumer and producer prices are on their USD exchange rate and other import variables (infrastructure, market structures and tariffs) (FAO et al., 2020). This study aimed to investigate the impact of agricultural gross domestic product (agricultural GDP) and imports on rice, maize, and wheat prices in Nigeria for 1981-2018.

Materials and methods

The study used yearly time series data for the producer price of food commodities (maize, rice, and wheat) expressed in Nigerian currency (the naira per metric tonne), the production output of these food commodities (metric tons), importation value (metric tons), agricultural GDP (2012 constant price), and exchange rate (annual USD/Naira value) from 1981 to 2018. The data for the study was obtained from the Food and Agriculture Organisation of the United Nations (FAO, 2020), the National Bureau of Statistics (NBS, 2020), and the Central Bank of Nigeria (CBN, 2020). The precise motive for yearly frequency data was the non-availability of updated monthly data set for some series, hence annual data set uniformity.

Empirical Model: ARDL Bounds Tests for Cointegration

After establishing that the variables have a combination of level (I(0)) and first differencing (I(1)), the ARDL bounds testing technique (Pesaran et al., 2001) was adopted to estimate the relationship between the variables.

Cointegration serves as a powerful tool in ascertaining the occurrence of long-run interactions or equilibrium between variables (Nkoro and Uko, 2016). Many cointegration methods have been developed to empirically analyse the long-run relationships between time series, such as the residual-based technique (Engle and Granger, 1987) and the maximum likelihood test (Johansen and Juselius, 1990; Johansen, 1991). However, these methods restricted all series in consideration to be integrated of the same order. ARDL, a cointegration approach, was developed (Pesaran et al., 2001).

The ARDL method can be applied when the variables of interest are integrated of order zero (I(0)), order one (I(1)) or a mixture of both. This approach is more efficient for validating cointegrating relationships with small and finite sample sizes. Also, the ARDL method allows the time series to have different optimal lags. With the use of a single reduced form equation, it will enable the estimation of unbiased long run and short-run parameters of the model.

The ARDL model estimated for this study was specified as follows:

$$\Delta lnFP_t^{maize} = \alpha_0 + \varphi_1 lnFP_{t-1}^{maize} + \varphi_2 lnPD_{t-1}^{maize} + \\ + \varphi_3 lnIMP_{t-1}^{maize} + \varphi_4 lnY_{t-1} + \varphi_5 REXH_{t-1} + \\ + \sum_{i=1}^{p} \tau_i \, lnFP_{t-i}^{maize} + \sum_{i=1}^{p} \omega_i \, \Delta lnPD_{t-i}^{maize} + \\ + \sum_{i=1}^{p} \delta_i \, \Delta lnIMP_{t-i}^{maize} + \sum_{i=1}^{p} \vartheta_i \, \Delta lnY_{t-i} + \\ + \sum_{i=1}^{p} \psi_i \, \Delta REXH_{t-i} + \varepsilon_t \quad (1)$$

$$\Delta lnFP_t^{rice} = \alpha_0 + \varphi_1 lnFP_{t-1}^{rice} + \varphi_2 lnPD_{t-1}^{rice} + \\ + \varphi_3 lnIMP_{t-1}^{rice} + \varphi_4 lnY_{t-1} + \varphi_5 REXH_{t-1} + \\ + \sum_{i=1}^{p} \tau_i \, lnFP_{t-i}^{rice} + \sum_{i=1}^{p} \omega_i \, \Delta lnPD_{t-i}^{rice} + \\ + \sum_{i=1}^{p} \delta_i \, \Delta lnIMP_{t-i}^{rice} + \sum_{i=1}^{p} \vartheta_i \, \Delta lnY_{t-i} + \\ + \sum_{i=1}^{p} \psi_i \, \Delta REXH_{t-i} + \varepsilon_t \quad (2)$$

$$\Delta lnFP_t^{wheat} = \alpha_0 + \varphi_1 lnFP_{t-1}^{wheat} + \varphi_2 lnPD_{t-1}^{wheat} + \\ + \varphi_3 lnIMP_{t-1}^{wheat} + \varphi_4 lnY_{t-1} + \varphi_5 REXH_{t-1} + \\ + \sum_{i=1}^{p} \tau_i \, lnFP_{t-i}^{wheat} + \sum_{i=1}^{p} \omega_i \, \Delta lnPD_{t-i}^{wheat} + \\ + \sum_{i=1}^{p} \delta_i \, \Delta lnIMP_{t-i}^{wheat} + \sum_{i=1}^{p} \vartheta_i \, \Delta lnY_{t-i} + \\ + \sum_{i=1}^{p} \psi_i \, \Delta REXH_{t-i} + \varepsilon_t \quad (3)$$

where Δ = change operator; *ln* = natural logarithm; p = 2 (number of lags used guided by Akaike Information Criterion); FP_t^{maize}, FP_t^{rice}, and FP_t^{wheat} = prices per metric tons for maize, rice and wheat, respectively; PD_t^{maize}, PD_t^{rice}, and PD_t^{wheat} = production output for maize, rice and wheat, respectively; IMP_t^{maize}, IMP_{trice}, and IMP_t^{wheat} = values of importation for maize, rice and wheat, respectively; Y_t = Agricultural Gross Domestic Product proxy for agricultural income; *REXH* = effective exchange rate in Nigeria; α_0, φ_1, φ_2, φ_3, φ_4, φ_5, τ_i, ω_i, δ_i, ϑ_i, and ψ_i are the parameters estimate; and ε_t = error term of the regression.

The ARDL bounds test was used to test the null hypothesis that no cointegration exists against the alternative hypothesis that cointegration exists. The null hypothesis is defined as H_0: $\varphi_1 = \varphi_2 = \varphi_3 = \varphi_4 = \varphi_5 = 0$. The test is based on F-statistics and compared with the critical values developed by Narayan (2005) because of its suitability for a small sample size. If the value of the com-puted F-statistic is greater than the upper bound (I(1)), the stated null hypothesis of no cointegration will be rejected. If the computed value of F-statistic is less than the lower bound (I(0)), we will fail to reject the null hypothesis that no cointegration exists. Furthermore, if the value of F-statistic is found between I(0) and I(1), the test would be inconclusive.

Long-run and short-run functions

Having estimated the ARDL bounds test to establish the long-run relationships among the observed series, there is a need to specify and estimate the long-run (LR) and short-run (SR) functions for the equation that rejected the null hypothesis of no cointegration between the series. As proven (Table III), the bounds test for equation 1 reveals a long-run relationship among the observed variables, requiring LR and SR estimations.

Long-run supply function

The equation for long-run supply response is presented thus:

$$lnFP_t^{maize} = \beta_0 + \phi_1 lnFP_t^{maize} + \phi_2 lnPD_t^{maize} + \\ + \phi_3 lnIMP_t^{maize} + \gamma_1 lnY_t + \gamma_2 REXH_t + u_t \quad (3)$$

where *ln* = natural logarithm; FP_t^{maize} = price per metric tons for maize; PD_t^{maize} = production output for maize; IMP_t^{maize} = value of importation for maize; Y_t = Agricultural GDP proxy for agricultural income; *REXH* = real effective exchange rate in Nigeria; β_0, ϕ_i, and γ_i = parameters to be estimated; and μ_t = random error of the regression.

Short-run supply function

We described the short-run dynamics of the observed variables by adopting ECM (Lütkephol, 2005). The ECM is specified as follows:

$$\Delta lnFP_t^{maize} = \sigma_0 + \sum_{i=1}^{p} \rho_i \, lnFP_{t-i}^{maize} + \sum_{i=1}^{p} \ell_i \, \Delta lnPD_{t-i}^{maize} + \\ + \sum_{i=1}^{p} \lambda_i \, \Delta lnIMP_{t-i}^{maize} + \sum_{i=1}^{p} \gamma_1 \, \Delta lnY_{t-i} + \\ + \sum_{i=1}^{p} \gamma_2 \, \Delta REXH_{t-i} + \lambda ECM_{t-1} + \xi_t \quad (5)$$

where $ECM_{t-1} = \hat{u}_{t-1}$ which is the error correction or cointegration term (it is equivalent to the lagged value of the error term in equation (4)); p = 1 and is the number of lagged used (according to AIC, maximum of one lag is expected to catch up with the most recognized dynamic adjustment in the series); l_i, and λ_i = short-run price elasticities; γ = impact of income and real exchange rate on the short-run maize price; ξ_t = regression error term; λ = coefficient ECM and is "the speed of adjustment of a parameter presenting how speedily the series can return to its long-run equilibrium position". The sign of the coefficient must be negative and significant (Dube et al., 2018).

Some diagnostic tests (Durbin Watson and Breush-Godfrey Serial Correlation LM test, Jarque-Bera statistics for error normality (JB), the ARCH statistics for autoregressive conditional heteroskedasticity, skewness and kurtosis) were estimated to guarantee the acceptability of the model. The cumulative sum (CUSUM) and the cumulative sum of squares (CUSUMQ) were tested on the series to assess the coefficients' stability.

Results and discussion

Table 1 shows a description of the variables considered for this study. The minimum and maximum values reflect the range of the variables change to agricultural production and prices, reflect the data trend, and reflect the centre value of the data trend. The mean values of the variables express a striking pattern and have reasonable returns due to their positive nature over the period. It reflects the degree to which the data distribution aggregates to its centre value. Shreds of evidence show that the standard deviation of the series demonstrates the degree of dispersion and the stability of these data sets.

The more significant deviation of maize, rice and wheat outputs indicates that the food commodities' outputs fluctuate widely, indicating that the production outputs are enormous over the years considered for the study. Furthermore, the result shows that all the variables are positively skewed except maize output with negative skewness. This implies that the positively skewed variables/series have an asymmetric distribution with a long right tail, while maize output has a left tail (Table 1).

The kurtosis indicates that only import values of maize exhibit leptokurtic showing the heavy outliers in the series. Rice and wheat production output show mesokurtic distribution, showing that the variables follow a normal distribution while other series are platykurtic or follows a subtle/pale curve. The curves signify the small number of outliers in the distribution, and there is a lesser probability of producing extreme returns. Overall, according to JB outcome, the series (the commodity prices, production outputs, importation values, income, and exchange rate) are not normally distributed and follow a fluctuation pattern suggesting instability (Table 1).

Time series unit root test

Most monetary or economic time series are non-stationary and, therefore, crucial to investigate the unit root and cointegrated relationship (Adeoye et al., 2014). The ARDL bounds test assumes that the variables are I(0) or I(1). Before applying this test, integrating all variables must be determined using the unit root tests estimation. This is to certify that the observed variables are not I(2) to circumvent

Variable	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	JB
Maize prices	30127.26	82452	210	26735.93	0.286	1.605	3.601
Rice prices	33566.29	76261	400	27110.09	0.180	1.561	3.483
Wheat prices	32824.82	80500	280	25631.10	0.083	1.646	2.948
Maize output	6012688	11547980	720000	2731918	-0.103	2.764	0.155
Rice output	3472398	7564050	1241000	1621392	0.750	3.083	3.569
Wheat output	67966.45	165000	26000	32763.05	1.059	3.816	8.159
Maize import	12240.08	132314	0	26668.07	2.969	12.439	196.92
Rice import	473608.5	1167406	94478	323064.30	0.523	1.913	3.604
Wheat import	619411.9	1589017	8469	460053.20	0.366	1.819	3.056
Income	7693.52	17544.15	2303.51	5159.29	0.611	1.837	4.502
Exchange rate	88.54	306.08	0.62	87.14	0.803	2.974	4.085

Source: Authors' calculations (2020)

Table 1: Descriptive statistics of the variables.

spurious results. If the variables are integrated into order two, Pesaran et al. (2001)'s F-statistics will be inappropriate and not be interpreted. To ascertain robustness in the model, the Augmented Dickey-Fuller (ADF) test and two other advanced unit root tests (Dickey-Fuller Generalized Least Squares (ADF-GLS) test and Ng–Perron (Ng-P) test) were employed because of their strength to produce reliable results for small sample data sets and power.

The unit root test results on the modelled variables are shown in Table 2 based on constant and no deterministic trends of Akaike information criteria (AIC) for the optimal lag order. The ADF statistics at the level explained the non-stationary nature of all variables. However, they became stationary when subjected to first differencing. Dickey-Fuller GLS showed that series (variables) are stationary at first difference except for wheat output stationary at the level I(0). The Ng-Perron test reveals that all the variables became stationary after first differencing. This confirmed that they were all generated by the same stochastic processes and exhibited long run spatial equilibrium. Since the tests indicate none of the variables is I(2), there is a need to proceed to the bounds testing procedure.

Cointegration tests

The existence of cointegration among the series used for this study was verified by adopting the bound test for cointegration approach with unrestricted constant and no trend. The test was carried from the three equations with the commodity prices (maize price, rice price and wheat price) being the dependent variables. The results in Table 3 show that the calculated F-statistic (6.183) and t-statistics (-4.893) when maize price is the dependent variable rejected the null hypothesis, establishing a long-run relationship between the series. It means cointegration exists among the modelled variables. Thus, cointegration among the variables helps analyse the short-run and long-run relationship of the dynamics influencing maize prices in Nigeria.

When rice price is the dependent variable, F-statistics (3.504) and t-statistics (-2.941) values cannot reject the null hypothesis, indicating the non-existence of a long-run relationship among observed variables. Also, there is no long-run relationship

Variables	Form	ADF	ADF GLS	Ng-Perron
Maize price	Level	-3.320	-0.820	-7.802
	First difference	-7.705	-7.502	-16.997
Rice price	Level	-3.471	-0.222	0.443
	First difference	-6.932	-6.718	-17.679
Wheat price	Level	-2.630	-0.653	-0.462
	First difference	-3.855	-3.775	-14.75
Maize output	Level	-3.796	-0.489	0.392
	First difference	-3.687	-3.736	-14.734
Rice output	Level	-1.141	0.310	1.104
	First difference	-9.455	-9.424	-14.594
Wheat output	Level	-3.637	-2.207	-7.083
	First difference	-5.587	-5.758	-10.011
Maize import	Level	-1.189	-0.886	-1.825
	First difference	-5.218	-5.304	-1268.27
Rice import	Level	-0.430	-0.913	-2.091
	First difference	-8.444	-3.141	-8.321
Wheat import	Level	-12.712	-1.097	-3.089
	First difference	-6.655	-2.334	-1.570
Income	Level	0.024	0.675	1.158
	First difference	-5.851	-5.758	-17.964
Exchange rate	Level	1.737	0.544	1.929
	First difference	-4.211	-4.141	-15.856

Note: Critical Value (CV) for ADF = -2.951, ADF-GLS = -1.952 and Ng-Perron = -8.10
Source: Authors' computation (2020)

Table 2: Unit root test result of the series.

Variable	Statistics	10%		5%		1%		p-value		Cointegration
Level		I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	I(0)	I(1)	
Maize price	F = 6.183	2.639	4.138	3.278	5.031	4.896	7.274	0.003	0.021	Yes
	t = -4.893	-2.437	-3.572	-2.835	-4.045	-3.665	-5.035	0.001	0.013	
Rice price	F = 3.504	2.674	3.966	3.265	4.742	4.702	6.613	0.038	0.151	No
	t = -2.941	-2.525	-3.64	-2.89	-4.068	-3.642	-4.946	0.045	0.257	
Wheat price	F = 3.136	2.691	3.933	3.275	4.686	4.684	6.486	0.059	0.206	No
	t = -2.531	-2.549	-3.659	-2.907	-4.079	-3.642	-4.933	0.103	0.409	

Source: Authors' computation (2020)

Table 3: Bounds test for cointegration: unrestricted constant and no trend (k=4; N=34).

amongst the variables when the wheat price is the dependent variable as the F-statistic (3.136), and t-statistics (-2.531) values cannot reject the null hypothesis of no cointegration among the variables (Table 3). This aids the ARDL framework's choice to analyse only the short-run relationship between rice and wheat prices in Nigeria.

Factors affecting the food commodity price

Using Akaike Information Criterion (AIC), ARDL (4 3 3 1 1) reveal to be the best model for the series when maize price is the dependent variable, ARDL (2 2 1 0 0) was used when rice price is the dependent variable while ARDL (2 0 1 0 0) was the best when the wheat price was the dependent variable. Table 4 presents the model estimation of the short-run and long-run relationship among commodity prices and the hypothesized variables (ECM) when the maize price is the dependent variable. Similarly, Tables 5 - 6 present the ARDL model estimation when rice and wheat prices are dependent on the variables. Before drawing inferences, various diagnostic statistics test was conducted to judge the adequacy of the dynamic specification.

According to diagnostics testing, the three models indicate no autocorrelation problem based on the Durbin-Watson statistic test. Furthermore, the Breusch-Godfrey Serial Correlation LM Test results show no serial autocorrelation problem in the specified models. Also, there was no problem of heteroscedasticity signifying the validity of the specified models and that the models were fit for cointegration analysis. Finally, the stability test results of the CUSUM and CUSUMQ indicated a correctly specified and stable model.

Parameters long-run and short-run estimation of maize price model

Long-run estimation

The parameter estimates for the long-run maize price function are presented in Table 4. Evidence from the result revealed that maize price was swiftly responsive to its import value and exchange rate consistent with trade theories. Specifically, the result indicates that a 1% movement (upswing) in maize import value results in about 0.91% increases in the price of maize. This implies that importing more maize may accumulate foreign debt thereby escalating positive food price shocks. Furthermore, a decline in consumption, increasing poverty and government expenditure, and borrowing show positive food price shocks, thus worsening food security (Meerman and Aphane, 2012).

The partial elasticity of maize price to the change in the exchange rate exhibits a positive and significant relationship at a 1% probability level (Table 4). This shows that a 1% increase in the long-run exchange rate coefficient significantly increased the maize price by about 0.03% in Nigeria. In Nigeria, the maize price may increase as the exchange rate can make maize export more lucrative and attractive, thereby posing competition between domestic availability and maize exportation. In tandem with Ajibade et al. (2018) findings, the annual exchange rate positively influenced Nigeria's maize prices. This is a sign that certain economic variables may influence food prices. The results emphasize the policy relevance that the exchange rate affects the commodity prices' performance via its volatility and depreciates or appreciated value. Depreciation in the local currency's value makes the product prices cheaper such that more revenue will be obtained.

Short-run estimation

The ECM was estimated to determine the series' short-run dynamics in the specified model. Table 4 presents the evidence of short-run relationships existing amongst the residuals of the specified series included in the model of the equation. The ECM (ECMt-1) coefficient was negative and significant. This establishes the occurrence of cointegration among the modelled variables for the study.

Variable	Coefficient	Std. Err	t	P>|t|
Long-Run Equation				
Maize Output	0.756	0.545	1.39	0.183
Maize Import Value	0.910***	0.222	4.09	0.001
Income	1.486	3.252	0.46	0.654
Exchange rate	0.031**	0.011	2.84	0.011
Short-Run Equation				
$\Delta(\text{Maise Price})_{t-1}$	-0.649***	0.170	-3.82	0.001
$\Delta(\text{Maise Price})_{t-2}$	-0.585***	0.167	-3.49	0.003
$\Delta(\text{Maise Price})_{t-3}$	-0.210	0.175	-1.2	0.248
Δ(Maize Output)	-1.072**	0.435	-2.46	0.025
$\Delta(\text{Maise Output})_{t-1}$	-1.071**	0.412	-2.6	0.019
$\Delta(\text{Maise Output})_{t-2}$	0.378	0.401	0.94	0.360
ΔMaize Import Value	-0.242***	0.065	-3.71	0.002
$\Delta(\text{Maise Import Value})_{t-1}$	-0.165***	0.042	-3.9	0.001
$\Delta(\text{Maise Import Value})_{t-2}$	-0.070**	0.023	-3	0.008
Δ(Income)	-0.160	0.691	-0.23	0.820
Δ(Exchange rate)	0.004	0.004	1.24	0.233
$(\text{ECM})_{t-1}$	-0.349***	0.071	-4.89	0.000
Constant	-0.218	3.051	-0.07	0.944
R-squared	0.7973		Adj R-sqd	0.6064
Log-likelihood	10.6304			
Number of obs	34			
Diagnostics tests				
DW	1.828			
LM	0.047	p-value	0.8278	
Heteroskedasticity	34	p-value	0.4192	
Skewness	22.37	p-value	0.1317	
Kurtosis	0.55	p-value	0.4575	
J-B	1.784	p-value	0.4098	

Note: *, **, *** Significance level at 1%, 5% and 10% respectively; DW = Durbin-Watson; LM = Breusch-Godfrey LM test for autocorrelation; JB = Jarque-Bera normality test
Source: Authors' computation (2020)

Table 4: The estimated coefficient of maize price.

The Error Correction term (ECTt-1) coefficient, representing the speed of adjustment for both estimators, is significantly different from zero with an expected negative sign. The error correction coefficient for the model was -0.349, which reveals a fast convergence to equilibrium immediately adjusted by the differenced terms in each period. Therefore, this result confirms a steady relationship among the variables established in the equation. It may be recognised that the current maize price-sensitive to its deviation from equilibrium during the past period. When there are no variations among the hypothesised series (exogenous variables), the model tends to correct its deviation from the long-run relationship by a 34.9% increase in the future price of maize.

The regression result shows that in the short run, the first and second lags of maize price, maize output, first lag of maize output, maize import value and the lags (first and second) of maize import value were the significant variables hypothesized to influence the price of maize within the reviewed period in Nigeria. The partial elasticity of the first and second lags of maize price was -0.649 and -0.585, respectively and statistically significant at a 1% significance level. This implies that a 1% increase in maize prices in the previous years will cause a decrease in the current price of maize by 0.65% (one lag) and 0.59% (two lags). The result agrees with Eldukhey et al. (2010) that the past or previous prices of grains yield a decrease in the current price.

Evidence from Table 4 reveals that a one-unit increase in maize output results in a 1.072 unit decrease in maize price. Also, the lag of maize output has a considerable influence on the price movement of maize. This is consistent with standard production theory and expected since an increase in production results in overwhelming supply that suppresses the efficacy of demand resulting in price fall needed to rejuvenate the market equilibrium. This result is in tandem with Ajibade et al. (2018), which shows that an increase in maize output decreased its price in Nigeria. The import value of maize is another essential and significant variable that affects maize price performance in Nigeria. Its partial elasticity was 0.242 in the short-run, implying that a unit increase in the maize imported within the reviewed year might decrease Nigeria's maize price by 0.242 units.

It is also observed that the earlier import value of maize (both the first and second lags) significantly influenced the price movement of maize in the country. Both have a negative relationship with the price of maize. This is expected since the importation of maize will increase the quantity of the commodity available for consumption and use (Table 4). According to supply theory, the increase in maize production will invariably decrease maize price. The result contrasts Ogundari (2016) that an increase in maize supply significantly increases maize price.

Parameters estimation of rice price model

Having established the cointegration existing among the series, we estimate the ARDL long-run model for rice price with the ARDL (2 2 1 0 0) specification. The results obtained for the factors influencing rice price in the long-run are reported in Table 5. The results indicate that three variables, price of rice (first and second lags), rice output, and the lagged value of rice imported in the immediate year significantly affected rice price in Nigeria over the reviewed period. In the past years (first and second lags), the lagged rice price values coefficients are 0.641 and 0.269 in Nigeria, statistically significant at 1% and 10%, respectively. The implication is that if there is a 1% increase in rice lagged price in the past years (first and second lags), rice's current price increased by 0.64% and 0.27%. The finding agrees with Hermawan et al. (2017) that rice's lagged value significantly affects rice's current price in the market.

Speculations about rice's previous price might

Variable	Coefficient	Std. Err	P>|t|
Constant	0.995***	0.305	0.003
$(\text{Rice Price})_{t-1}$	0.641***	0.159	0.000
$(\text{Rice Price})_{t-2}$	0.269*	0.150	0.085
Rice Output	0.695**	0.317	0.038
$(\text{Rice Output})_{t-1}$	0.589	0.354	0.109
$(\text{Rice Output})_{t-2}$	0.403	0.313	0.210
Rice Import Value	0.078	0.159	0.628
$(\text{Rice Import Value})_{t-1}$	0.387**	0.167	0.029
Income	-0.025	0.622	0.969
Exchange rate	-0.003	0.003	0.222
F(9, 25)	133.51***	Prob>F	
R-squared	0.9796	Adj R-sqd	
Log-likelihood	5.3413		
Number of obs	35		
Diagnostics tests			
DW	2.217		
LM	1.734	p-value	
Heteroskedasticity	36	p-value	
Skewness	6.39	p-value	
Kurtosis	1.63	p-value	
JB	21.03	p-value	

Note: *, **, *** significance level at 1%, 5% and 10%, respectively; DW = Durbin-Watson d-statistic (10, 36); LM = Breusch-Godfrey LM test for autocorrelation; JB = Jarque-Bera normality test
Source: Authors' computation (2020)

Table 5: Estimated coefficient for rice price.

determine the current price, especially in nations with weak commodity price regulations. The rice output also positively affected its price in the country with a coefficient of 0.695 ($p < 0.05$), implying that a percentage increase in rice output would increase the product's price by 0,70 % The latter result underscores the relevance of rice production in Nigeria. It becomes evident that in Nigeria, increases in rice production led to a rise in the price of the food commodity because the rise in population drives the increase in total demand for rice. However, rice demand is being met through imports, increasing rice prices. The lagged value of rice imported in the immediate year positively influenced the price of rice. On average, the rice price increased by 0.387 units in the previous year. This implies that the import value changes in some sectors due to rice price increase show that domestic production cannot meet domestic needs (Table 5). This result is in resonance with the outcomes of Suryadi et al. (2014) increased import value of rice has a positive impact on the price of rice. It is said that Indonesia was importing all commodities in a colossal amount. However, the import of other services and industries tends to decrease because the decrease is minimal by the increase in rice price.

Parameters estimation of wheat price model

Table 6 shows the coefficients of the variables influencing the price of wheat. The results show that the lagged price (first and second lags) of wheat and its import value and the lagged value of wheat import (wheat import value in the immediate past year) were statistically significant in influencing wheat price in Nigeria. The coefficients of the lagged value of wheat price in the past years (first and second lags) are 0.432 and -0.736, respectively and are significant at 5% and 10% levels of significance, respectively. This implies that a 1% increase in the lagged wheat price will increase wheat's current price by 0,43% in the immediate past years. In contrast, the lagged wheat price will decrease the current wheat price by 0.74 % in the past two years. Thus, the result agrees with Enghiad et al. (2017) that the lagged wheat prices were found among the factors affecting wheat prices.

The import value of wheat exerted a significant and negative effect on the price of wheat at a 1% level of significance. Its coefficient was 0.31, implying that a unit increase in the wheat imported within the reviewed year will decrease its wheat

Variable	Coefficient	Std. Err	P>|t|
Constant	3.209**	2.56	0.017
$(\text{Wheat Price})_{t-1}$	0.432**	3.04	0.006
$(\text{Wheat Price})_{t-2}$	-0.736***	-4.80	0.000
Wheat Output	-0.098	-0.94	0.358
Wheat Import Value	-0.310***	-4.83	0.000
$(\text{Wheat Import Value})_{t-1}$	0.165**	2.69	0.013
Income	-0.771	-1.60	0.121
Exchange rate	0.001	0.47	0.644
F(7, 25)	7.62***	0.0001	0.969
R-squared	0.6808	0.5914	0.222
Log-likelihood	11.7634		
Number of obs	33		
Diagnostics tests			
DW	2.172		
LM	1.309	0.2525	
Heteroskedasticity	36	0.4215	
Skewness	6.99	0.4303	
Kurtosis	1.14	0.2859	
JB	16.62	0.0000	

Note: *, **, *** significance level at 1, 5 and 10% respectively; DW = Durbin-Watson d-statistic (10, 36); LM = Breusch-Godfrey LM test for autocorrelation; JB = Jarque-Bera normality test

Source: Authors' computation (2020)

Table 6: Estimated coefficients for wheat price.

price by 0.31 units. The lagged wheat import value in the immediate past year (first lag) equally exerted a significant but positive effect on wheat's current price in Nigeria (Table 6). The finding agreed with Enghiad et al. (2017) that the importation of wheat is one factor that significantly affects the price of wheat. In Nigeria, there is an increase in wheat flour-based products, which results in heavy wheat demand. There is a need for the country to increase wheat imports to satisfy the market even in high tariffs and exchange rates, thereby influencing the commodity's price behaviour.

Conclusion

This study analyses the implication of agricultural production and importation on food commodity prices in Nigeria using the time series data for 1981–2018. The ARDL bound test approach proposed by Pesaran et al. (2001) was adopted to analyse the cointegration between selected food commodity prices and hypothesized variables. It was established that the variables under study were all stable after first differencing that led to further econometric testing. According to the bound test for cointegration, both short-run and long-run relationships exist among Nigeria's determinants of maize price. Simultaneously, there was no evidence of long-run relationships among the modelled variables for both rice and wheat prices' equations. The diagnostics test conducted certified the model to be statistically fit for estimation.

Application of ECM form of the ARDL approach for maize price model shows that the error correction coefficient, which determines the speed of adjustment, has an expected and highly significant negative sign. The results show that maize import value and exchange rate significantly affect maize's price in the short-run. In contrast, lagged prices (first and second lags) of maize, maize output (and the lagged value of maize output), and the past value of maize imports are the factors that influenced the current price of maize within the review period. Also, the price of rice (first and second lags) and the lagged value of rice imported in the immediate year exerted significant influences on the price of rice in Nigeria. The study indicates that the lagged price (first and second lags) of wheat, wheat import value, and the lagged value of wheat import (wheat import value in the immediate past year) were statistically significant in influencing wheat price in Nigeria.

The ARDL model showed that shock in the exchange rate has high transmission effect on maize price. Intuitively, the accessibility to fund by the producers is determined by the lending rate and exchange rate has great effect on food prices, due to the high importation of agricultural raw material and agricultural product (net importer of food). Market intervention and price fixing policy could be the main impediments to exchange rate in Nigeria. Commodities' price setting and marketing policies aimed at price stability preclude exchange rate effects domestic producer prices. These measures can also insulate the nation's principal source of foreign exchange from instability in the world market.

Also, the responses of rice and wheat prices to their lagged values is significant and positive. The estimated prices though not high, point to the fact that price policy can still partly be used to increase maize and wheat production in Nigeria. This implies that if government must reduce the future price of these commodities, significant measures need to be implemented. The government can subsidize the inputs to enhance production growth and in the long run impose importation tariff to encourage purchase of own produced commodities. This would help in mitigating the effects of rising prices challenge faced by rice and wheat farmers.

It could be concluded that the price of these food commodities has been on the increase over the years which resonates the global surge in the market prices. Due to the unpredictable movement in food prices, the government should ensure the provision of soft agricultural credit scheme to farmers with a low lending rate through Cooperative and Rural Development Banks so as to encourage small holder farmers to increase agricultural production and to overcome the threat of food insecurity in the country.

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Consumers' Preference and Future Consideration Toward Organic Instant Noodles: Evidence from Indonesia

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Abstract

The consumption of instant noodles in Indonesia is the second highest globally. However, people are now more aware of sustainable lifestyles and the health risks of consuming food additives, so some opt for more organic choices, including instant noodles. Research on customers' preferences in this area remains lacking, so the current study aims to fill the gap. This study also analyses the relationship between the choices and consumers' future considerations. Discrete Choice Experiment (DCE) method was used to reveal the perception of sustainable attributes in organic instant noodles. The future considerations were measured using the Future Consequences Consideration (FCC) scale. As many as 592 respondents participated in the study, selected using the convenience sampling method. Data were analyzed using conditional logit via package support.CEs on R software. The findings show that Indonesian consumers' preferences are primarily based on the extrinsic attributes: organic labels and packaging materials, but they also consider the health claims. They will likely prefer instant noodles with organic characteristics for future considerations. The results of this study have implications for instant noodle product development. Young consumers take up a large portion of the market, and they are now more aware of sustainability and health. The current study can inform the product development and the approach to the targeted market. To the best of the authors' knowledge, this is the first study on consumer perception on sustainability attributes in organic instant noodles.

Keywords

Consumer preference, future consideration, discrete choice experiment, organic instant noodle.

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Introduction

Currently, food safety attracts special attention globally, especially on the consumers' side. In recent years, many consumers have been willing to purchase food products that are guaranteed to be safe to consume (Chen et al., 2020). Consumers also notice how products are made, the ingredients, and the safety (Güney and Giraldo, 2019; McFadden and Huffman, 2017; Meas et al., 2015). Therefore, they avoid food containing chemical substances, such as pesticides and antibiotics (Siderer et al., 2005). Consumers are also aware of the carbon footprint of the products they consume. They believe that they should safeguard the environment by purchasing environmentally friendly products (Chiu et al., 2019). Therefore, more and more consumers now opt for organic food products. For instance, between 2000 and 2015, the global organic market increased more than quadrupled (Willer et al., 2018), and currently, the sales have reached USD 90 billion. In Asia, China became the top organic foods producer with more than two million hectares of land and a market share of €5.9 billion in 2016 (Lin et al., 2020). Meanwhile, Indonesia has also contributed to the global organic foods supply. The country is at the top fifth agriculture producers in Asia (Najib et al., 2021; Toiba et al., 2020).

With the rising consumption of organic foods globally, producers innovate based on the trends and changing preferences. There have been substantial studies that investigate the consumers' willingness

to pay for various organic food products, such as organic eggs (Güney and Giraldo, 2019), organic pork (Wang et al., 2018), organic vegetables (Bhattarai, 2019), and organic rice (Jitrawang and Krairit, 2019). However, producers also need to pay attention to consumers' desire to increase consumer interest in organic foods. For instance, modern lifestyles are likely to prioritise time efficiency to reduce time spent preparing and cooking. In this case, consumers likely prefer instant foods (Nagy, 2018). In Indonesia, instant noodles are popular, which can be seen from the number of consumptions that reached 12.52 billion servings—the second after China (World Instant Noodle Association, 2020). The first recorded consumption of instant noodles was dated back to 1972. They are chosen for convenience, low cost, and taste, although they contain monosodium glutamate (MSG) and other chemical additives that could be bad for health (Blossom et al., 2021). Organic instant noodles, therefore, are considered a good alternative.

To date, there have been several studies investigating consumers' preference for the attributes in instant noodles (Akachukwu, 2018; Cha and Wang, 2020; Pangaribuan et al. 2020; Torres et al. 2019). For instance, Cha and Wang (2020) claimed that the essential attributes are affordability, quality, brand, and design; and that these attributes affect consumers satisfaction. Akachukwu (2018) investigated the consumption choice in Nigeria and found that the choice of instant noodles was mainly influenced by taste and availability, consumer's age and family choice. Torres et al. (2019) also summarised that food labelling is an essential attribute to increase the consumers purchasing decision—they purchase when the label shows the nutritional content. Pangaribuan et al. (2020) examined the factors associated with the purchase intention of organic instant noodles in Indonesia. Using the theory of planned behaviour, they indicated that consumers attitudes, subjective norms, and perceived behavioural control significantly influence purchase intention.

Although research on product development has been extensive, research on consumers' perception of the organic instant noodle attributes is limited. Therefore, this study investigates consumers' perception of instant noodles' organic labelling, eco-friendly labelling, and nutrition claims. Furthermore, this study also examines the relationship between future preference, measured by the Future Consequences Consideration (FCC) scale, and preference on organic instant noodles, as well as the consumers' willingness to pay for organic instant noodles.

Theoretical background

Neoclassical economic theory states that rational consumers lean to products with maximum utilities despite budget constraints. They choose a product because of its attributes (Lancaster, 1966), most likely with the highest utility (Manski, 2001). With this premise, researchers can reveal consumers' product preferences because: (1) each choice can be described as a utility-scale index; (2) consumers will choose an alternative with the highest utility index (Lancaster, 1966). Börsch-Supan (2012) denotes the number of n consumers, each of which chooses one among i discrete alternatives. Each alternative is associated with a utility index (U_{in}) that provides an advantage or disadvantage for consumers. Then the utility index is assumed to consist of a deterministic component (V_{in}) and an error component (ε_{in}) as shown in the following equation:

$$V_{in} = U_{in} + \varepsilon_{in} \quad (1)$$

The Discrete Choice Experiment (DCE) approach is a stated preference method with a clear and robust basis (McFadden's Random Utility Theory and Lanchasterian Consumer Theory). Compared to other stated preferences such as Contingent Valuation, DCE has a better external validity (Noor et al., 2022). Respondents are placed in a buying situation with trade-off options like real-life purchasing activities. This method has been widely used to investigate consumer preferences for organic food products (Chakrabarti et al., 2019; Chen, et al., 2019; Li et al., 2019; Wang et al., 2019).

The organicity of food products is a credence attribute only known for certain by sellers or producers. In various DCE studies, organic claims are often presented in labels (Dominici et al., 2019; Risius and Hamm, 2017; Wongprawmas and Canavari, 2017). While organic products hold an essential value for the environment, consumers consider health benefits more. Since Go Organic movement in Indonesia started, organic products have become increasingly consumer-oriented (David and Ardiansyah, 2017).

Instant noodles, a popular source of calories in Indonesia (Dewi, 2016), contain MSG, which is harmful to health if consumed continuously over a long period (Charles et al., 2018; Huh et al., 2017; Tan et al., 2019). In addition, the plastic waste generated from the packaging

has also become an issue (Aday and Yener, 2014; J. Wang et al., 2018). One measure to reduce this plastic waste is to incentivise the use of biodegradable materials (Kakadellis et al., 2021; Mancini et al., 2017; Loo et al., 2019). To date, the organic quality in instant noodles is only about the raw materials of noodles and not so much about the plastic packaging. Considering this, researchers have attempted to develop instant noodles with both quality ingredients and sustainable packaging.

Materials and methods

Samples and surveys

The sample research is determined by convenience sampling because the actual population, instant noodle consumers in Indonesia, is unknown. Screening questions related to the consumption of instant noodles were firstly asked to select the suitable respondents. The data collection was carried out in May-August 2021. Questionnaires were prepared using a google form and distributed online through WhatsApp groups and social media. A total of 592 respondents (from 878 respondents) passed the screening questions and completed all the questions.

Four sections in the questionnaire must be completed by respondents: screening, demographic questions, FCC and DCE. The screening questions revealed whether or not they had purchased instant noodles before and the frequency. The exclusion was if they never consumed instant noodles. After filling in the questionnaire about demographics, they filled in six FCC questions adopted from De Marchi, Caputo, Nayga Jr, and Banterle (2016). This was to look at consumer psychological factors related to future preferences. After that, the respondents received a cheap talk script about the terms used in DCE before filling in the DCE questionnaire.

Experimental design

The initial stage in DCE is the determination of attributes and levels. Based on the literature review (Al-Azawi et al., 2020; Farrand et al., 2017; Li et al., 2021; Marciniak-Lukasiak et al., 2019; Montandon and Colli, 2016; Naspetti et al., 2019), the attributes are organic labels, tastes, packaging materials, food additives, health claims, and prices. Organic labels and packaging materials are sustainable attributes that affect the environment, whereas MSG content and health claims are heatlh attributes. Price is a monetary attribute, and taste is a common attribute for food products. Each attribute consists of three levels, as detailed in Table 1.

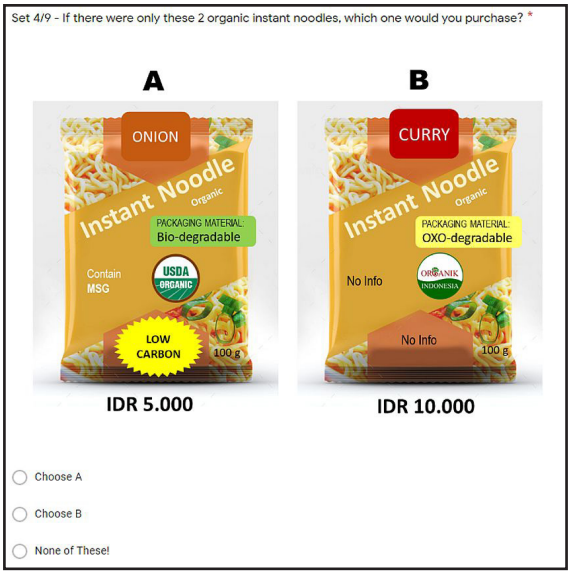
Attribute	Levels
Organic Label	No info*; Organic Indonesia; USDA
Packaging Material	Plastic*; Oxodegradable; Biodegradable
Taste	Onion*; Soto; Curry
Food additive	No info*; Contain MSG; MSG free
Health Claim	No info*; Low Carbon; Low Fat
Price (IDR)	5,000; 10,000; 15,000

Note: * = Reference level; IDR 1= € 0.0000614 (Exchange rate on November 28, 2022)

Source: Authors

Table 1: Attribute and Levels of DCE.

The complete factorial design of the attributes and levels above is 729 combinations of product choices (36). These are too many for respondents to choose from, so the number had to be reduced (Jin et al., 2017). To do so, this study applied the rotation design technique: orthogonal array run using the support.CEs package in the R software (Aizaki et al., 2014; Jin et al., 2017). The final design resulted in 18 combinations that are grouped into two blocks (nine sets per block). Each combination consists of two alternatives and a 'none of the above' option to ensure the external validity. An example of one of the choice sets can be seen in Figure 1.



Source: Authors

Figure 1: One example of choice set.

Data analysis

First, descriptive statistical analysis was performed on the demographic and FCC data, whereas conditional logit was used to analyse the DCE data. The study was carried out using the survival package in the R software. If ASC is an alternative

specific constant that denotes the likelihood of not choosing, β is the effect of product attributes, ε_{ij} is an unobservable error component, then the choice of respondent i in alternative to j is as follows:

$$V_{ij} = ASC + \beta org_{OI} + \beta org_{USDA} + \beta taste_{soto} + \\ + \beta taste_{curry} + \beta pack_{oxo} + \beta pack_{bio} + \\ + \beta msg_{contain} + \beta msg_{free} + \beta health_{fat} + \\ + \beta health_{carbon} + \varepsilon_{ij} \quad (2)$$

Marginal willingness to pay (mWTP) indicates the amount of money consumers spend on organic instant noodle products with specific attributes. An example is how much money consumers are ready to spend on upgrading feature A to feature B. The word 'marginal' refers to the fact that WTP is relative depending on the reference level. If V_j is the coefficient value of the $_j$ level and V_p is the price coefficient value, then mWTP is an absolute comparison of V_j and V_p (Aizaki et al., 2014).

Result and discussion

The respondents' profiles can be seen in Table 2. The most of respondents (62.7%) was women. In terms of age group, most consumers were between 17 and 23 years old (48.1%). Most of them had a bachelor degree (49.3%). The majority's occupation was student (46.8%). As many as 63.2% of respondents were single, and 62.3% did not have children, while 53.5% had 3-4 people in their household. Most respondents had incomes of IDR 1-3 million (€ 61.54 - € 184.62) per month (33.1%) or IDR 7-10 million (€ 430.80 - € 615.75) per month (21.8%). The majority spent between IDR 500 thousand (€ 30.77) and IDR 1 million (€ 61.54) per month (37%). These values are in line with previous study by Toiba et al. (2022).

The results of the FCC measurement are shown in Table 3. In general, respondents showed a high future preference. They think that their current choices will have implications for future

Variable		Freq	%
Gender	Male	221	37.3
	Female	371	62.7
Age	17 - 23 years	285	48.1
	24 - 29 years	93	15.7
	30 - 35 years	42	7.1
	36 - 40 years	37	6.3
	41 - 45 years	37	6.3
	46 - 50 years	55	9.3
	51 - 60 years	43	7.3
Education	Elementary school	1	.2
	Junior High	2	.3
	Senior High	165	27.9
	Diploma	14	2.4
	Bachelor	292	49.3
	Master	89	15.0
	Doctor	29	4.9
Occupation	Student	277	46.8
	Housewife	30	5.1
	Private employee	127	21.5
	Government employee	99	16.7
	Entrepreneur	59	10.0
Marital status	Not married	374	63.2
	Has been married (widow/widower)	11	1.9
	Married	207	35.0

Note: IDR 1 equals to € 0.0000614 (Exchange rate on November 28, 2022)

Source: Authors

Table 2: Respondents' profiles. (To be continued).

Variable		Freq	%
Number of children	Zero	369	62.3
	One child	61	10.3
	Two children	96	16.2
	3 children	44	7.4
	4 children	21	3.5
	More than 4 children	1	.2
Number of family members	1-2 people	42	7.1
	3-4 people	317	53.5
	5-6 people people	207	35.0
	7-8 people	26	4.4
Income (IDR)	< 1 million	93	15.7
	1 - 3 million	196	33.1
	3 - 5 million	101	17.1
	5 - 7 million	72	12.2
	7 - 10 million	129	21.8
	> 10 million	1	.2
Expenses (IDR)	< 500 thousand	73	12.3
	500 thousand - 1 million	219	37.0
	1,5 - 2 million	150	25.3
	2,5 - 3 million	75	12.7
	3,5 - 4 million	35	5.9
	> 4 million	40	6.8

Note: IDR 1 equals to € 0.0000614 (Exchange rate on November 28, 2022)

Source: Authors

Table 2: Respondents' profiles. (Continuation).

Items	Mean	Med	SE
Future consideration and daily behaviour influence	5.91	6.00	0.04
Achieving not immediate outcomes	5.26	5.00	0.05
Sacrificing immediate wellbeing for future outcomes	5.69	6.00	0.05
Avoiding negative outcomes seriously	5.47	5.00	0.05
Performing necessary to distant consequences behaviour	5.74	6.00	0.05
Future-based decision making	5.92	6.00	0.04
Future consequences behaviour	5.73	6.00	0.05

Note: 1 = strongly disagree; 7 = strongly agree

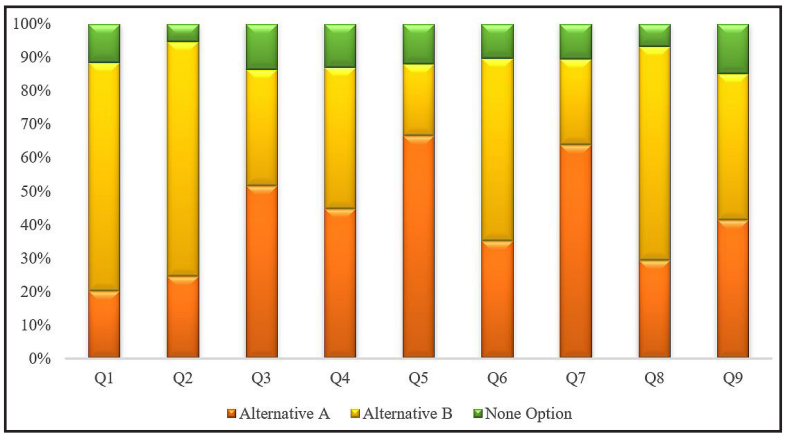
Source: Authors

Table 3: Descriptive statistic of Future Consequences Consideration (FCC).

preferences. They are also willing to delay gratification for a more long-term benefit. In other words, their decision making is primarily based on future benefits and consequences rather than any immediate satisfaction.

Figure 2 Shows the proportion of consumers who did not choose each alternative given in the choice set by selecting the 'none of the above' option. In DCE, this option is stated as Alternative Specific Constant (ASC), which is always present in every choice set. The proportion of opting-out in each choice set is at 14.8%, which means that more than 80% of consumers selected their option, either alternative A or B.

The conditional logit estimation results (Table 4) show that consumers prefer organic instant noodles more than the non-organic alternatives. The probability of selecting instant noodles with Indonesian Organic and USDA certificates is 2.2 times compared to the non-organic instant noodles. Furthermore, the coefficient value of oxo-degradable and biodegradable packaging



Source: Authors

Figure 2: Opt-Out rate of DCE scenarios.

Level	Main Effect			FCC Interaction		
	β	Exp(β)	SE	β	Exp(β)	SE
ASC	-0.08	0.90	0.10	0.20	1.02	0.10
Organik Indonesia	0.80***	2.21	0.07	0.10***	1.00	0.01
USDA	0.80***	2.21	0.05	0.10***	1.01	0.01
Soto Flavour	-0.04	1.03	0.06	-0.02	1.00	0.01
Kare Flavour	-0.10*	0.91	0.06	-0.04**	1.01	0.01
Oxodegradable packaging	0.80***	2.05	0.06	0.10***	1.00	0.01
Biodegradable packaging	1.00***	3.02	0.06	0.20***	1.03	0.01
Contain MSG	0.20**	1.02	0.06	0.02**	1.00	0.01
Without MSG	0.72***	2.00	0.06	0.10***	1.00	0.01
Low Carbohidrate	0.70***	2.03	0.06	0.10***	1.02	0.01
Low Fat	0.70***	2.00	0.05	0.10***	1.01	0.01
Price	0.00***	1.02	0.00	0.00***	1.00	0.00

Note: *** = $p < 0.001$; ** = $p < 0.01$; * = $p < 0.05$

Source: Authors

Tabel 4: Conditional logit estimation of main effect and FCC interaction.

materials shows a significant positive number, which means that consumers are more inclined to select environmentally friendly packaging. The probability that consumers choose biodegradable packaging is the highest, which is three times more likely than plastic packaging. In terms of ingredients, consumers show a significant preference for noodle products without MSG. The probability of choosing instant noodles without MSG is two times higher than those without MSG content information. Meanwhile, low-carbohydrate and low-fat claims have a significant influence on consumer preferences. Consumers prefer instant noodles with the claims to those without any claims. The price coefficient calculated linearly showed a negative coefficient value, which means that consumers tend to choose low prices.

The conditional logit estimation on the interaction model with the FCC shows similar patterns. In general, consumers with future preferences (high FCC) are one-time more likely to choose organic instant noodles with sustainable packaging and health claims and without MSG. The interaction between consumer and time preferences can be seen in Table 4. Consumers with future preferences have a higher chance to choose organic over non-organic instant noodles.

In aggregate, consumers are willing to pay higher prices for organic instant noodles, both with Indonesian organic certification for (€ 1.14) and USDA (€ 1.13). Biodegradable packaging materials received the highest rating, indicated by consumer mWTP for € 1.64, while

oxo-degradable packaging materials scored mWTP for € 1.13 compared to plastic packaging. Consumers are willing to pay more for instant noodles with MSG-free claims (€ 1.02). Regarding health claims, consumers are willing to pay more for low-carbohydrate (€ 0.93) and low-fat claims (€ 1.03).

Using DCE, this study reveals that consumers have specific preferences and are willing to pay more for organic instant noodles. Public awareness about a healthy lifestyle plays a role in increasing the consumption of organic foods (Asif et al., 2018). The utility values of the Indonesian organic certification and USDA are not much different, which means that whether a product is locally or internationally certified does not affect the choice of Indonesian consumers. In line with several studies (Li et al., 2019; Nesselhauf et al., 2019), these findings indicate that Indonesian consumers rely more on a third party (certification provider) upon in ensuring the quality of organic instant noodles.

Biodegradable packaging materials are the most preferred packaging materials for organic instant noodle consumers. This preference is related to consumer awareness of sustainability, where food packaging materials from plastic have become pollution on earth (Kakadellis et al., 2021). This packaging material also received the highest mWTP value among other level attributes. In line with Lago et al. (2020), this study shows that young Indonesian consumers are willing to pay higher for the sustainability features in organic instant noodle packaging.

Health claims have a significant impact on consumer preferences. Information about the MSG content in organic instant noodles determines consumers' purchasing due to their health concerns (Sikander et al., 2017). This perception significantly influences the health attributes (MSG-free, low fat and low carbohydrate).

The first implication of this research is on the product development. Consumers show the highest preference for biodegradable packaging materials, which means that the development of organic instant noodles should concern about both the ingredients and the packaging materials. In other words, the product development must be both customers- and environment-oriented. Lastly, certification is essential because consumers still lean to a third party in ensuring the quality of food products.

Conclusion

This study aims to analyse consumer preferences for sustainability and health attributes on organic instant noodles and their influence on future considerations. This study involves 592 respondents to participate in an online survey. A discrete choice experiment model is used to determine consumer preferences, and the data were analysed using conditional logit via package support.CEs on R software.

The analysis results show that consumer preference for organic instant noodles is higher than traditional instant noodles. Organic labels and packaging materials, extrinsic attributes score high among the consumers, similar to the health attributes. Psychological factors about future preferences as measured using the Future Consequences Consideration (FCC) scale show a similar pattern to the current tendencies. The direction of organic instant noodle product development is to consider consumers' needs and the environmental impacts.

This study implies that consumers have a high preference for sustainability attributes, such as biodegradable packaging of noodle products. This fact provides evidence that sustainability branding positively influences the assessment of a product. If companies can communicate this issue well to consumers, the market expansion is promising. Practically, product advantages for environmental sustainability might be a marketing strategy's main focus. Through marketing initiatives, consumers might be persuaded that by purchasing organic instant noodle products, they not only receive healthier food but also have contributed to a better environment.

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