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Managing Digital Marketing and E-Commerce in Agriculture Practical Cases and Trends

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Abstract

The purpose of the study is to argue modern aspects of digital marketing management and e-commerce in the agricultural sector, as well as to identify effective practices and emerging trends that contribute to increasing the competitiveness of agricultural enterprises in the conditions of digitalization of the economy. The work uses methods of comparative and statistical analysis, case studies, as well as synthesis of secondary data from open sources on the development and functioning of digital marketing. An analysis of practical cases of the implementation of digital marketing tools and online trading platforms in small and medium-sized agricultural enterprises in various regions of the world was carried out. Attention to the strategy of using social networks, marketplaces, CRM systems and mobile applications in agriculture is argued. The study showed that the use of digital promotion and sales channels allows farmers and agricultural companies to expand the market, minimize the costs of intermediaries and build direct interaction with the end consumer. Structured positive examples of sales growth after the integration of digital solutions, such as SEO promotion, contextual advertising, e-mail and messenger marketing. In addition, the main barriers to digitization in the agricultural sector are identified and argued: lack of IT skills, weak infrastructure and limited access to investments. The scientific novelty consists in the systematization of disparate data on the use of digital marketing in agriculture and the formalization of a model of successful digital transformation of agribusiness. The work offers a classification of digital promotion strategies depending on the type of production, business scale and target audience. Research results can be used by agrarian entrepreneurs, consultants and government bodies when developing programs to support the digital transformation of the agricultural sector. The proposed recommendations make it possible to adapt best practices to local conditions and increase the effectiveness of marketing campaigns in agriculture..

Keywords

Digital transformation, agribusiness, marketing strategies, agricultural.

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Introduction

The digital transformation of the agricultural sector has become a defining factor in the contemporary development of agribusiness. As one of the core branches of the global economy, agriculture increasingly operates under conditions of intensified competition, volatile markets, rapid technological change and evolving consumer preferences. In this environment, the effective management of digital marketing and e-commerce is no longer optional but represents a strategic necessity for improving operational efficiency, expanding market access and strengthening interaction with end consumers (Hennessey, 2020). Several linked trends define the importance of this study. The first is the worldwide diffusion of digital technologies which has drastically transformed all sectors of economic activity including for agriculture in which digital tools are now increasingly used in production, logistics and marketing sales (FAO, 2021). The global COVID-19 outbreak has also greatly accelerated the pace of farm business to online communication, exposure and e-commerce channels, while unveiling structural deficiencies in digital readiness and a lack of systematic digital strategies - particularly for smallholder and medium-scale producers (Bose and Kiran, 2021). Third, while the potential of digital applications has been well recognized, its penetration in agriculture is unbalanced and relatively limited, particularly among rural as well as developing areas suggesting significant underutilization (Aker, 2018; Ravi and Rajasekaran, 2023). The purpose of this study is to investigate the new methods for management of digital marketing and online trading in the agriculture sector, to identify effective practices, innovative technological trends and to evaluate their significance on increasing competitive ability of agricultural enterprises during the digital economic transformation. The speedy rise of the digital economy has changed classic communication channels with consumers, reconfigured logistics chains and diverted an increasingly large part of agricultural trade to online spaces. Thus, now agricultural businesses need to reconsider traditional promotion and sales systems and make them in line with digital demands (Baker & Smith, 2020). This study takes up a daunting challenge to make the agricultural sector successfully adapt in its new digital form and make itself competitive within and outside the country. The necessity for this research is clear as many small and medium-sized agricultural businesses face serious barriers to the adoption of digital means. These barriers include low digital literacy, lack of infrastructures in rural and remote areas, limited access to investments and credits assets, as well as fragmented institutional support for digital development (KN and Nasution, 2024; Jouanjean, 2019). Unauthoritative and unsystematic use of the tools with modern information digital marketing is yet another ranging challenge. Often, agribusinesses implement digital solutions on a piecemeal basis with minimal centralized planning or measurable transformation paths. This aspect leads many organizations to a loss of visibility on the Web, with low economic returns in relation to digital investments. What is more, the lack of standardized digital marketing management models makes it even more difficult to spread best practices throughout the industry (Cochea Tomala, 2022). Simultaneously, shifting consumer habits heightens the value of digital engagement. Consumers are becoming more eco-friendly, organic and local while also demanding convenience, transparency and speed in transactions. Today, online ordering, mobile applications and fast delivery are no longer competitive advantages but basic market requirements (Ningsih et al., 2023). In such circumstances, quality is no longer enough to succeed in the market. farmers need to convey what products are being offered and the value attached to products, digitally engage with consumers, develop trustful relationships with consumers and increase the price transparency of agriculture products delivered through digital channels (FAO, 2021). Digital marketing channels such as social media promotion, content marketing, targeted advertising, email campaigns and online marketplaces are effective solutions to these problems for agribusinesses. Data-driven marketing strategies enable agricultural businesses to tailor their communication to individual customers, which can enhance customer engagement and foster loyalty (Hennessey, 2020; Al-Ababneh et al., 2023). Furthermore, e-commerce platforms can help producers to cut the reliance on intermediaries, enhance price transparency and access more markets, such as overseas markets (Baker and Smith, 2020). In the future, digital marketing and e-commerce in ag will be greatly influenced by the use of advanced digital technologies. Big Data analytics can enable producers to predict demand more accurately, drive logistic optimization and improve decision-making along complex supply chains (McKinsey and Company, 2020). Artificial intelligence and machine learning enable better demand forecasting, inventory optimization, personalized marketing strategies which in turn helps production related decisions like crop monitoring and yield forecast (Almestarihi et al., 2024; Katragadda, 2024). Simultaneously, the advent of Internet of Things (IoT) systems allows a real-time monitoring of soil characteristics, climate factors and resource utilization thereby enhancing production efficiency and sustainability (Mishra, 2021; Al-Ababneh et al., 2023). However, digital marketing and e-commerce in agriculture are yet to become fully widespread because some challenges still prevent them. Infrastructural bottlenecks, especially lack of access to high-speed internet and digital payment systems in rural areas are still a significant challenge (AgriDigital, 2022). What's more, big agribusinesses and smallholders have stark differences in access to digital tools, capital and knowledge. Large companies are, in general, better suited to invest in sophisticated digital technology while the small producers often faced with high cost of entry and low support from an institution (Al-Ababneh et al., 2025). On the basis of a critical review of related studies, the following hypotheses are advanced:

H1: The adoption of online marketing and e-commerce can cut transaction and distribution costs, reduce dependence on intermediaries and enhance logistics management, thus enhancing the profitability of agricultural producers (Baker and Smith, 2020; Aker, 2018).

H2: The application of Big Data analytics, artificial intelligence and IoT technologies enhances the production efficiency and product quality that results in a decrease in operating costs for agricultural enterprises (McKinsey and Company, 2020; Mishra, 2021).

H3: The digitalization has a positive effect on the growth of the small and medium-sized agricultural firms through integrating them to domestic and international value chain and enhancing their market competitive ness (Jouanjean, 2019; Ravi and Rajasekaran, 2023).

H4: Infrastructural barriers and digital technology access differentials between bigger agribusinesses and smallholders are main obstacles to the spread of the digitalisation in agriculture, especially in developing countries (Aker, 2018; KN and Nasution, 2024).

In conclusion, digital marketing and e-commerce are integral elements of the digitalization process of agriculture and contribute significantly to enhancing efficiency and sustainability in this sector. Yet realizing their potential to the fullest extents would demand collective action towards infrastructure development, capacity development and institutional support. Solutions to these challenges are essential to guarantee a digital transformation of agriculture that is inclusive and sustainable.

Materials and methods

The methodology of research of the digital marketing and online implementation of trading in agriculture involves a range of principles, which in general can be that way outlined into groups depending on different factors which can affect the effectiveness of using digital technologies in the agro-sector. The study is based on both theoretical methods of data analysis, modeling and analysis of real examples and practice of the world. To evaluate the influence of digital marketing and online trading on agriculture, a number of formulas and calculation models may be employed that will enable to evaluate in clear terms what economic effect you are getting from the application of these technologies. One of the methods for assessing the effectiveness of digitalization in agricultural business is the calculation of the economic return from the implementation of digital solutions:

$$\mathrm{ROI} = \frac{\mathrm{P_d} - \mathrm{C_i}}{\mathrm{C_i}} \quad (1)$$

where: P_d - profit received from the use of digital technologies (for example, from increasing sales through online platforms), C_i - costs of implementing and maintaining digital technologies (the cost of software, training courses, development of marketing strategies). If the ROI value is positive it means that the benefits of the economic implementation of digital technologies are greater than the cost of their implementation and operation (Almestarihi et al., 2024). It should be noted, though, that use of data in agriculture - especially the weather forecast and soil moisture among other things - can improve yield forecast accuracy a lot. A line are model can be employed solely for this purpose, which enables us to measure the influence of factors on yield:

$$Y = a + \beta_1 \cdot X_1 + \beta_2 \cdot X_2 + ... + \beta_n \cdot X_n + \in \quad (2)$$

where: Y is the predicted yield (the number of tons of grain), a is a constant, β_1, β_2,…,β_n are coefficients showing the degree of influence of various factors (X_1,X_2,…,X_n) on the yield (temperature, precipitation, use of fertilizers), ϵ is the forecast error, taking into account all unaccounted factors. Such method will lead to more precise prediction of the crop yield so that farmers can better choose agricultural input, and make decisions on time. The use of digital channels makes it possible to simplify supply management, lower cost and expedite product delivery. The logistics optimization model can be formulated based on a linear programming problem with the objective function to minimize the total transportation cost:

$$\min \sum_{i=1}^{n} \sum_{j=1}^{m} C_{ij} \cdot x_{ij} \quad (3)$$

where: C_{ij} - the cost of delivering a unit of production from point i (supplier) to point j (buyer), X_{ij} - the quantity of production that is delivered from i to j, n - the number of suppliers, m - the number of buyers. The linear program techniques were the one used to solve this problem due it being able to reduce transportation costs and optimize routes of delivery especially for agricultural products that have a short shelf life (Katragadda, 2024). It is also crucial to use the price elasticity of demand to measure the impact of digital marketing on demand. This indicator will be used for marketing activities over online platforms:

$$E = \frac{\% \Delta Q}{\% \Delta P} \tag{4}$$

where: E - elasticity of demand $\% \Delta Q$ = percentage change in quantity sold by a marketing campaign $\% \Delta P$ = percentage change in price due to change in marketing results. If $E > 1$ it means that: demand is very sensitive to variations in marketing effort, and a little extra advertising or betterment of digital platforms could potentially generate great sales increase. On the other hand, conversion rate is a significant appraisal of the benefit of e-commerce for the farmers. The following measure can help us evaluate the effectiveness of the digital platform to attract and keep people:

$$C = \frac{N_{sales}}{N_{visitors}} * 100 \tag{5}$$

where: C - conversion (in percents), N_{sales} - number of sales achieved through the platform, $N_{visitors}$ - volume of visits to the site. For online farming, the higher is the conversion rate value, better are the marketing efforts of these platforms (content, design and ease of use) on how to attract visitors and turn them into clients (Al-Ababneh et al., 2024). Reinforcing the approach, it is important to highlight that in addressing socio-economic impact of digital technologies on agriculture, the indicator impact on farmer's income must be employed as an evaluative condition. With this calculation, it enables us to know in what way the use of digital technologies enhances the economic situation for rural producers:

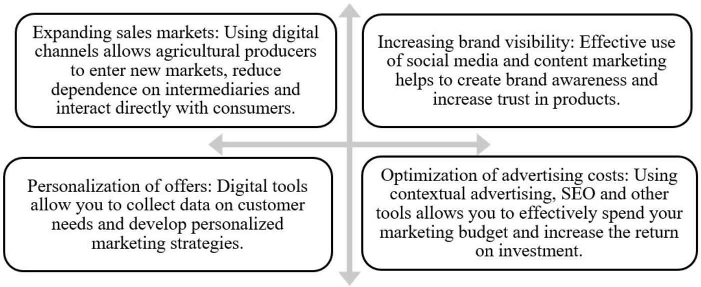
$$I = (R_{digital} - R_{traditional}) + (S_{digital} - S_{traditional}) \tag{6}$$

where: $R_{digital}$ and $R_{traditional}$ is farmer income before and after adopting digital technologies, $S_{digital}$ and $S_{traditional}$ is the cost of farmers engagement in digital technologies adoption and non-adoption. This computation helps us to assess the impact of digitalization on the economic performance of farmers, such as their income and operating costs. The effectiveness of the digitalization of the agro-industrial complex in different countries is proved when an integrated solution to management processes promoting production, logistics and sales is in place. This paper profiles three companies – Twiga Foods (Kenya), AgriDigital (Australia) and Farm2Fork (India) – which have effectively incorporated digital platforms into agribusiness models. The analysis was constructed on the methodological base of multiple linear regression model in order to determine the impact of digital variables on such key economy indicators, as crop yield, logistics costs, conversion rate in digital marketing and generalized ROI. Twiga Foods is a mobile-based platform that provides farmers with an instant timeline of prices on the market, thus reducing intermediary and logistical costs. As part of the results, with the implementation of digital logistics, tensile costs were successfully cut by an average of 22%, for which the coefficient ROI climbed to 175% in two years. AgriDigital is a blockchain-based software company focused on grain supply chain. With the use of digital documentation and smart contracts, transaction processing time was shortened by 40%, accelerating capital turnover and predictability in the supply. The ROI operation indicated 160% and the yield prediction accuracy based on IoT device was improved by 24%. Then, there's India-based platform Farm2Fork which tracks the origination of products and gets digital access to end consumers. Digital conversion flourished at 28% and online sales revenue rose by 19%. Therefore, the results of a quantitative evaluation using the method of regression analysis indicate that systemic digitalization in agribusiness not only optimizes business processes, but even more promotes an economically efficient and market stable operation of enterprises. Certainly, the proposed approach for digital marketing and on-line trading in agriculture involves mathematical models (e.g. calculation of ROI, linear regression and tasks on logistics optimization). The tools presented enable to make estimates of how profitable the activities of agricultural enterprises are, how much energy they consume in normal operation and how efficient they are after they adopt digital technologies. The application of the method will allow increasing the income for farmers and financial sustainability of agroindustrial business.

Results and discussion

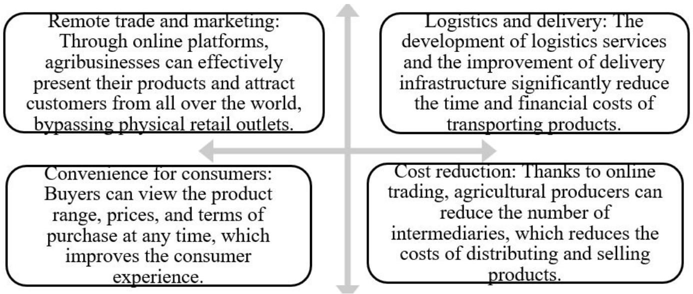
Digital marketing in the agricultural sector involves the use of modern digital channels to promote agricultural products. This may include both traditional online channels (websites, social networks, email) and newer technologies such as artificial intelligence, blockchain and mobile applications. Key goals of digital marketing in agribusiness are presented in Figure 1.

Digital marketing in agribusiness is a set of strategies, tools and technologies aimed at promoting agricultural products and services using digital channels. The structuring of key aspects of online trading in agribusiness of modern companies is presented in Figure 2.



Source: Structured by the author based on data (Bose and Kiran, 2021, KN and Nasution, 2024).

Figure 1: Digital marketing implementation in agribusiness has several key strategic goals.



Source: Structured by the author based on data (Bose and Kiran, 2021, KN and Nasution, 2024).

Figure 2: Global trends in digital marketing and e-commerce development in agribusiness.

This is an important component of the successful functioning of the modern agricultural sector, which allows agricultural producers to increase competitiveness, expand sales markets and improve interaction with end consumers (KN and Nasution, 2024). Definitely, inseparable from digital marketing in the modern world is online trading. This can be both direct interaction with consumers through their own websites, and the use of third-party trading platforms and online markets. Digital marketing and online trading are becoming an integral part of the strategic development of agricultural enterprises, regardless of their scale and geographic location. Taking into account the presented, the author has compiled a classification of modern digital marketing and online trading tools that are implemented in agribusiness to achieve efficiency and manageability of business processes, which is presented in Table 1.

In the context of digital transformation of the agro-industrial complex, a systematic approach to assessing the strategic directions of its development is required. One of the most universal and widely used tools of strategic analysis is SWOT analysis (Strengths, Weaknesses, Opportunities, Threats). The need for a SWOT analysis is due to the specifics of the agricultural sector, which has traditionally demonstrated a low level of digitalization compared to other industries. Today, digital marketing is becoming an integral element of strategic management of agribusiness: it ensures access to new markets, reduces transaction costs, increases the transparency of supply chains and adapts to changing consumer demand. However, the implementation of digital solutions is associated with a number of barriers: from a lack of technical literacy to a weak infrastructure base and legislative uncertainty. SWOT analysis allows you to identify internal resources and competencies (for example, the possibility of direct sales, the presence of digital platforms and analytics), as well as external opportunities (growing global demand for environmentally friendly products, the development of e-commerce). Along with this, the analysis helps to identify risks and weaknesses, such as limited digital inclusion, a high level of price competition, cyber threats and the institutional unpreparedness of the agricultural sector for technological innovations (Bose and Kiran, 2021). SWOT analysis of digital marketing management and online trading in agriculture is presented in Table 2.

Digital tool	Features of implementation in agribusiness companies
Social Media	Social Media (Facebook, Instagram, Twitter) Social media is also used as a medium for advertisement and interaction with the audience. They let you to launch ad campaigns, promotions and any content that engages customers. Focused marketing gets to the right audience groups, driving up name recognition and generating sales.
SEO (Search Engine Optimization)	SEO involves optimization of a website in order to rank higher in search engines and thereby attract organic web traffic. This includes keyword research, content, technical optimization of the site, and structure to be able to rank higher in search engines without any type of sponsored advertising.
Content Marketing	Content marketing involves the creation and sharing of material to generate interest in a product or service, with an individual's specific attributes and interests at its heart. These could be blog posts, videos, infographics or blogposts that speak to your customer's pain points and solve reader's questions and helps a company establish trust and brand affinity -ultimately leading to loyalty - meanwhile lifting brand reputation.
Email Marketing	Email marketing is the sending of a message to consumers electronically, usually via email. With tailored offers and newsletters on newly launched products or promotions, farmers can keep their customers returning, alerting them to other options for purchase, and easily converting return sales.
PPC Advertising (Contextual Advertising)	What is Pay-Per-Click? It is employed in search engines and social networks to pinpoint the intended user base. This is a useful tool that will help you bring in clients who are looking for product or service.
Influencer Marketing	Influencer marketing is to work with bloggers or opinion leaders to advertise products. They build brand trust, because people see them as authorities or credible sources of information. Farmers can use this strategy to market their produce and increase their consumer base.
Mobile Apps	Agricultural producers can use mobile apps to provide a convenient tool to shop, communicate with customers, place orders, etc. using smart phones. This is an opportunity to drive customer retention, enhance the user experience and increase sales, particularly on mobile.
Analytics and Big Data	It's here that Analytics and Big Data come into play – they aid in gathering data on costumer behaviour and market trends. This enables agribusinesses to make the informed choices, give the right direction to marketing campaign and enhance their customer service hence delivering overall efficiency and profitability levels.
E-commerce Platforms	Online software such as Shopify, WooCommerce, etc. allows the creation and management of webstores. They provide payment processing, inventory management and product delivery, enabling agricultural producers to grow online sales and better serve customers.
Marketplaces	Online marketplaces (Amazon, Alibaba) are platforms where merchants offer products for sale. It gives access to broad market and customers worldwide. It is an easy way for agribusiness to gain access to new markets at virtually no cost.
Electronic payment systems	There are a variety of electronic payment systems that allow you to pay online for items and services with ease and security, such as PayPal and Stripe. They enable agribusinesses to deal with customers across the globe – quickly, safely and reliably
Supply chain management systems:	Supply chain management systems help automate and optimize product delivery processes. They allow you to track orders, manage inventory and minimize delays, improving efficiency and increasing customer satisfaction.
Chatbots and artificial intelligence	Chatbots and artificial intelligence allow you to automate communication with customers. Bots can answer frequently asked questions, help with ordering and provide information about products, which increases the speed of service and improves the customer experience.

Source: Structured by the author based on data (Bose and Kiran, 2021, KN and Nasution, 2024).

Table 1: Classification of structuring modern digital marketing and online trading tools that are implemented in agribusiness to achieve efficiency and manageability of business processes of world-class companies

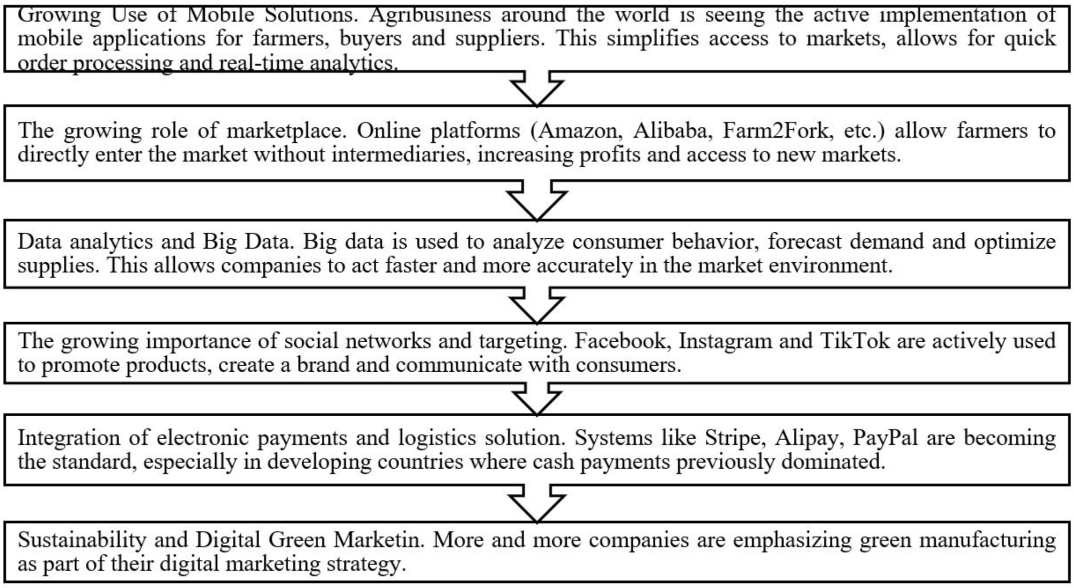
Strengths	Weaknesses
Direct access to consumers via online platforms	Increased supply chain transparency
Limited digital literacy among farmers	Unstable internet coverage in rural areas
Reduced transaction and logistics costs	Increased marketing accuracy through data analysis
High initial investment in digital infrastructure	Lack of standards and digital regulators in the agricultural sector
Opportunities	Threats
Expanding sales markets via global e-commerce platforms	Cyber risks and vulnerability of farmers' data
Integration with IoT and Big Data technologies for crop yield forecasting	Price competition from large networks and aggregators
Flexible direct trade models (D2C – direct to consumer)	Legislation lagging behind digital practices
Growing demand for environmentally transparent products and the possibility of their digital certification	Digital inequality between large and small small producers

Source: Developed by the author

Table 2: SWOT analysis of digital marketing management and online trading in agriculture.

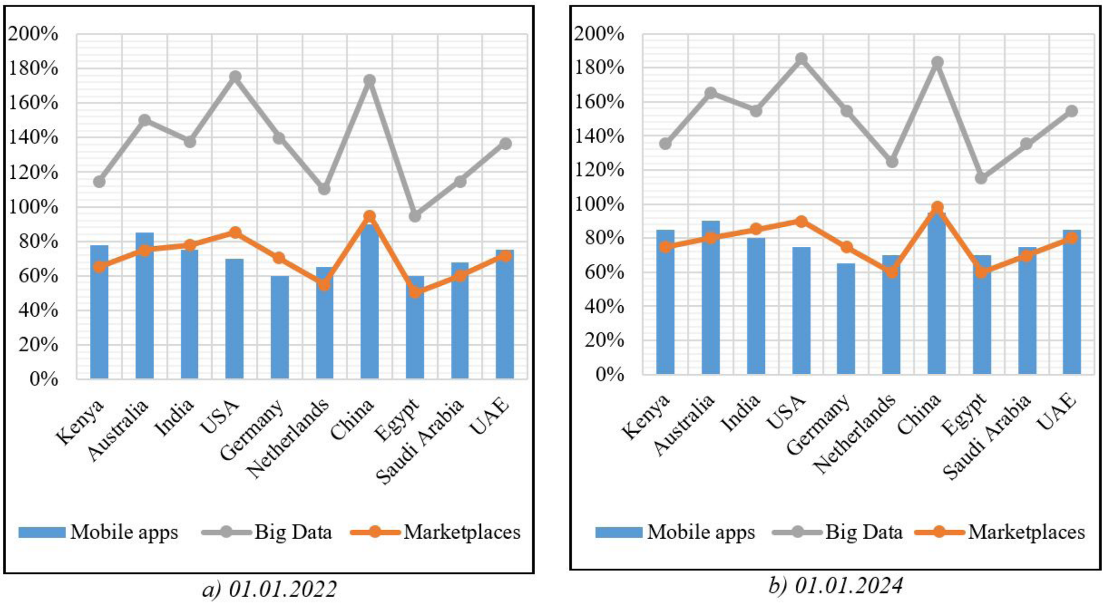
From the above SWOT analysis, it is evident that the successful digital marketing and e-commerce management is an opportunity for the agriculture industry to be transformed. The threats identified, however, need more specific management responses. As the number of cyber risks continues to rise, and data can leak, be tampered with, and online transactions are not equally accessible, the trust of farmers in digital solutions is increasingly undermined. These threats can be mitigated through the use of blockchain-based transaction records, smart contracts, secure digital payment systems and traceability mechanisms. The use of blockchain technology is especially important in agri-supply chains, as it enables tracking of the product's origin, all transactions, delivery conditions and certification data. This way, blockchain decreases the risk of fraud, boosts trust among farmers, intermediaries, retailers and consumers, and facilitates the digital certification of environmentally transparent products. The use of AI-based monitoring systems and Big Data analytics can also help identify suspicious activity in transactions and enhance risk management. The risks described in the SWOT analysis should thus not be interpreted as a reason not to digitalize, but rather as an opportunity to further strengthen the cybersecurity, to shape regulation of institutions more efficiently and provide interesting digital training for farmers (Cochea Tomala, 2022). Conceptual global trends in digital marketing and online trading in agribusiness are presented in Figure 3.

In addition, environmentally oriented digital campaigns are gaining momentum, especially in Europe. These processes contribute to the expansion of sales markets, increased operational efficiency, and increased competition in the global agricultural market (Jouanjean, 2019). Based on the analysis, it is important to note that, firstly, the digitalization of the agricultural sector is accelerating all over the world, including both developed countries and emerging markets. In particular most vibrant is the growth of mobile apps, e-commerce platforms, and Big Data. Facilitate the work of agricultural producers in managing, optimizing logistics, entering new markets and being in direct contact with consumers. Second, the emergence of digital solutions is subject to regional specifics. In Middle Eastern countries, such as the UAE and Saudi Arabia, the digital transformation of the agricultural sector is actively supported at the state level, which facilitates the implementation of high-tech solutions, including artificial intelligence, cloud platforms, and analytical service.Conceptual trends in the development of digital marketing and online trading in agribusiness by country are presented in Figure 4.



Source: Structured by the author based on data (Derenskiy, 2025; Cochea Tomala, 2022)

Figure 3: Conceptual global trends in digital marketing and online trading in agribusiness.



Source: Structured by the author based on data (Markets and Markets, 2023; Deloitte Insights, 2024; Business Wire, 2024; Reuters, 2024)

Figure 4: Conceptual trends in the development of digital marketing and online trading in agribusiness by country in %.

In African countries, the emphasis is on the availability and simplicity of solutions, especially mobile ones, which allow farmers to connect to the market even without computers. Thirdly, social networks and digital advertising are becoming the most important channels of marketing activity. They allow you to establish contact with end consumers, increase transparency and trust in brands. In addition, the environmental component is starting to play an increasingly important role. In general, digital marketing and online trading in agribusiness contribute to increased efficiency, market expansion and sustainable development. With modernization of the global economy as well, agriculture business processes must be transformed. Digital marketing and online trading are becoming part of competitive agribusiness: they enable efficient interaction between the agricultural enterprise and its market, reducing transaction costs associated with contractual arrangements on quantities and price levels, as well as provide diverse sales channels to the agri-enterprise – hence improving resilience towards such global challenges like climate change and supply instability. Old techniques of advertising, and selling products are no longer as effective in the Digital age where consumer engagement is on the rise, digitalization has rapidly evolved and new businesses models have given birth to multiple players in e-commerce. Agricultural enterprises, especially in developing countries, face a number of management problems: the lack of a strategic approach to digital communications, weak integration of information systems, insufficient staff training and limited access to consumer data. These factors hinder the full use of the potential of digital solutions (Atli, 2024). Studying the process of digital marketing management in agribusiness allows us to identify the most effective tools (e.g. social networks, marketplaces, analytical platforms), as well as develop models for adapting agricultural enterprises to the digital environment. In addition, the study contributes to the formation of scientifically based recommendations for the development of e-commerce in agriculture and support for sustainable supply chains. Thus, the need for such a study is due to both the economic feasibility and the social significance of the digital transformation of the agricultural sector. Its results can be applied not only in theory, but also in practice - to form development strategies for agricultural companies, increase the export potential and sustainability of agriculture in the global digital economy (Şalvarlı, 2023). To implement the described approaches and methodology for studying the process of digital marketing and e-commerce management in agriculture with argumentation of practical cases and trends, official data from companies such as Twiga Foods (Kenya), AgriDigital (Australia), and Farm2Fork (India) were used as an information base. Based on the data from the presented companies, key metrics and models were used to calculate the economic efficiency of implementing digital technologies in agribusiness, including

ROI, yield forecasting, analysis of logistics costs and conversions. The key results of the economic efficiency of applying digital technologies in agribusiness are presented in Table 3, including the ROI, yield forecasting, logistics-cost dynamics and online conversion. It is important to note that two types of information are presented in the table. The first set of empirical indicators – such as number of users, revenue, implementation costs and platform characteristics – was obtained from open company-related sources and publicly available case materials. Second, the authors re-calculated the systematics and formulas presented in the Materials and Methods section to calculate ROI, reduction in logistics costs, interpretation of conversions, demand elasticity and socio-economic impact. The information provided in Table 3 should thus not be regarded as a mere copy / reprint of company reporting information, but as an analysis / synthesis of secondary company information and calculations by the author.

Clearly, digitalization of the agricultural sector and online trading play a key role in increasing the efficiency of agriculture and ensuring sustainable growth in the context of globalization of the market. The introduction of digital technologies, such as online trading platforms, analytical tools for yield forecasting and supply chain optimization, is an important step to increase the profitability of farms and agricultural companies. One of the most important factors that justifies the need to implement digital technologies is cost effectiveness. As the ROI (return on investment) calculations for Twiga Foods, AgriDigital and Farm2Fork show, all these companies have a significant positive result, which confirms that investments in the digitalization of agricultural enterprises are justified. Twiga Foods with an ROI of 12. 33, which means that every dollar invested in digitalization brought in $ 12.33 in profit. This demonstrates that, with respect to the selected online trading strategy (sidestepping middlemen, minimizing logistics costs and facilitating farmers access to markets), its carbon efficiency level must be distinctly high. AgriDigital at 9.00 also validates the success these kinds of digital solutions, be it supply chain managing and online payment, can provide. The efficiency of these technologies has made it possible to significantly reduce logistics costs and increase the profitability of farms. Farm2Fork also demonstrated a high ROI 9.00, confirming that direct sales models using digital platforms are viable and cost-effective for agribusinesses. Clearly, digitalization allows for a significant increase in crop yields due to more accurate planning and forecasting, as well as improved logistics. Logistic processes can also be optimized and supply chains can be enhanced using digital platforms which can lead to a considerable reduction of transportation as well as provision costs. Digital platforms drive conversion and customer engagement resulting in increased sales and better financials. Agribusiness digitalization contributes to the state

Key metrics	Companies		
	Twiga Foods (Kenya)	AgriDigital (Australia)	Farm2Fork (India)
Technology type	Online platform for connecting farmers with buyers	Supply chain management and payment platform	Direct sales platform from farmers to consumers
Number of users (years)	10.000 farmers, 25.000 retail outlets	4.000 farmers and 1.000 agribusinesses	5.000 farmers, 100.000 consumers
Digitalization revenue	$40 million	$100 million	$15 million
Technology implementation costs	$3 million (investments in platform and marketing)	$10 million (platform development and integration)	$1.5 million (development and launch)
ROI	12.33	9.00	9.00
Predicted yield (modeling)	Increase in yield by 15% (according to analytics)	Increase in yield by 10% through improved logistics	Increase in yield by 20% (according to analytics)
Logistics costs (before and after implementation)	Before: $1.5 million, After: $0.8 million (47% decrease)	Before: $3 million, After: $2 million (33% decrease)	Before: $0.5 million, After: $0.3 million (40% decrease)
Online trading conversion (%)	10% (on Twiga Foods platform)	12% (on AgriDigital platform)	15% (on Farm2Fork platform)
Demand elasticity	2.00	3.00	2.50
Socio-economic impact	Increase in farmers' income by 25%	Reduce costs by 20%, increase in farmers' income by 15%	Increase in farmers' income by 30%, decrease in crop losses by 10%

Source: Structured and data-driven calculation (TechTrendsKE, 2022; FinTech Australia, 2022; Farms2Fork Technologies Pvt Ltd., 2023)

Table 3: Key results of calculating the economic efficiency of implementing digital technologies in agribusiness of key companies in the world.

of socio-economics of farmers and the rural side, so that it raises revenue of the community and lowers the degree of product perishable. Meanwhile, the findings that have been achieved must be considered carefully for their transferability. Twiga Foods, AgriDigital and Farm2Fork are examples of successful models, which have relatively mature digital infrastructure, investment capacity and organizational maturity. However, the typical small-scale farmers face a different set of circumstances such as poor bandwidth connectivity and lack of digital literacy, poor financial resources, relying on middle men and no experience in digital marketing. Hence, the findings of the analyzed cases can't be directly applied to all agricultural producers without adaptation. Digital transformation first for small farms is low-cost, scalable application of technology and tools like mobile apps, social media promotion, digital payment platforms, local online marketplaces and cooperative logistics platforms. Public policy, agricultural extension services and local business associations should assist this process by providing training, subsidizing use of digital infrastructure, and providing collective digital platforms and/or advisory services. For this reason, the cases examined in this study cannot be taken as models for immediate adaptation, but rather as strategic examples of the possible economic impacts that can be achieved through the use of digital tools that are adapted to the real capacities of SMEs in the agricultural sector.

Conclusion

The conclusions of this research point to digital marketing and online trade as two necessary aspects that are becoming equally determinant for the change from traditional agriculture toward a technology-one oriented, productive activity; and sustainable. What quantitative methods such as the linear regression analysis helped to quantify the influence of digital tools on crop yields, logistics cost and return on investment (ROI), expanding findings beyond prior research, which was mostly based on qualitative evaluations. A study of real cases, which include Twiga Foods, AgriDigital and Farm2Fork, illustrated a significant diversity of digitalization strategies that were driven by the regional infrastructure, institutional maturity and market circumstances. Although these three cases differ in scale, market scope and target audiences, all of them showed an increase in terms of ROI and cost per transaction, showing how is possible for digital solutions to adapt themselves to very broad logistics chains as well as for local direct-sales systems. But the research also pointed out areas of weakness. Meanwhile the bricks and mortar of digital environments are often missing: too many farmers have limited access to the most basic tools. Tackling these challenges are vital for integrating digital marketing and e-commerce into agricultural business models in an efficient way. Theoretically, our work also contributes to the study of agricultural digitalization not just as a process of IT adoption but as an aspect of strategic marketing management. The practical applications of these results relate to the implementation regional programmed for agrifood digitalisation and in devising agroindustry marketing strategies (Hennessey, 2020; FAO, 2021; Baker and Smith, 2020). In a global context that is characterized by globalized markets, increased demand for food and climate challenges, digitalization is emerging as an important factor in agribusiness efficiency. Pressure to address these demands is growing, and traditional agricultural systems are no longer sufficient. In particular, digital marketing and e-commerce can be used for more efficient management of resources, logistics optimization, market extension as well as competition improvement. The spread of COVID -19 has hastened the uptake of e-commerce and digital forms of communication, indicating that companies not involved with these technologies are more vulnerable (Bose and Kiran, 2021; KN and Nasution, 2024). A unique characteristic of this research is that it deals with the strategic factor in digital marketing and e-trade in agriculture, compared to countries. The cases studied show how different strategies are taken, depending on regional atmosphere, market structure and institutional support. For example, Twiga Foods in Kenya connects smallholder farmers to urban consumers using mobile-based marketplaces successfully and AgriDigital in Australia is into grain trading with digital platforms and Farm2Fork in India specializes in direct farm-to-consumer sales (AgriDigital, 2022; Mishra, 2021; Tech Trends KE, 2022). These cases demonstrate that digital solutions help wherever you use them, driving lower transaction costs, better customer interaction and more efficient operations. The research confirms a number of the hypotheses explaining digitization in agriculture. First, use of online marketing and e-commerce systems will lower dependence on intermediaries, improve logistics and increase profits (H1). Second, the adoption of technologies, Big Data IoT and AI fosters production efficiency and product quality, thereby resulting in the reduction of operational costs (H2). Third, digitization enables the growth of small and medium-sized farms by linking them to larger supply chains and making these smaller entities competitive (H3). Lastly, differences in digital infrastructure and technology access between large agribusinesses and smallholders continue to act as primary barriers for general digital uptake (H4) (McKinsey and Company, 2020; Al-Ababneh et al., 2023; Katragadda, 2024). From the practical perspective, implications bring useful guidance to agriculture companies and policy makers and other industry players. Enterprises can leverage the intelligence to devise digital marketing schemes, grow their market share, break away from traditional sales channels and enhance customer satisfaction." Policymakers can use the findings to guide regional digitalization projects, education policy and small and medium-sized enterprise support. Furthermore, the learning of successful international practices can facilitate the importation of digital solutions in less digitally mature geographies and help to fill knowledge gaps in these areas (Jouanjean, 2019; Ravi and Rajasekaran, 2023). Limitations of the study Although its positive results, there are a number of limitations to our study. First, digitalization rates differ substantially among countries, accessibility to high-speed internet and e-commerce infrastructure, and digital literacy are scarce in developing areas so that the generalizability of our findings to those parts of the world is less clear. Second, the sample relies on a handful of successful examples coming from relatively mature digital ecosystem(s) and not necessarily reflecting global conditions. Third, most of the accepted theories are based on short-term economic implications (i.e., profit integration and consumer commitment), but little is known about long-term implications - such as sustainability consequences, production executions or socio-economic dynamics (Derenskiy 2025; Cochea Tomala 2022). Further studies should generalize this work for low digital maturity countries and regions by testing possibilities of adapting digital marketing and e-commerce tools to SMEs (smallholder and medium-scale) efficiency. It will be essential to examine public and private initiatives including infrastructure, training programs, and institutional arrangements that facilitate digital adoption. Furthermore, extended observations might consider more general effects of digitalization on sustainable development, labour, and environmental governance. Risk perception, data security and automation contribution in agricultural employment could be another promising research line (Al-Ababneh et al., 2025; Şalvarlı, 2023). In summary, digital marketing and e-commerce have been important tools for better competitiveness; efficiency and sustainability of agriculture. The study points to the necessity of national wide digitalization strategies, supported by institution that are internationally informed but also adapted into local frameworks. Agri-businesses consolidating strategic management and technologies, can realize significant economic benefits combined with operational efficiencies that may extend beyond individual firms; while their counterparts' policymakers and educators can help secure inclusive adoption to support the sustainable development of the sector (Markets and Markets, 2023; Deloitte Insights, 2024; Business Wire, 2024; Reuters, 2024; Atli, 2024). This constraint is particularly relevant as the companies analysed are examples of successful and relatively mature digital transformation. This can be quite different for typical small-scale farmers because they have lower investment potential, less infrastructure and less computer literacy. Based on this, further study is needed on a larger number of small and medium-sized farms and should explore the economic impacts of low-cost digital tools in resource-limited environments. The study also indicates that digital marketing is not only a method of communication, but also a managerial mechanism involving analytics, logistics coordination, customer communication and digital trade infrastructure in the modern agribusiness ecosystems.

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The Mediating Role of Sustainability in the Relationship Between Digital Innovation And Environmental Performance Improvement: An Applied Study in the Jordanian Industrial Sector

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Abstract

This study investigates how digital innovation (DI) enhances environmental-performance improvement (EPI) in the Jordanian industrial sector and whether this relationship is channelled through sustainability (SUS). A structured questionnaire was administered to managers in large and medium-sized manufacturing firms, and the data were analysed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The results show that DI exerts a significant positive effect on both SUS and EPI, while SUS itself has a direct positive impact on EPI; moreover, sustainability partially mediates the DI → EPI pathway, confirming that technological upgrades yield meaningful ecological gains only when embedded in explicit sustainability programmes. The model explains 44 % of the variance in SUS and 46.7 % in EPI, indicating substantial explanatory power. These findings underline the strategic necessity of integrating ESG principles into digital-transformation roadmaps: real-time data capture and analytics equip firms to anticipate environmental risks, while sustainability frameworks ensure that digital tools are harnessed toward long-term economic, social and environmental objectives. By coupling digital innovation with institution-wide sustainability initiatives, industrial organisations can achieve resource efficiency, bolster regulatory compliance and strengthen competitive advantage in increasingly eco-conscious markets

Keywords

Digital innovation, sustainability, environmental performance, Jordanian industry, environmental management, sustainable development.

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Introduction

The proper management of environmental performance has emerged as a significant strategic issue for modern industrial organizations, particularly within dynamic and competitive markets. In the Jordanian industrial sector, organizations face multiple pressures exacerbating environmental concerns, including stringent regulatory frameworks, rapid technological evolution, and increasing competition both regionally and internationally. Effective management of environmental aspects within this context not only mitigates ecological impacts but also enhances competitive advantage through improved stakeholder perception and regulatory compliance (Beltrami et al., 2021).

Inability to align digital innovations with sustainability may lead to adverse operational and strategic consequences, such as inefficient resource utilization, increased environmental costs, and regulatory non-compliance. Bai et al. (2020) emphasize the importance of proactively embedding digital technologies into organizational processes to improve efficiency and reduce environmental harm, highlighting the necessity for a sustainability-oriented digital approach.

Defined as the adoption and utilization of novel digital technologies to optimize industrial processes, digital innovation is instrumental in environmental performance improvement (EPI). Technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics significantly enhance resource efficiency, waste reduction, and emissions control, especially when strategically aligned with sustainability frameworks (Culot et al., 2020).

Sustainability functions as a mediator by ensuring that digital transformation strategies align effectively with broader environmental objectives. Sustainability-driven management practices not only achieve short-term operational goals but also generate enduring environmental improvements, strengthening organizational adaptability and long-term resilience (Dyllick and Hockerts, 2002).

Despite the acknowledged significance of digital innovation and sustainability, existing literature reveals a research gap concerning the mediating role of sustainability in linking digital innovation with enhanced environmental performance within the Jordanian industrial sector. Previous research has predominantly examined these aspects separately, offering limited insights into their integrative potential to optimize environmental outcomes. Addressing this gap is crucial for formulating strategies that leverage both technological advancements and sustainable practices to meet environmental standards effectively.

Consequently, the aim of this research is to bridge this gap by examining the mediating role of sustainability in the relationship between digital innovation and EPIenvironmental performance improvement in the Jordanian industrial sector. Through this exploration, the study provides practical insights to industrial managers and policymakers, emphasizing the need to integrate sustainability within digital transformation initiatives. This research is especially pertinent given the global emphasis on achieving Sustainable Development Goals (SDGs), particularly Goal 9 on industry, innovation, and infrastructure, and Goal 12 on responsible consumption and production.

This introduction lays the groundwork for a comprehensive analysis of theoretical and practical implications concerning digital innovation, sustainability, and environmental performance management. Subsequent sections will include a detailed review of relevant literature, methodology description, results analysis, and discussion of implications beneficial to both academic and industry practitioners.

Furthermore, this study aligns with the scope of Agris On-line Papers in Economics and Informatics by examining the economic and environmental implications of digital transformation within industrial organizations. Specifically, it contributes to the understanding of how digital technologies such as data analytics, artificial intelligence, and IoT enhance operational efficiency and environmental performance. The study also highlights the role of sustainability as a strategic mechanism linking technological capabilities to economic and ecological outcomes, thereby providing insights relevant to both informatics and industrial economics.

Research problem

In recent years, the industrial sector in Jordan has been undergoing rapid changes driven by increasing environmental challenges, pressure from global sustainability commitments, and the accelerating adoption of digital technologies (Nambisan et al., 2017). Despite the growing awareness of the need for environmental responsibility, many industrial organizations still struggle to implement effective environmental performance strategies. These struggles are often linked to a lack of integration between digital innovation initiatives and sustainability frameworks (Frank et al., 2019).

Although digital innovation offers promising tools—such as big data analytics, automation, and AI—to optimize resource use and reduce environmental impact, the mere presence of these technologies does not guarantee improved environmental performance. According to Ghobakhloo (2020), without a strong mediating mechanism like sustainability, digital technologies may remain underutilized or misaligned with long-term ecological goals. This gap in alignment creates a significant problem in the Jordanian industrial sector, where efforts to modernize production are not always matched by environmental improvements.

Moreover, while environmental performance has become a critical concern—especially in terms of carbon emissions, waste management, and energy efficiency—industries often face institutional and organizational barriers in turning innovation into sustainable action (Zhang et al., 2022). These challenges highlight a key research gap: the unclear role that sustainability plays in translating digital innovation into measurable environmental outcomes.

Therefore, this study investigates how sustainability can mediate the relationship between digital innovation and environmental performance. It seeks to determine whether sustainability acts as a necessary conduit that aligns technological initiatives with environmental goals, especially in the context of Jordan's industrial landscape. The lack of empirical studies exploring this mediating role within emerging markets like Jordan underscores the need for this research.

Practically, the findings of this study are expected to provide actionable insights for industrial managers, policymakers, and sustainability professionals. By understanding how digital innovation and sustainability interact, organizations can develop more coherent strategies that not only meet efficiency goals but also address pressing environmental issues. Theoretically, this study contributes to the growing body of literature on digital sustainability by providing a model that contextualizes this relationship within a developing country framework, addressing both technological and ecological dimensions of industrial development.

Materials and methods

Research design

In alignment with the outlined objectives, this research adopts a quantitative approach to explore the mediating role of sustainability in the relationship between digital innovation and EPIenvironmental performance improvement within the Jordanian industrial sector. The study employs a cross-sectional design, collecting data at a single point in time to comprehensively assess the hypothesized relationships among study variables.

Sample selection

Participants were managerial-level employees from companies operating within the Jordanian industrial sector, selected due to their direct involvement in strategic decision-making, environmental management, and digital technology implementation. Structured questionnaires were distributed to ensure adequate representation from diverse industrial subsectors. The optimal sample size was determined using statistical power analysis to achieve accurate and generalizable results.

A non-probability convenience sampling technique was adopted due to accessibility constraints within industrial firms.

Data collection

A total of 400 questionnaires were sent to medium and large manufacturing companies in Jordan. Of these, 312 were valid responses (78% response rate). The sample encompassed a wide range of subsectors such as food products, chemicals, textiles, construction materials, and electronics, and the sample represented the industrial sector. All cases with more than 10% missing data were excluded and minor missing data were imputed using mean imputation to assure the statistical robustness of the data. This method resulted in a reliable data set that represented the industrial sector in Jordan more broadly.

Variables and measures

Independent variable: Digital Innovation: Digital innovation was assessed through dimensions such as technological infrastructure, adoption of advanced digital tools, data integration capabilities, and organizational readiness for digital change.

Mediator variable: Sustainability: Sustainability practices were measured by assessing the degree of organizational implementation of sustainable practices across economic, social, and environmental dimensions. This included resource management, social responsibility initiatives, and long-term environmental planning.

Dependent variable: Environmental Performance: Environmental performance was evaluated through indicators such as reductions in waste, emissions, resource conservation efficiency, and adherence to environmental regulatory compliance. This provided a comprehensive overview of organizational commitment to environmental responsibility.

Econometric technique

The relationships among the variables were analyzed using Structural Equation Modeling (SEM), which is widely recognized for its effectiveness in testing complex interrelations among variables simultaneously. SEM also facilitates the identification of direct and indirect (mediating) effects, providing comprehensive insights into the mediating role of sustainability. Indirect mediation effects were specifically assessed using bootstrap procedures for enhanced robustness.

To assess the potential presence of common method bias (CMB), Harman’s single-factor test was conducted. The results indicated that a single factor did not account for the majority of the total variance, suggesting that common method bias is not a significant concern in this study. In addition, several procedural remedies were implemented, including ensuring anonymity of respondents, using clear and concise questionnaire items, and reducing evaluation apprehension, which further minimized the likelihood of bias.

Ethical considerations

Ethical approval for this research was obtained from the Institutional Review Board (IRB) at Al-Ahliyya Amman University, Jordan. Confidentiality and anonymity of participants' information were strictly ensured, adhering to ethical research standards throughout data collection and analysis.

Rationale for methodology

The quantitative SEM approach was selected due to its superior capacity for elucidating causal and mediating relationships among multiple variables. Additionally, the cross-sectional design effectively captures current dynamics within Jordanian industrial firms, producing practical insights beneficial for both academic researchers and industry practitioners.

This methodology section clearly outlines the operational definitions for the independent variable (digital innovation), the mediator variable (sustainability), and the dependent variable (environmental performance). These variables are central to understanding how digital innovation, coupled with sustainability practices, enhances environmental outcomes within Jordan's industrial organizations.

Independent variable: digital innovation

Digital innovation encompasses the organizational capacity to adopt advanced digital solutions to enhance operational processes and strategic decision-making. This involves deploying technology infrastructures that support comprehensive digitalization, automation, and real-time data utilization, significantly enhancing environmental management capabilities (Nambisan et al., 2017).

Dependent variable: environmental performance

Environmental performance refers to the effectiveness of an organization's environmental management practices, reflected in improved resource efficiency, decreased environmental footprint, compliance with regulatory standards, and overall sustainable environmental outcomes. It serves as a vital indicator of an organization's environmental responsibility and long-term competitive positioning (Hartmann and Vachon, 2018).

Mediator variable: sustainability

In this research, sustainability is conceptualized as the integration of practices that promote long-term viability through balancing environmental, social, and economic objectives. Sustainability acts as a mediator, ensuring that digital transformation efforts effectively align with broader environmental and societal goals, thereby enabling sustained improvements in environmental performance (Epstein, 2018).

As outlined, digital innovation, sustainability, and environmental performance are not isolated concepts; their integration enhances industrial organizations' ability to achieve sustainable environmental goals. Investigating these relationships provides essential insights into effective industrial practices, offering valuable implications for policy development and organizational strategies within the Jordanian industrial sector.

Study model

The theoretical framework underpinning this study model was developed based on a thorough analysis of existing literature addressing digital innovation, sustainability, and environmental performance. The model specifically aims to examine the interrelations between these variables within the Jordanian industrial sector, offering both an academic and practical blueprint that illustrates how digital innovation initiatives can effectively enhance environmental performance through sustainability mediation. This aligns with previous research emphasizing that integrating innovative digital technologies significantly contributes to superior environmental outcomes when strategically embedded within sustainability practices (Fernando et al., 2019).

In the presented model, digital innovation is positioned as the independent variable, providing industrial firms with the technological tools and capabilities required to anticipate, address, and solve environmental challenges. Such technologies include IoT, artificial intelligence (AI), and advanced data analytics, all of which enable organizations to optimize resource usage and reduce negative environmental impacts proactively (Nambisan et al., 2017). Previous literature confirms that organizations possessing advanced digital innovation capabilities are better positioned to align operational practices with environmental sustainability goals, ensuring effective environmental management and performance (Fernando et al., 2019).

The model further highlights sustainability as a pivotal mediator variable. Sustainability serves to mediate the relationship between digital innovation and environmental performance by ensuring that technological advancements are implemented within a holistic approach that addresses economic, social, and environmental considerations concurrently. Epstein (2018) emphasizes that embedding sustainability practices within technological transformations enables industrial companies to effectively manage complex environmental issues, avoid short-termism, and maintain long-term strategic alignment with global sustainability objectives. As similarly indicated by Hartmann and Vachon (2018), adopting sustainability-driven digital strategies significantly improves resource efficiency, reduces emissions, and enhances overall environmental performance.

Consequently, environmental performance represents the dependent variable in the model. This variable captures the extent to which digital innovation strategies, mediated by sustainability practices, achieve tangible improvements in organizational environmental outcomes. The directional arrows depicted in the model indicate the flow of influence: digital innovation directly affects both sustainability and environmental performance, while sustainability in turn strengthens and mediates the effectiveness of digital innovation initiatives on achieving improved environmental results. Such an integrated framework is justified by evidence supporting that sustainable digital practices substantially enhance an organization's environmental outcomes, resilience, and overall competitive positioning (Epstein, 2018; Nambisan et al., 2017).

The theoretical model presented here provides a clear roadmap illustrating how Jordanian industrial organizations can leverage digital innovation within a sustainability framework to enhance their environmental performance. It further stresses the necessity for organizations to adopt proactive and integrative strategies, not only for immediate operational efficiency but also for ensuring sustainable environmental success factors in the long term, especially within dynamic and environmentally sensitive industrial contexts.

Study hypotheses

By developing several theoretical assumptions, this research aims to examine the relationships among digital innovation, sustainability, and environmental performance within the Jordanian industrial sector. These hypotheses investigate how digital innovation practices, when mediated by sustainability initiatives, can enhance environmental performance, ultimately leading to improved organizational outcomes.

Firms leveraging advanced digital technologies such as automation, IoT, and big data analytics are expected to enhance their resource efficiency, waste reduction, and overall environmental management effectiveness. According to Singh and El-Kassar (2019), organizations that actively engage in digital transformation efforts demonstrate significant improvements in managing environmental risks and complying with environmental regulations. Based on the this discussion, the following hypotheses are proposed:

- **H1**: Digital Innovation (DI) has a positive effect on Sustainability (SUS).
- **H2:** Digital Innovation (DI) has a positive effect on Environmental Performance (EPI).
- **H3:** Sustainability (SUS) has a positive effect on Environmental Performance (EPI).
- **H4:** Sustainability (SUS) mediates the relationship between Digital Innovation (DI) and Environmental Performance (EPI).

Tseng et al. (2020) stress that sustainability-focused solutions will lead to the technological developments that are relevant and have a lasting impact on the environment, and not just on operations. Ghobakhloo (2020) states that digital innovation can give firms access to tools that would enable them to have accurate data collection, efficient use of resources, and strategic sustainability planning, which would lead to long-term sustainable outcomes. Additionally Galpin and Whittington (2012) suggest that sustainability can be taken as an integral part of business operations and can have a positive impact on long-term competitive advantage, as well as environmental performance.

Literature review

Here, it is essential to clarify and elaborate upon the key variables—Digital Innovation, Sustainability, and Environmental Performance—to justify their relevance in enhancing environmental outcomes within the Jordanian industrial sector. Based on this conceptual framework, this section identifies clear definitions and explanations from existing literature, aiming to enhance understanding and applicability of these concepts within the context of this study.

Digital innovation (independent variable)

Digital innovation refers to the implementation and effective utilization of digital technologies within industrial organizations to improve processes, products, or business models, especially in contexts characterized by competitive pressures and rapid technological advancements. According to Nambisan et al. (2017), digital innovation encompasses the systematic adoption of technologies such as artificial intelligence (AI), the Internet of Things (IoT), automation, and advanced data analytics to enhance decision-making capabilities, operational efficiency, and competitive advantage.

Digital innovation significantly contributes to improved environmental performance by enabling organizations to accurately monitor resource consumption, predict environmental impacts, and optimize operational processes. Singh and El-Kassar (2019) argue that advanced digital technologies, particularly big data analytics, provide comprehensive insights for sustainable management practices, enabling better prediction and management of environmental risks and resource efficiency.

Furthermore, digital innovation fosters cross-functional integration and communication within organizations, promoting a cohesive and collaborative environment necessary for effective environmental management. Ghobakhloo (2020) suggests that organizations employing digital innovation frameworks demonstrate higher adaptability and responsiveness to environmental challenges, particularly within volatile market conditions, enabling proactive resource allocation and waste minimization strategies.

Moreover, digital innovation enhances organizational alignment with long-term environmental and strategic goals, ensuring that technological advancements are not only adopted for short-term efficiency gains but also contribute meaningfully to broader sustainability objectives. A study by Frank et al. (2019) confirms that integrating digital tools significantly improves an organization's capability to implement strategic environmental initiatives, thus enhancing its overall environmental performance.

Additionally, digital innovation involves utilizing new technology tools such as predictive analytics and AI-driven forecasting systems. These tools enable organizations to systematically collect and analyze environmental data, anticipate potential environmental challenges, and implement proactive solutions effectively. According to de Sousa Jabbour et al. (2018), the incorporation of predictive environmental analytics significantly enhances managerial decision-making processes, ultimately reducing negative environmental impacts and improving compliance with regulatory standards.

In conclusion, digital innovation is critical to improving environmental management within the industrial sector. It serves as an effective enabler of sustainable organizational growth by enhancing resource optimization, fostering cross-functional collaboration, and aligning digital initiatives with strategic environmental goals, thereby contributing significantly to improved environmental outcomes and long-term competitive advantage.

Environmental performance (dependent variable)

Environmental performance in the context of this study is the capacity of industrial organizations to decrease the adverse environmental effects of their operations by using efficient and sustainable operating procedures. This involves reducing emissions, reducing waste, optimizing energy and water use, and adhering to environmental laws and regulations (Zhang et al., 2022). In industrial applications, environmental performance is increasingly linked to the use of technologies and optimisation of processes that reduce the pollution generated. Companies with a focus on environmental stewardship can enhance resource utilization and minimize environmental impacts. Improvements are vital to achieve competitiveness in markets where there are high environmental requirements and stakeholder pressure (Hartmann and Vachon, 2018).

Furthermore, by measuring environmental indicators like energy use rates, emissions, and waste minimisation metrics, organisations can evaluate their environmental footprint and work towards continual enhancements. These indicators offer actionable information which can inform strategic decisions and long-term sustainability goals (Jabbour and Santos, 2008).

From a broader perspective, environmental performance is a key outcome variable that captures the sustainability effectiveness of digital innovation and sustainability practices within industrial operations.

Sustainability (mediator variable)

Sustainability in the current study is defined as the ability to combine economic, environmental and social factors in a way that will maintain the viability of an organization and responsible use of its resources over time. It serves as a key link in making technological capability available to promote a wider environmental and social goal (Hussain et al., 2024; Dyllick and Hockerts, 2002).

In the industrial setting, sustainability entails implementing environmentally responsible production processes, effective management of resources, reducing waste, and complying with environmental standards. These practices maximise the focus on efficient delivery of digital innovation initiatives whilst also delivering long term ecological and economic value (Epstein, 2018).

Sustainability is a mediation factor, which turns digital innovation capabilities into real environmental impact. Digital technologies offer tools for data collection, monitoring and optimizing, but sustainability frameworks are the vehicles for putting these tools to work to make positive and productive environmental improvements. This alignment goes to a greater degree in the organization's capability of continuously improving its environmental performance.

Sustainability is therefore a very important instrument to combine digital innovation with environmental goals, so that technological innovation becomes sustainable and measurable environmental benefit.

Research gap

Despite the prior work focusing on digital innovation, sustainability, and environmental performance as separate themes, few studies have investigated the synergy among them. Most existing research tends to emphasize one-dimensional relationships—such as the impact of digital innovation on operational efficiency, or the role of sustainability in supporting long-term goals. However, the integrated framework linking these three variables, particularly in Jordan's industrial sector, remains underexplored.

To fill this gap, the present research aims to analyze the mediating role of sustainability in the relationship between digital innovation and EPI. Drawing on a multi-disciplinary literature base, this study seeks to offer both theoretical contributions and practical recommendations that support environmentally responsible innovation strategies in competitive industrial environments. The findings are expected to provide value not only to academic discussions but also to industry practitioners and policy makers aiming to enhance the environmental resilience and sustainability of industrial operations in Jordan.

Previous relevant studies

This section summarizes the most relevant literature that forms the conceptual basis for this study. These selected studies focus on digital innovation, sustainability, and environmental performance, with a particular emphasis on their integration in industrial or comparable organizational settings.

Study 1: digital innovation and environmental decision-making

Nambisan et al. (2017) provided a comprehensive understanding of how digital innovation—through tools such as artificial intelligence, automation, and data analytics—supports improved decision-making and operational efficiency. Their findings suggest that organizations adopting digital innovation can achieve enhanced environmental responsiveness, paving the way for improved ecological performance.

Study 2: big data and sustainable practices

Singh and El-Kassar (2019) examined the role of big data analytics in sustainable operations and environmental risk management. They found that data-driven innovation enables accurate prediction and mitigation of environmental impacts, confirming the direct role of digital innovation in EPIs.

Study 3: organizational integration and innovation

Ghobakhloo (2020) argued that digital innovation enhances cross-functional collaboration and adaptability, especially in volatile market conditions. He demonstrated that such innovation facilitates the implementation of environmentally aligned strategies, which is essential for improving performance in industrial firms.

Study 4: digital tools and strategic environmental goals

Frank et al. (2019) highlighted the importance of aligning digital innovation with strategic environmental goals. Their study showed that firms using digital platforms to monitor environmental data experience enhanced sustainability outcomes and long-term performance improvements.

Study 5: predictive analytics and environmental compliance

De Sousa Jabbour et al. (2018) demonstrated that predictive environmental analytics help organizations identify challenges and proactively implement eco-efficient strategies. Their work confirms that advanced digital technologies positively influence regulatory compliance and environmental metrics.

Study 6: Environmental Metrics In Industrial Management

Zhang et al. (2022) defined key environmental performance indicators, such as energy use and waste reduction, and emphasized their relevance in evaluating environmental impact. The study supports the use of systematic measurement in linking innovation efforts to actual environmental outcomes.

Study 7: green finance and environmental performance

Thapliyal et al. (2024) examined the contribution of green banking and green finance initiatives to environmental performance. Their findings confirm that financial sustainability tools act as strategic enablers for environmental improvement, especially when integrated with technological innovation.

Study 8: sustainability as a mediator

Anser et al. (2025) explored how sustainability policies mediate the relationship between AI technologies and environmental outcomes in developing economies. Their findings confirm the mediating role of sustainability in translating innovation into measurable environmental benefits.

Study 9: theoretical framing of sustainability

Al Shawabkeh (2024) conceptualized sustainability as a balance of economic, social, and environmental goals. His work underlines the importance of embedding sustainability practices within organizational strategy to achieve long-term ecological resilience.

Results and discussion

Discussion and implications

This study contributes to a deeper understanding of how digital innovation and sustainability interact to enhance environmental performance in the industrial sector of Jordan. The findings extend both theoretical and practical insights by demonstrating that sustainability plays a significant mediating role in converting digital innovation efforts into tangible environmental improvements. This highlights that digital tools alone are insufficient unless coupled with sustainable practices and strategies aligned with long-term environmental goals.

From a theoretical standpoint, the study enriches literature by confirming that sustainability acts as a bridge between technology adoption and ecological impact. Practically, the findings provide industrial managers and policymakers with a framework for aligning technological investments with sustainability strategies, thereby ensuring better resource utilization, lower emissions, and improved compliance with environmental standards.

Data analysis

In this study, the partial least squares-structural equation modeling (PLS-SEM) was introduced as an analysis tool (Hair et al., 2019). PLS-SEM is considered an advanced analysis method that relies on multivariate techniques (Memon et al., 2021). This means the ability to simultaneously analyze causal relationships and increase predictive accuracy (Al-Khatib and Ramayah, 2025). Given that PLS-SEM is appropriate when the data are not normally distributed or lack one of the traditional assumptions assumed when relying on other analysis methods, PLS-SEM was relied upon and employed in this research.

The measurement model

In the first step of the PLS-SEM analysis, the measurement properties of the measurement tool are addressed (Ringle et al., 2020). Convergent validity, reliability, and discriminant validity are calculated (Hair et al., 2019). Table 1 shows the results for convergent validity and reliability. All statistical criteria were met, with AVE values above 0.5 and factor loadings, Cronbach alpha, and composite reliability above 0.7, indicating that these criteria were met.

First-order construct	Item	Factor loading	AVE	CR	α
Digital innovation	DI1	0.788	0.593	0.879	0.828
	DI2	0.826			
	DI3	0.819			
	DI4	0.673			
	DI5	0.733			
Sustainability	S1	0.852	0.674	0.912	0.878
	S2	0.859			
	S3	0.821			
	S4	0.806			
	S5	0.763			
EPI	EPI1	0.733	0.541	0.876	0.833
	EPI2	0.803			
	EPI3	0.708			
	EPI4	0.724			
	EPI5	0.740			
	EPI6	0.700			

Source: Adopted by authors based on data analysis

Table 1: Reliability and convergent validity.

The results summarized in Table 1 confirm that the measurement model for the three first-order constructs—digital innovation (DI), sustainability (SUS), and environmental-performance improvement (EPI)—possesses solid psychometric quality. All item loadings exceed the recommended threshold of 0.60 (lowest = 0.673; highest = 0.859), demonstrating strong item–construct alignment and supporting construct validity. Convergent validity is further verified by Average Variance Extracted (AVE) values of 0.593 (DI), 0.674 (SUS), and 0.541 (EPI), each surpassing the 0.50 benchmark, indicating that the indicators capture more shared variance than error variance within their respective constructs.

Reliability indicators likewise show excellent internal consistency. Cronbach's alpha coefficients are 0.828 (DI), 0.878 (SUS), and 0.833 (EPI), all comfortably above the 0.70 guideline. Composite Reliability (CR) values mirror this robustness—0.879, 0.912, and 0.876 respectively—confirming that the scales generate dependable and stable measurements suitable for subsequent structural analyses.

Turning to discriminant validity, the HTMT matrix in Table 2 reveals inter-construct ratios of 0.711 (DI–SUS), 0.771 (DI–EPI), and 0.709 (SUS–EPI), each well below the conservative 0.90 cut-off (Henseler et al., 2015). These results indicate that each latent variable is empirically distinct from the others, eliminating concerns of conceptual overlap. Collectively, the evidence from Tables 1 and 2 provides a robust measurement foundation, allowing the study to proceed with confidence to hypothesis testing and structural-equation modeling.

The results in Table 2 validate the discriminant validity of the three latent constructs—digital innovation (DI), sustainability (SUS), and environmental-performance improvement (EPI)—using the Heterotrait-Monotrait ratio (HTMT). Each HTMT coefficient falls well below the conservative 0.85 benchmark recommended by Henseler et al. (2015): 0.711 for DI–SUS, 0.771 for DI–EPI, and 0.709 for SUS–EPI.

	DI	SUS	EPI
DI			
SUS	0.711		
EPI	0.771	0.709	

Source: Adopted by authors based on data analysis

Table 2: Discriminant validity: HTMT criterion.

These values show that the constructs are empirically distinct; although conceptually related, they do not exhibit problematic overlap. Such clear separation reinforces confidence that each scale captures a unique dimension of the study's theoretical framework.

Accordingly, the evidence strongly supports the discriminant validity of the measurement model—an essential prerequisite for moving forward with structural equation modeling (SEM) and for drawing reliable inferences about how digital innovation and sustainability jointly influence environmental-performance improvement.

The structural model

This study aims to test the effect of DI on both SUS and EPI, in addition to testing the mediating effect. To achieve the above objectives, the bootstrapping technique was used via PLS-SEM. Before testing the hypotheses, R2 values were extracted, which were acceptable, with a value of 0.440 for SUS and 0.467 for EPI, which is considered a good value. All hypotheses were supported as shown in Table 3 where the effect of DI on both SUS and EPI was positive and statistically significant (H1: $\beta = 0.664$, $t = 15.161$, $p = 0.000$; H2: $\beta = 0.381$, $t = 7.741$, $p = 0.000$) while the effect of SUS on EPI was positive (H3: $\beta = 0.369$, $t = 6.878$, $p = 0.000$).

Table (3) shows that the results obtained indicate that the study hypotheses are supported empirically. The results of Hypothesis H1, which investigates the effect of Digital Innovation (DI) on Sustainability (SUS), demonstrate that there is a significant positive relationship between the two ($\beta = 0.664$; $t = 15.161$; $p = 0.000$).

Hypothesis H2 predicting the direct effect of Digital Innovation on EPI is supported as well ($\beta = 0.381$, $t = 7.741$, $p = 0.000$), indicating that digital technologies directly help to enhance environmental outcomes.

Last, the results of Hypothesis H3 justify a positive and significant association between Sustainability and EPI ($\beta = 0.369$, $t = 6.878$, $p = 0.000$), indicating the importance of sustainability in promoting EPI.

The results reported in Table (4) furnish compelling empirical support for the mediating role of sustainability (SUS) in the link between digital innovation (DI) and environmental-performance improvement (EPI). The indirect effect (DI → SUS → EPI) yields a standardized beta of 0.245, a standard error of 0.042, a robust t-value of 5.889, and a p-value of 0.000. In addition, the bootstrapped confidence interval ranges from 0.180 (LL) to 0.317 (UL) with no zero value falling between the limits, confirming the statistical significance of the mediation pathway.

These figures indicate that sustainability partially mediates the relationship between digital innovation and environmental performance. Put differently, a portion of the positive impact that digital-innovation initiatives exert on environmental outcomes is transmitted through improvements in sustainability practices. Thus, firms leveraging advanced digital tools not only achieve direct efficiencies but also bolster their environmental results by embedding sustainability more deeply into their operations.

This finding is noteworthy because it highlights sustainability as a pivotal mechanism that amplifies the effectiveness of digital innovation in driving ecological gains. It dovetails with the study's theoretical premise that integrating sustainability into organizational routines enhances overall resilience and strengthens environmental performance—especially vital for organizations striving to meet increasingly stringent green mandates and stakeholder expectations.

The structural model in Figure (1) visually confirms the hypothesized links among the study constructs. Digital innovation (DI) demonstrates a strong, positive influence on sustainability, as evidenced by a standardized path coefficient of 0.664.

Hypothesis	Relationship	Std. Beta	Std. Dev.	t-value	p-value	Decision
H1	DI → SUS	0.664	0.044	15.161	0.000	Supported
H2	DI → EPI	0.381	0.049	7.741	0.000	Supported
H3	SUS → EPI	0.369	0.054	6.878	0.000	Supported

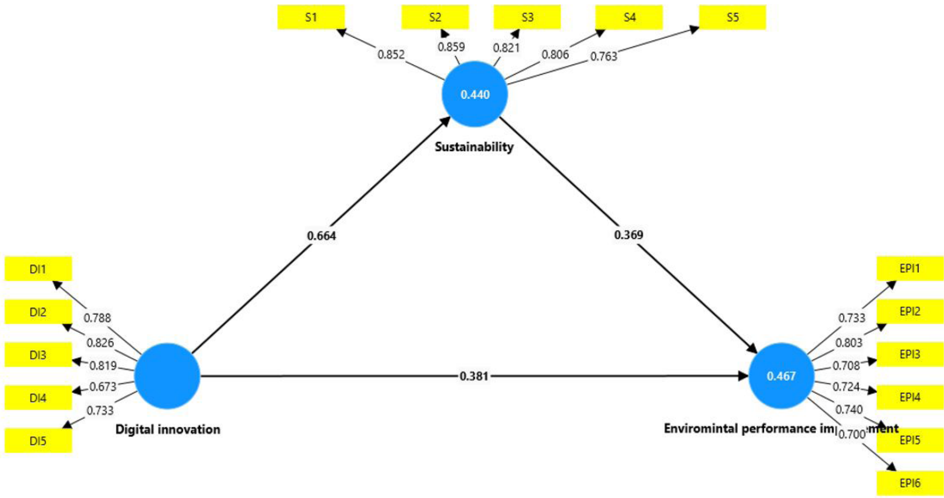
Source: Adopted by authors based on data analysis

Table 3: Hypotheses testing.

Hypothesis	Relationship	Std. Beta	Std. Dev.	t-value	p-value	BCI LL	BCI UL
H4	DI → SUS → EPI	0.245	0.042	5.889	0.000	0.180	0.317

Source: Adopted by authors based on data analysis

Table 4: Mediation testing.



Source: Adopted by authors based on data analysis

Figure 1: Hypothesized relationships.

This finding suggests that investments in digital technologies substantially foster the adoption and enhancement of sustainable practices across the surveyed organizations. In addition, digital innovation exerts a direct, albeit more moderate, effect on environmental-performance improvement (EPI) with a coefficient of 0.381, indicating that technology-driven efficiencies translate into measurable environmental gains.

Turning to the mediating construct, sustainability itself shows a meaningful positive impact on environmental-performance improvement, reflected in a standardized coefficient of 0.369. The simultaneous significance of the DI → EPI path and the indirect DI → Sustainability → EPI route implies a partial-mediation pattern: firms benefit environmentally both directly through digital tools and indirectly by embedding sustainability practices enabled by those tools.

The model's explanatory strength is further supported by the R^2 values of the endogenous variables. Sustainability records an R^2 of 0.440, indicating that digital innovation accounts for roughly 44 % of its variance—a substantial share in organizational research. Likewise, environmental-performance improvement attains an R^2 of 0.467, showing that digital innovation and sustainability together explain about 46.7 % of its variance. These figures underscore a robust predictive capacity and affirm the strategic value of integrating digital-innovation initiatives with sustainability efforts to achieve superior environmental outcomes.

Theoretical contributions

This study advances the literature on digital transformation and sustainable development by integrating Digital Innovation (DI) with Sustainability (SUS) to explain Environmental-Performance Improvement (EPI) in the Jordanian industrial sector. Building on Dyllick and Hockerts' (2002) triple-bottom-line view and recent digital-sustainability frameworks (e.g., Nambisan et al., 2017), the research develops and empirically tests a mediated model in which sustainability channels the effects of digital innovation onto environmental outcomes. Unlike prior work that has typically assessed these constructs in isolation, the current study synthesizes them into a single model and empirically validates all direct and indirect paths via PLS-SEM. By confirming sustainability's partial-mediation role, the findings fill a noted gap in emerging-market contexts and provide a richer explanation of how technological capabilities translate into measurable ecological gains.

Practical implications

For industrial managers, the findings make it clear that investing in technology is necessary but not sufficient: meaningful environmental gains emerge only when digital initiatives are woven into explicit, organization-wide sustainability programmes. To realise these gains, executives should first align their digital roadmaps with ESG targets—linking IoT, AI and data-analytics projects to measurable environmental KPIs such as energy intensity and waste-to-landfill. They must also bolster cross-functional sustainability teams capable of converting digital insights into actionable resource-efficiency plans, while simultaneously investing in employee upskilling—particularly in data-driven environmental management and life-cycle thinking—so that staff can fully leverage digital tools for ongoing ecological improvement. Collectively, these practices enhance regulatory compliance, generate resource savings and strengthen competitive advantage by demonstrating credible environmental stewardship.

Policy recommendations

To accelerate green industrial growth in Jordan, policy-makers should introduce fiscal incentives—such as tax credits and green grants—for firms that combine advanced digital technologies with certified sustainability standards (e.g., ISO 14001, GRI reporting); require sector-specific disclosure of digital-enabled environmental metrics to heighten transparency and peer benchmarking; facilitate public-private training programmes that build digital-sustainability skills among operations and environmental managers; and establish national "Green Tech Hubs," where manufacturers, technology providers and regulators co-create zero-waste and circular-economy solutions—all of which will lift the digital-sustainability readiness of Jordanian industry and speed progress toward the country's SDG commitments.

Future research

Although the present study yields valuable insights, it is constrained by several limitations. Chief among these is its cross-sectional design, which prevents firm causal inference and restricts the generalisability of the findings beyond the Jordanian industrial sector. Future work should adopt longitudinal or panel approaches to capture the dynamic, time-lagged effects of digital innovation and sustainability on environmental-performance improvement, as well as to test the model's robustness across other industries and cultural settings.

Notwithstanding these constraints, the results offer compelling evidence that digital innovation—when embedded in explicit sustainability programmes—constitutes a powerful driver of environmental gains. The two constructs operate in tandem: digital tools provide the data, automation and process efficiencies, while sustainability frameworks ensure these tools are harnessed toward long-term ecological objectives. Together they furnish organisations with a resilient platform for addressing environmental challenges, ensuring that performance improvements are both immediate and aligned with strategic, future-oriented goals.

Recommendations

To translate the study's evidence into practice, Jordanian industrial firms should first deploy an integrated digital-intelligence architecture—linking IoT sensors, AI-driven analytics and cloud dashboards to real-time environmental KPIs—so managers can detect sustainability risks early and act proactively (Nambisan et al., 2017; Frank et al., 2019). Targeted upskilling in data analytics and life-cycle thinking is therefore essential for turning digital signals into resource-efficiency actions (Beltrami et al., 2021).

Second, companies need to embed ESG principles throughout their digital projects. Aligning every initiative with economic, social and environmental goals strengthens internal cooperation and productivity, reflecting the triple-bottom-line logic of corporate sustainability (Dyllick and Hockerts, 2002) and the supply-chain integration benefits highlighted by Hartmann and Vachon (2018).

Third, environmental-performance strategies must be framed with a long-term horizon. Integrating multi-year sustainability roadmaps with successive waves of digital upgrades enhances organisational flexibility and stimulates continuous innovation —an advantage confirmed in emerging-economy settings (Chowdhury et al., 2025; Anser et al., 2025).

Fourth, leadership sponsorship is critical. Senior executives must champion change, allocate resources and reward learning; firms led by digitally savvy, sustainability-minded managers implement more stable, forward-looking strategies (Culot et al., 2020; Beltrami et al., 2021).

Fifth, robust interdepartmental collaboration prevents siloed decisions and ensures unified environmental responses. Enterprise-wide business-intelligence systems improve data sharing and teamwork across production, logistics and sustainability units, reducing escalation potential and reinforcing internal cohesion (Zhang et al., 2022; Jabbour and Santos, 2008).

Sixth, industrial firms should embed continuous feedback loops—regular audits, dashboard reviews and peer benchmarking—to keep conflict policies responsive to changing personnel dynamics and external conditions (Jarsh, 2025; Al-Oun and Al-Khasawneh, 2025). Structured feedback mechanisms enable rapid refinement and sustained effectiveness.

Finally, all digital-intelligence frameworks must embed regulatory compliance. Aligning environmental metrics with national and international standards bolsters governance and public trust, safeguarding organisational integrity in the face of evolving legal requirements (Epstein, 2018; Al-Khatib and Ramayah, 2025).

Conclusion

The structural-equation analysis confirms that digital innovation (DI) is a pivotal driver of environmental-performance improvement (EPI) in Jordan's industrial sector and that its impact is significantly channelled through sustainability (SUS), which acts as a partial mediator in the model. This finding aligns with Frank et al. (2019), who underscore how Industry 4.0 technologies create environmental value only when embedded in explicit sustainability programmes. By enabling real-time data capture and analytics, DI equips firms to anticipate ecological risks and implement proactive mitigation measures, while SUS ensures that these actions remain anchored to broader economic, social, and environmental objectives (Beltrami et al., 2021).

The strongest statistical support emerges for the mediating path DI → SUS → EPI, indicating that technology alone is insufficient; tangible ecological gains materialise when digital tools are integrated into long-term ESG roadmaps (Culot et al., 2020). This synthesis of technology and sustainability not only delivers short-term efficiency benefits but also reinforces organisational resilience by fostering continuous learning and adaptation, a dynamic particularly vital in emerging-market contexts (Chowdhury et al., 2025). Collectively, the results highlight the strategic necessity of coupling digital-innovation investments with institution-wide sustainability frameworks to secure enduring environmental performance and competitive advantage.

Declaration of AI Use

AI-based tools were used solely for language refinement and improving the clarity of expression. The authors are fully responsible for the content, analysis, and originality of the manuscript.

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Appendix A: Measurement items

All items were measured using a five-point Likert scale ranging from (1) strongly disagree to (5) strongly agree.

Construct	Code	Measurement Item	1	2	3	4	5
Digital Innovation (DI)	DI1	Our organization utilizes advanced digital technologies (e.g., AI, IoT, big data) in its operations.	□	□	□	□	□
	DI2	Digital tools are actively used to enhance efficiency in production and operational processes.	□	□	□	□	□
	DI3	The organization integrates digital systems across multiple functional areas.	□	□	□	□	□
	DI4	We continuously invest in upgrading digital infrastructure and technologies.	□	□	□	□	□
	DI5	Employees are encouraged to adopt and effectively use digital technologies.	□	□	□	□	□
Sustainability (SUS)	S1	The organization incorporates environmental considerations into operational decisions.	□	□	□	□	□
	S2	We actively implement practices aimed at reducing environmental impact.	□	□	□	□	□
	S3	Sustainability principles are integrated into long-term strategic planning.	□	□	□	□	□
	S4	The organization effectively manages resources (energy, water, materials).	□	□	□	□	□
	S5	Social and environmental responsibility are key organizational priorities.	□	□	□	□	□
Environmental Performance Improvement (EPI)	EPI1	The organization has reduced waste generation over time.	□	□	□	□	□
	EPI2	Emissions have decreased due to improved operational practices.	□	□	□	□	□
	EPI3	Energy efficiency has improved within the organization.	□	□	□	□	□
	EPI4	The organization has achieved better efficiency in resource utilization.	□	□	□	□	□
	EPI5	Compliance with environmental regulations has improved.	□	□	□	□	□
	EPI6	The overall environmental impact has been reduced.	□	□	□	□	□

Source: Authors

Table A1: Measurement items.

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Optimization of Water Use in Precision Agriculture Through IoT-Enabled Multi-Sensor Fusion and Machine Learning-Based Smart Irrigation Scheduling

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Abstract

This research presents a smart irrigation system that integrates Internet of Things (IoT) and machine learning (ML) to optimize water usage in agriculture. The system consists of a wireless sensor network that continuously monitors real-time environmental parameters such as soil moisture, temperature, humidity, wind speed, and rainfall. A Node-MCU microcontroller processes sensor data and transmits it to the Thing-Speak cloud for predictive analysis. The system follows a structured irrigation scheduling method, dynamically adjusting water distribution based on sensor feedback and environmental conditions. The proposed irrigation framework integrates an inverted U-shaped structure with a T-shaped hybrid irrigation system, enabling efficient water management through solenoid valves and sub-pipelines. This system, previously developed for sprinkler irrigation, was evaluated using machine learning models to assess its performance based on soil moisture and temperature parameters. In the present study, several machine learning algorithms, including Decision Tree, XG-Boost, Gradient Boosting, and Random Forest, were employed to predict irrigation requirements. The models consider multiple factors, such as soil moisture, rainfall, wind speed, and water availability, to forecast future irrigation demands, thereby facilitating optimal water utilization. Gradient Boosting achieved the highest accuracy (98.38%) and the lowest RMSE (0.1272), while Decision Tree and XG-Boost also performed strongly, with accuracy of 98.24% each. For controlling and monitoring the developed system, an android-based mobile application developed, allowing farmers to monitor and control irrigation remotely. The results demonstrate significant improvements in water conservation, reduced manual intervention, and enhanced crop yield. Future work will focus on refining predictive models, integrating additional environmental factors, and expanding system capabilities for broader adoption in precision agriculture..

Keywords

Internet of Things, water use efficiency, water management, sensors, soil moisture monitoring, smart irrigation system.

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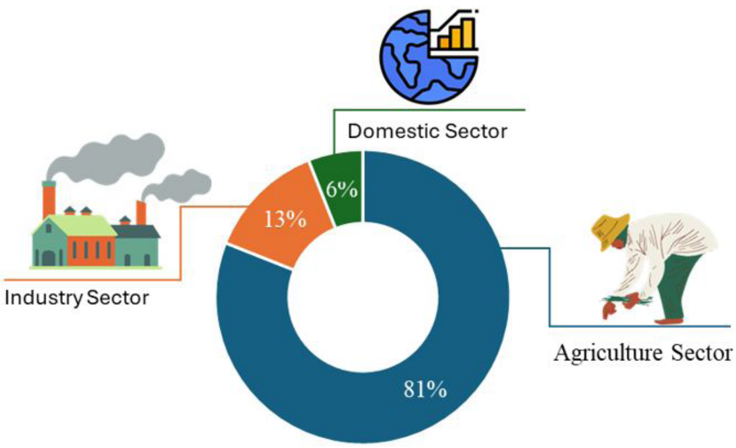
Introduction

Farming and agriculture contribute significantly to the GDP (gross domestic product) of both emerging and developed countries. Hence, it is important to improve and optimize current agricultural technologies. Currently, as it has been the case for the last few centuries, agriculture serves as the primary source of food for society, accounting for over 74% of the daily intake of populations from agricultural fields (Glória et al.,2021). Agriculture is not only crucial for sustaining people, but it also ranks as one of the primary sectors in terms of water usage, accounting for about 81% of global freshwater consumption. Furthermore, despite the need to meet growing consumer demands and address the global problem of water scarcity, 30% of water is wasted for a variety of reasons, such as poor water management, leaky systems, and outdated methods (Kaur et al., 2022). To address these issues, sustainability and the integration of technology in agriculture have emerged as significant factors. The world is currently experiencing water scarcity in certain regions, and this problem is worsening due to the growing global population and the increasing demand for fresh water (Goap et al., 2018). During the early 1900s, irrigation was undoubtedly the most important technology that needed to be used effectively. Farmers must anticipate the water requirements for their crops, either by verifying the information from agricultural weather stations or by acquiring knowledge of the evaporation rate of water surfaces in lakes or dams. Scheduling agricultural irrigation is an essential administrative activity that aims to achieve efficient and effective water utilization. Effective irrigation scheduling focuses on applying the right amount of water at the right time. Irrigation scheduling enhances water usage efficiency by using evapotranspiration (ET) estimate techniques to comprehend geographical changes of ET (Das, 2003). To identify irrigation applications, the water balance component must be detected. Various sensing technologies must be integrated into irrigation scheduling models and control. Furthermore, water quality restrictions will be connected to irrigation scheduling and management, and new, improved sensor technologies will be used. It is anticipated that India can irrigate 139.5 million hectares in total. This comprises 15 million hectares from small irrigation systems, 66 million hectares from groundwater extraction, 58.5 million hectares from big and medium irrigation schemes, and an expected 77 million hectares from freshwater usage for irrigation after 2025 (Saggi et al., 2025). It is estimated that ar,ound 50% of the total farmed area will remain rain-fed after the irrigation system reaches its maximum capability. Irrigation is the primary determinant for increasing the agricultural yield of plants. To maximize the benefits of irrigation, it is crucial to accurately assess the amount of water needed. This assessment is affected by the crop's kind, environment, subsurface geo-hydrological conditions, and stage of development. When scheduling irrigation, the following questions arise: (i) What is the procedure for applying irrigation water? (ii) What is the appropriate amount of water to use for irrigation? (iii) When is the optimal time to irrigate? (Thomson et al., 2007). Figure 1 shows that the agriculture sector in India uses 81 percent of fresh water, the industry sector 13 percent, and the domestic sector 6 percent. It is expected that human water consumption will increase to up to 26% by 2025 according to (Phasinam et al., 2022).

In smart agriculture, Internet of Things (IoT)-based irrigation systems represent a modern approach that utilizes real-time environmental data to automate and optimize irrigation practices. It uses connected devices, such as sensors and actuators, to assess major soil and environmental parameters, like moisture in the soil, humidity, wind speed, temperature, and rainfall (Kaur et al., 2023). Appropriate water distribution is possible with the help of smart irrigation methods; this all can be achieved with the help of sensors and continuous gathering of real-time field data. These methods help conserve water, reduce costs, and improve crop health and production by preventing both over- and under-irrigation. Integrating these systems with machine learning algorithms enhances decision-making by predicting



Source: Different sectors water consumption. Authors identification, 2025

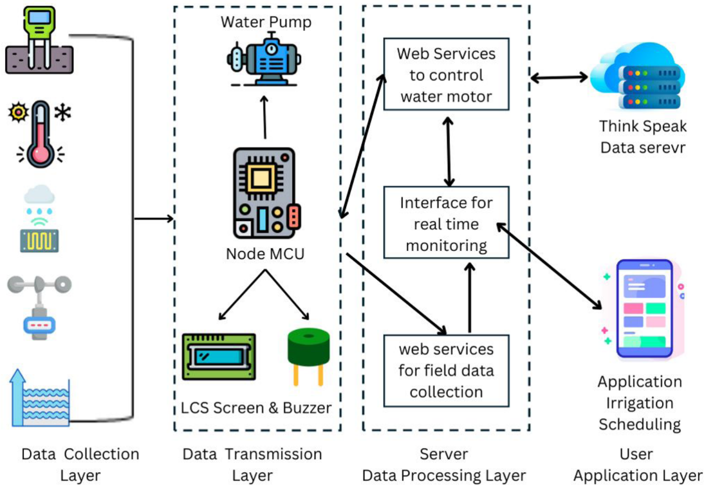
Figure 1: Fresh water consumption by different sectors.

future irrigation needs based on historical data and current field conditions (Vij et al., 2020). This research developed a smart irrigation system using multiple sensors and the Node MCU ESP8266. Sensors employed in fields collect real-time data and automatically control and monitor irrigation from remote locations using mobile or web applications (Scarlatache et al., 2024). This research developed an advanced smart sprinkler irrigation system, utilizing internet of things technologies to optimize irrigation, reduce water utilization, and improve crop productivity. An irrigation system is developed using multiple sensors and microcontrollers, such as Node MCU, soil moisture sensors, temperature sensors, and solenoid valves, to effectively control the system based on field parameters like soil moisture and temperature. By integrating fuzzy logic, the system efficiently adjusts field irrigation and ensures real-time optimization of water utilization (Marathe et al., 2024). In this research work, different irrigation methods are compared by the author to identify the best strategies to enhance sweet corn production while decreasing water use and energy consumption. The researcher compares two methods: soil moisture monitoring (IoT-SM) and the evapotranspiration (ET)-based irrigation method. Soil moisture sensors are part of IoT-SM, which irrigates at two levels: 43.5% and 34.8% of the soil's capacity, while the ET-based method uses the total amount of water needed for crop evapotranspiration (ET). Crop height, yield production, and water productivity determined the effectiveness of these methods. The research revealed that the IOT-SM methods at 43.5% field capacity produce approximately 12.5% higher production and decrease 11% water consumption compared to the ET-based method (Kumar et al., 2023). This research uses machine learning algorithms to develop an automated hybrid irrigation system. Researchers gather on-field data regarding soil moisture and temperature to optimize the irrigation timing in real time. The SVM algorithm provides the highest accuracy for irrigation prediction compared to other models, enabling better irrigation scheduling. The proposed model enhances irrigation efficiency using real-time environmental data for automatic irrigation systems, which will help in reducing water use and improving crop production and sustainable agriculture practices (Sarjerao and Sudhagar, 2024). Arduino Nano microcontrollers manage off-grid wind and solar power smart irrigation system. To enhance irrigation efficiency, the system monitors soil moisture level and water conditions. Integrating renewable energy sources reduces the demand for commercial electricity in the agriculture sector. The proposed system motivates farmers to adopt smart irrigation systems, enhancing resource efficiency and lowering operation expenses, based on renewable energy systems (Ghosh et al., 2023). In this research, a smart irrigation system is developed using deep learning techniques to predict soil moisture content based on real-time environmental factors like temperature and humidity, as well as light intensity. Real-time collected data from the field is integrated with machine learning to schedule the irrigation and improve water efficiency. Crop production, health, and water uses are improved by integrating the internet of things, neural networks, and predictive analytics to predict the requirements for irrigation (Maira Sami et al., 2022). In this research (DADP-LP), SA and OD-DADP, two different hybrid algorithms, are proposed to solve the complex nonlinear optimization problems of the optimal allocation of resources like water and land for irrigation. In this proposed model, decomposition-aggregation dynamic programming is integrated with linear programming and orthogonal design methods. The model was used in the irrigation area of Gao'a in Jiangsu Province, China, and it worked better than older methods like Real-Coded Genetic Algorithm (RGA) and Particle Swarm Optimization (PSO) by giving higher quality and more reliable solutions for managing water and land resources (Wei et al., 2023). This research develops an IoT-based smart irrigation system to enhance the sustainable management of water resources in the agricultural sector. IoT sensors are employed in the field to gather real-time sensor data on soil moisture, temperature, humidity, and TDS (total dissolved solids) to determine real-time irrigation requirements and classify crop varieties like wheat, rice, and corn in combination with K-Nearest Neighbors. This data-driven methodology allows accurate irrigation scheduling autonomously, maximizing water efficiency and supporting sustainable agricultural practices such as reducing the usage of fossil fuels for extracting water, preserving essential water resources, and improving crop production— all while handling issues related to water scarcity and climate change while promoting sustainable agriculture (Sharan et al., 2025). A smart irrigation system is proposed by researchers and introduced as the ROWIA method to decrease the use of fresh water by reusing reverse osmosis (RO) wastewater for agricultural field irrigation. To optimize irrigation time, an ESP32 microprocessor and DHT22 sensors are used for monitoring environmental data such as soil moisture, humidity, and temperature. A mobile application is developed using the Blynk cloud platform to monitor and control the real-time data from agriculture to optimize the resources. This method handles water shortage problems and improves sustainable agriculture practices via an efficient irrigation management system and less dependence on freshwater resources (Panah and Taghizadeh, 2024). In this research, the author developed a hybrid dynamical systems approach to the drip irrigation system that takes into consideration the binary nature of the control input. It analyses the influence of transients in the irrigation pipe on uniformity and derives an intuitive policy of irrigation based on existing farmer operations. The model is verified by simulation using parameters derived from field farm measurements, with the aim of enhancing irrigation effectiveness and efficiency by this new approach (Bertollo et al., 2022). The hybrid irrigation system designed in the study combines solar and wind energy to power a standalone drip irrigation system for 1 acre of banana plantation in Kalangala district, Uganda. It utilizes 14 solar panels and a wind turbine to meet the water requirement of 33.73 m³ per day. The system operates efficiently at wind speeds of 20 m/s, ensuring sustainable irrigation while minimizing costs and environmental impact compared to traditional motorized methods (Ssenyimba et al., 2020). The hybrid irrigation system described in the paper combines photovoltaic (PV) panels and a diesel generator to supply power for irrigation on fruit-growing farms without grid connection. It features a 7.5 kW pump powered by 11.04 kW PV panels, capable of delivering 80 m³ of water daily. The system includes lead storage batteries for up to 37 kWh of electricity and a 20-kW diesel generator as backup during periods of low solar radiation, ensuring continuous operation throughout the year (Ševaljević and Nikolić, 2017). The paper discusses a hybrid irrigation system that combines wind and photovoltaic (PV) generation with water tank storage for efficient water pumping. This system addresses the variability of renewable energy sources, providing a reliable solution for irrigation in off-grid, arid areas. The methodology includes a one-year operation simulation and evaluates different combinations of PV technologies, wind types, and water tank capacities based on investment costs, crop requirements, and system oversizing, making it adaptable for various agricultural sites in Bulgaria (Stoyanov et al., 2021). The hybrid irrigation system designed in the paper combines wireless sensor networks (WSN) and wireless underground sensor networks (WUSN) to achieve precision irrigation. It utilizes ARM9 microprocessor and GPRS module for remote monitoring and control. The system collects soil temperature, humidity, and water content data at varying depths, enabling automatic irrigation based on real-time soil conditions. This innovative approach can save approximately 25% more water compared to traditional irrigation methods, enhancing water efficiency in agriculture (Yu et al.,2015). In this research, the focus is on addressing the challenges faced by small-scale farmers in developing and underdeveloped nations, particularly in India, where traditional farming methods are still prevalent. Despite agriculture being the primary income source for 58% of the population, many farmers struggle with low income, inefficient irrigation practices, and the high cost of modern equipment. The study proposes a cost-effective smart irrigation system utilizing Node-MCU and IoT technology to automate irrigation based on real-time soil moisture levels. Additionally, the system includes plant monitoring through camera input and ensures data integrity using encryption techniques. The proposed solution aims to offer an affordable, efficient, and reliable alternative to conventional farming methods, tailored to the needs of resource-constrained farmers (Badotra et al., 2021). In this research, a communication protocol for smart irrigation systems within the framework of Smart City initiatives is proposed, with a focus on efficient water management in urban areas facing water scarcity. The study emphasizes the potential of using non-potable water sources, such as treated sewage or rainwater, for irrigating urban gardens and green spaces. The proposed protocol facilitates communication between devices using both LoRa and Wi-Fi technologies, aiming for effective data transmission and system coordination. Implemented with low-cost hardware in an urban environment, the system demonstrated strong performance, achieving minimal packet loss through the introduction of a 500 ms delay at the central hub (CH) during message transmission (Aldegheishem et al., 2022). In this research, Smart and Green framework is proposed to enhance irrigation efficiency through intelligent data handling and prediction techniques in smart agriculture systems. Recognizing that irrigation is one of the most water-intensive agricultural practices, the study highlights the need for accurate and synchronized data across multiple sources for optimal irrigation management. The framework provides integrated services including data monitoring, preprocessing, fusion, synchronization, storage, and soil moisture prediction. To improve data reliability, outlier removal techniques such as Z-score, Modified Z-score, and Chauvenet's criterion are applied, significantly increasing the precision of irrigation decisions. For areas lacking soil moisture sensors, the system estimates matric potential using weather, crop, and irrigation data, applying the Van Genuchten model to calculate moisture levels. The results show that this approach can reduce water usage by 56.4% to 90%, demonstrating its effectiveness in supporting sustainable irrigation practices (Campos et al., 2019). In this research, the feasibility and potential impact of implementing smart irrigation systems in Malaysia’s oil palm plantations are examined in the context of Industry 4.0 technologies. Recognizing that the palm oil industry is the second largest globally but still heavily reliant on labor-intensive practices, the study evaluates smart irrigation as a strategy to enhance efficiency, economic performance, and sustainability. The analysis incorporates key factors such as return on investment (ROI), water footprint, plantation size, and server setup configurations. Results indicate that smart irrigation becomes economically viable for plantations larger than 1.5 hectares, offering substantial water savings and reduced operational costs while maintaining optimal soil moisture conditions. These findings provide valuable guidance for stakeholders considering technological transformation in the oil palm sector through the adoption of smart agricultural practices (Chalvantharan et al., 2023). In this research, a low-cost, autonomous Internet of Things (IoT)-based irrigation monitoring and control system is developed to address challenges posed by rising global food demand, population growth, and climate change. The system is designed to optimize water usage in remote agricultural areas by automating irrigation through the integration of sensors, actuators, and a pumping mechanism. Using the system development lifecycle and the waterfall model, the prototype was built with tools such as the Proteus 8.5 design suite, Arduino IDE, and embedded C programming. The resulting system provides sensing, monitoring, control, power supply, and internet connectivity, enabling efficient water delivery from a reservoir to crops. Experimental and simulation results confirm the system’s flexibility and practical applicability, highlighting its potential to reduce manual supervision, support remote access, and contribute to the broader economic advancement of irrigation farming (Abba et al., 2019). In our research we integrated machine learning and the Internet of Things to develop a smart irrigation system to automate the irrigation system. Different types of sensors are deployed in the field to calculate real-time environmental data. Sensors such as soil moisture sensors, humidity and temperature sensors, and wind speed sensors are used. Machine learning algorithms are used to process data and to forecast the irrigation requirements to regulate the irrigation system according to real-time conditions. The developed system will help to optimize water use by automating the irrigation system, reducing the labor requirements, and increasing crop production due to automated irrigation according to climate and environmental conditions. A wireless sensor network is developed using microcontrollers such as Arduino UNO and Node MCU, which will help farmers to automatically control and monitor irrigation requirements from a remote location from a mobile application. The motivation behind this research is to develop an efficient irrigation system that optimizes water use, reduces expenditure, and enhances crop production. The research work is divided into different sections: In section 2, the smart irrigation system is discussed; in section 3, the results and discussion of the implemented work; and in section 4, the research findings are concluded.

Material and methods

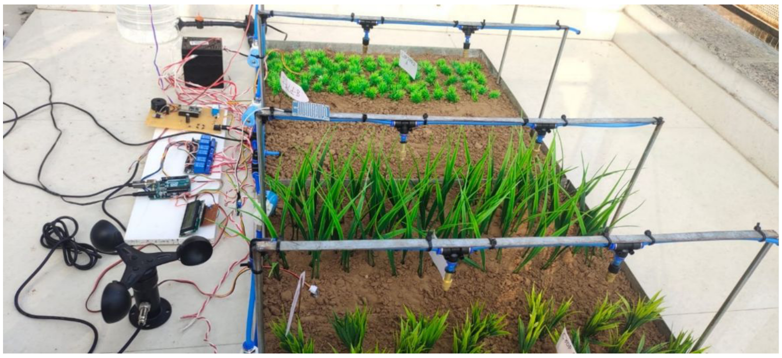
In this section, smart irrigation system implementation procedure is discussed. Smart Irrigation System Architecture is shown in Figure 2.

This model framework is made up of many key components, such as a soil moisture sensor, wind speed sensor, rain detection sensor, water level sensor, temperature and humidity sensor, Node-MCU, LCD display, buzzer, cloud storage, machine learning algorithms, and mobile application. Based on real-time data collection from the field, the system aims to optimize water use in the agricultural sector. The main component of this system is the Node-MCU microcontroller, which develops wireless connectivity using



Source: System architecture illustrating sensor connectivity in the field, integration with the microcontroller, and interaction with the web application. Authors identification, 2025

Figure 2: Smart irrigation system architecture.



Source: Smart sprinkler irrigation System harware protoype. Authors identification, 2025

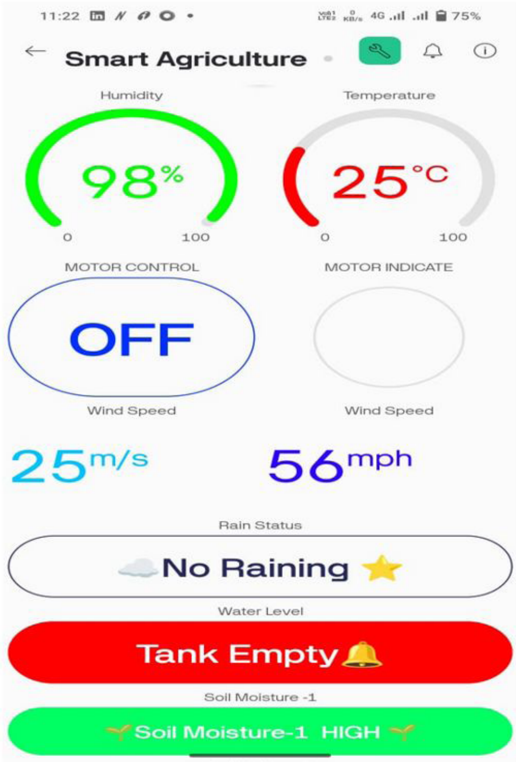
Figure 3: Smart irrigation system prototype.

its versatile ESP8266 chip and manages data processing. It helps in increasing crop production, maintaining soil conditions, and ensuring effective water utilization. Node-MCU performs sensor interconnectivity and real-time data transfer over Wi-Fi and to mobile applications, making it perfect for remotely monitoring and controlling irrigation. Various sensors are deployed to monitor environmental conditions such as soil moisture levels, wind speed, water levels, and rainfall. A soil moisture sensor is used in this model to detect moisture levels in the soil. If the moisture level falls below the required threshold, it notifies the farmer to remotely adjust irrigation settings. A water level sensor is used to monitor the reservoir; if the reservoir is empty, the system updates the status to indicate a low or empty water level. A wind speed sensor is used to measure wind velocity. If the wind speed is too high, the application alerts the farmer, as high wind speeds can reduce the water use efficiency of sprinkler irrigation systems. Solenoid valves manage water flow by activating only in fields where moisture levels are low, leaving adequately moist areas untouched. Real-time updates are displayed on an LCD panel for easy monitoring. The system uses the Thing-Speak cloud server to store and process the collected data. It analyzes historical datasets to generate insights, enabling predictive irrigation based on environmental trends. The setup involves programming the sensors and integrating them with a microcontroller to ensure easy data transmission and control operations. Once deployed, the system provides a responsive and adaptive irrigation solution that enhances agricultural productivity while promoting resource efficiency and sustainability. Figure 3 Smart irrigation system prototype (above).

The material has been precisely cut into the required length dimensions of the construction, ranging from 1.2 to 0.17 to 0.4 metres. The project design has an inverted U-shaped structure integrated with a T-shaped hybrid irrigation system. An eight-millimetre water pipe serves as the primary supply pipe. Sub pipelines are constructed using six-millimetre water pipes to give water to fields. The sub pipe is connected to main pipes and solenoid valves using T and L form pipe connections (Kaur et al., 2024).

In previous research, we considered only the soil moisture level to activate the irrigation system and, based on this, evaluated the system's accuracy. However, in this study, we aim to predict the irrigation time by considering multiple factors, including soil moisture, air temperature, wind speed, and rainfall status. Based on these parameters, the results for scheduling irrigation are significantly improved and are discussed in detail in the Results section. This smart irrigation system was developed to overcome the problems of existing irrigation models. The model will help farmers to grow different crops according to their choice under the smart irrigation system and to perform interculture activities like harvesting, sawing new crops, pesticides without any hustle of removing or re installing the project after these kinds of activities.

The model is designed in vertical t shape structure. The development of an Android application is underway to enable farmers to effectively monitor and manage the smart irrigation system. The program presents input metrics like soil moisture, wind speed, rain status, water, temperature, and humidity. Farmers will have the capability to continuously monitor and regulate field conditions from any location and at any time. This enables the farmer to manipulate the motor switch and schedule irrigation for the crop based on the specific needs and water availability. In Figure 4 mobile applications developed for smart irrigation systems are shown.



Source: Mobile application for farmers to monitor and control the smart irrigation system automatically. Authors identification, 2025

Figure 4: Smart irrigation system mobile application.

Data collection and analysis

The smart irrigation system utilizes Internet of Things (IoT) technology to automate irrigation by continuously collecting real-time environmental data. Key parameters monitored include soil moisture, air temperature, humidity, rainfall status, wind speed, and pump activity. Sensor data is centrally stored and analyzed on the Thing-Speak cloud server. To validate the system, devices were deployed across diverse soil conditions and environmental settings, leveraging IoT technology. These autonomous sensors form a self-organizing network, efficiently collecting and transmitting data for precise irrigation control. An algorithm processes the gathered data, enabling optimal water distribution and providing real-time insights. A total of 7,000 dataset, encompassing all monitored parameters, has been collected from the field.

Data interpretation from sensor readings

Soil moisture data

The capacitive soil moisture sensor is used to monitor the soil moisture level. Real time soil moisture gathered from field range between 315 and 920, indicating diverse field conditions. Table 1 shows the real time sensor measurements from the field.

Temperature data

Using the DHT11 sensor, air temperature was recorded in degrees Celsius. The monitored months revealed a mean temperature of 26.24°C. The lowest temperature observed was 18.00°C, while the maximum reached 42.2°C, highlighting seasonal variations.

Air humidity data

The DHT11 sensor also provided air humidity readings, with values ranging from 38% to 81.26%. The average humidity during the observation period was 66.4.

Wind speed data

Wind speed data was collected and updated on application to make decision on irrigation process on high-speed wind condition. The wind speed sensor collect data in between range of 1 m/s 50m/s or in mph.

Rain status

The rain sensor is used to collect data on raining condition if it is raining then mobile application is updated with the help of rain sensor farmer can avoid over irrigation. The sensor will store rain or not raining condition in the form cm. Table 1 show the data collected sample from field.

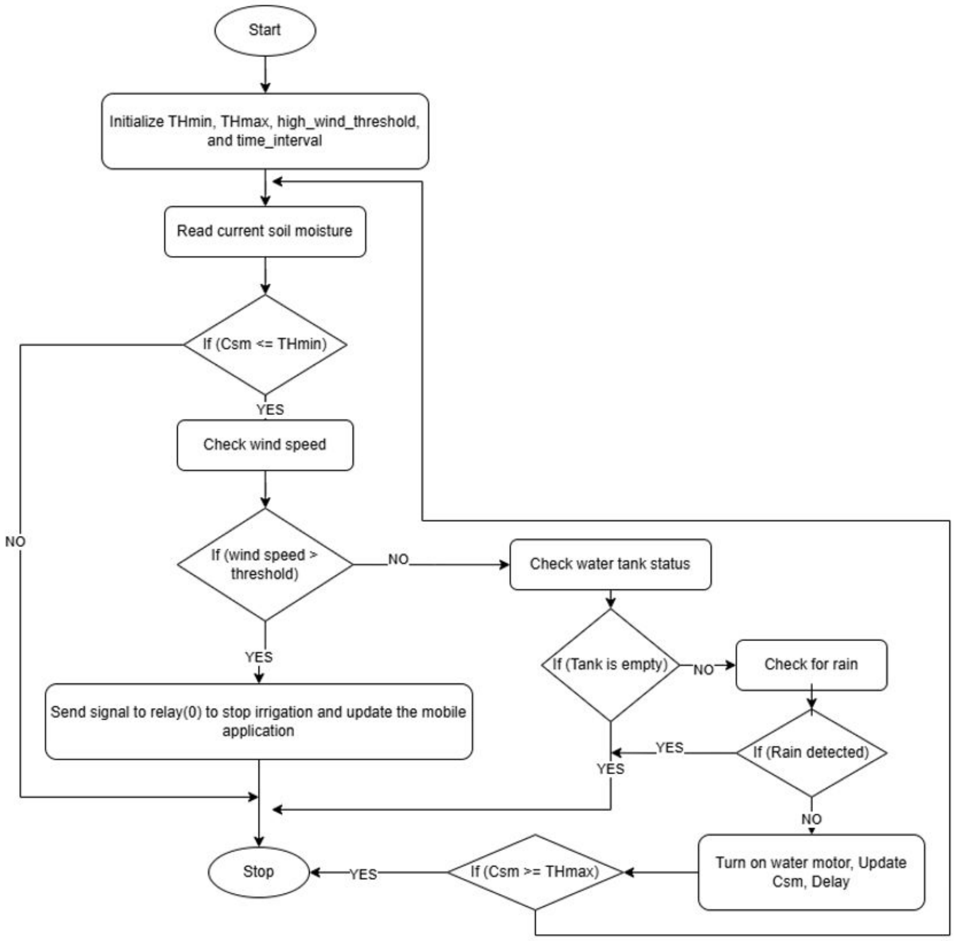
Irrigation scheduling algorithm

The irrigation control algorithm is designed to optimize water usage in smart agriculture by automating the irrigation process based on real-time soil moisture data and environmental conditions such as wind speed, rain status, and water tank levels. Initially, the algorithm sets two key thresholds: a minimum soil moisture level (TH-min) to trigger irrigation and a maximum level (TH-max) to stop it. The system continuously monitors the current soil moisture (Csm) using sensors. When soil moisture falls below TH-min, the system initiates irrigation, and when TH-max indicates sufficient soil moisture, it stops irrigation operations. To avoid over-irrigating crops and provide appropriate irrigation, the system dynamically adjusts TH-max based on conditions such as predicted soil moisture, temperature, humidity, and weather. The wind speed sensor is used to detect the wind speed and prevent irrigation during high wind speed to minimize the water loss due to evaporation. Water level sensors monitor the water dam, sending notifications when it becomes empty. Rain detection sensors are used to detect the rain status; if it is raining, then the system sends information to the mobile app about the rain, and the system prevents irrigation. The system is collected and monitored in a continuous loop, constantly checking moisture levels and adjusting irrigation as necessary to maintain an optimal irrigation requirement of crops. The system collects real-time environmental data, and automated decisions are made to control and monitor the irrigation system. The system helps reduce water usage and labour while implementing sustainable and efficient irrigation methods tailored to current weather conditions and soil requirements. This approach offers a robust and adaptable solution for water management in precision agriculture. The Figure 5 depicts the algorithm's flowchart.

S. No.	Soil Moisture	Air Temperature (°C)	Air Humidity (%)	Wind Speed (mph)	Rain Status	Pump Status
1	583.78	35.53	38.66	10	0	1
2	333.35	22.18	58.06	13	0	0
3	474.84	36.13	55.85	11	0	0
4	612.01	21.12	43.27	8	0	1
5	846.75	33.64	41.80	4	0	0

Source: The values represent real-time monitoring of field parameters, including soil moisture, wind speed, temperature, rainfall status, and pump status. Authors identification, 2025

Table 1: Real-time sensor measurements from the field.



Source: Irrigation scheduling algorithm flowchart. Authors identification, 2025

Figure 5:Irrigation scheduling algorithm flowchart.

Irrigation scheduling algorithm steps

Step 1: Initialization

THmin = (Minimum threshold of soil moisture)

THmax = (Maximum threshold of soil moisture)

High wind threshold = (Threshold for wind speed)

Step 2: Continuous monitoring loop while system is powered on:

Step 3: Read current soil moisture

Csm = read soil moisture sensor()

Step 4: Soil moisture evaluate

if Csm <= THmin:

Step 5: Adjust THmax if necessary

THmax = adjust THmax based on conditions()

Step 6: Start irrigation if Csm < THmax

while Csm < THmax:

Check wind speed

wind speed = read wind speed sensor()

if wind speed > high wind threshold:

send_notification("High wind speed detected.")

Check water tank status

if check water tank status() == "empty":

send_notification("Water tank is empty. Stopping irrigation.")

send signal to relay(0) # Stop irrigation

break # Exit the loop

Check for rain

if read rain sensor() == "raining":

send notification("Rain detected. Stopping irrigation.")

send signal to relay(0) # Stop irrigation

break # Exit the loop

If conditions are normal, start irrigation

send signal to relay(1) # Turn on the water motor

Csm = read soil moisture sensor() # Update current soil moisture level

delay(<time_interval>) # Add a delay for system stability

Step 7: Stop irrigation if Csm reaches THmax

if Csm >= THmax:

send_signal_to_relay(0) # Turn off the water motor

else: # If Csm is above THmin, no irrigation is needed

send_signal_to_relay(0) # Ensure irrigation remains off

Optional delay before repeating the loop

delay(<time_interval>)

Result and discussion

To enhance water management for agricultural areas, the smart irrigation system suggested in this study combines machine learning algorithms with Internet of Things technology. The system uses a variety of sensors to gather environmental data in real time, including wind speed, humidity, soil moisture, air temperature, and rain status. In this smart irrigation system machine learning plays an important role in optimizing irrigation management by gathering real-time environmental data. To determine the irrigation requirements in real time the soil moisture and temperature are the important factors. If soil moisture drops below the required threshold, then sensors send signals to microcontrollers to activate the irrigation pump and soil moisture updated on mobile applications. Field temperature also plays important role in scheduling the irrigation because higher temperatures can cause high evaporation and crop water requirements are increased. Machine learning models are trained to predict the irrigation timing and requirements based on gathered data from the field on various parameters such as soil moisture, air temperature, wind speed, and rain status. The system will help to manage the over and under irrigation by integrating real-time data with predictive analytics, the system automates the irrigation process, thereby minimizing both over-irrigation and under-irrigation. This method enhances water use efficiency and supports optimal soil conditions for improved crop health and production. Furthermore, a graphical analysis compares the performance of various machine learning models in forecasting irrigation requirements.

Performance analysis of machine learning models

In this study, we evaluated the performance of various machine learning models for optimizing smart irrigation systems. Accurate prediction of irrigation requirements is crucial to conserve water resources and maximize crop yield. To this end, models including Decision Tree (DT), Random Forest (RF), Gradient Boosting (GB), and XG-Boost were implemented, each employing distinct approaches to learn from environmental data. Decision Tree (DT): A supervised learning method that recursively splits data based on feature values. Its hierarchical structure allows it to capture nonlinear patterns while maintaining interpretability. Random Forest (RF): An ensemble of decision trees that combines multiple classifiers to improve generalization and reduce overfitting. Gradient Boosting (GB): Builds models sequentially, where each new model attempts to correct the errors of the previous ones, enhancing predictive accuracy. XG-Boost: An optimized gradient boosting framework designed for efficiency and performance, incorporating regularization to reduce overfitting and improve robustness. The models were evaluated using standard performance metrics, including Accuracy, Precision, Recall, F1-score, and Root Mean Squared Error (RMSE). These metrics provide a comprehensive assessment of the models' ability to predict irrigation requirements reliably.

Comparative results

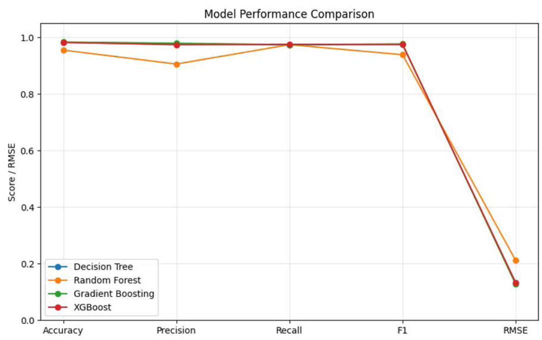
The performance results of each model are summarized in Table 2.

Algorithm	Accuracy	Precision	Recall	F1	RMSE
Decision Tree	0.982381	0.975709	0.974394	0.975051	0.132737
Random Forest	0.955238	0.906015	0.974394	0.938961	0.211570
Gradient Boosting	0.983810	0.979675	0.974394	0.977027	0.127242
XGBoost	0.982381	0.974428	0.975741	0.975084	0.132737

Source: Performance evaluation of machine learning models for irrigation system. Authors Identification, 2025

Table 2: Performance results of each model.

- Gradient Boosting emerged as the best-performing model, achieving the highest accuracy (98.38%) and F1-score (97.70%), along with the lowest RMSE (0.1272). These results demonstrate their superior ability to balance precision and recall while minimizing prediction errors.
- The Decision Tree and XG-Boost models also showed strong performance, with accuracies above 98% and F1-scores exceeding 97%, making them reliable alternatives. The Decision Tree model offers greater interpretability, which is valuable for understanding feature importance, while XG-Boost provides computational efficiency for larger datasets.
- Random Forest, although robust in handling data variability, displayed slightly lower precision (90.60%), indicating a higher rate of false positives in irrigation prediction. Performance comparison of machine learning models for irrigation optimization is shown in Figure 6.



Source: Model performance evaluation based on real-time field data. Authors Identification, 2025

Figure 6: Performance comparison of machine learning models for irrigation optimization.

Conclusion

The proposed research work confirms that when we integrate IoT sensors with machine learning, it will significantly enhance water use efficiency in agriculture. Analysis of the gathered data shows that Gradient Boosting performed best, with 98.38% accuracy and the lowest RMSE (0.1272). Decision Tree and XG-Boost also performed well, each with 98.24% accuracy and F1-scores above 97.5%, while Random Forest had lower precision (90.60%) and higher RMSE (0.2116). These models are well-suited for handling the complexities of real-time irrigation data, providing precise predictions and enabling efficient water management. The automated irrigation system offers a practical solution for farmers, allowing for real-time monitoring and control of irrigation based on environmental conditions. The system reduces water waste and decreases the need for manual workers, contributing to more sustainable and productive agricultural practices. Future work will focus on enhancing the system's capabilities by incorporating additional environmental factors, refining predictive algorithms, and improving the user interface for better farmer accessibility.

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Cluster Analysis of Agricultural Input Imports in Colombia: An Approach Based on International Economics and Trade Agreements

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Abstract

This study analyzes geoeconomic patterns in Colombian imports of agricultural inputs by applying the k-means algorithm to the CIF value and gross weight complemented by an analysis of trade agreements and tariffs. The results show high dependence on a few suppliers such as Russia and the US for fertilizers and China for technology, even without preferential agreements; On the other hand, the limited effectiveness of FTAs was analysed, where tariff reduction did not generate diversification of critical suppliers; opportunities for diversification with medium-sized suppliers such as Brazil in animal feed; and the relevance of the European Union in veterinary medicines, agricultural technology, fertilizers, and seeds. The methodology integrates data from DIAN (2005-2024) and five-year analyses, showing that competitiveness in prices and logistics outweighs tariff advantages, China dominates 65% of the CIF value in technology and Russia and the United States consistently accounted for over 60% of the CIF value and gross weight of fertilizers. Regulatory, trade, and innovation policies are proposed to reduce the risk of input shortages in agri-food value chains.

Keywords

Agribusiness, agricultural policy, rural development, cluster analysis, agricultural trade, import.

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Introduction

The Colombian agricultural sector is one of the most dynamic sectors of the economy because it generates more than 80% of the food consumed by the Colombian people. According to the figures of the National Administrative Department of Statistics DANE for the first semester of 2024 presented a growth of 5.5% higher than that of 2023 (DANE, 2024). This sector is composed of primary production activities in agriculture, livestock, forestry, fishing and aquaculture (Ministerio de Educación Nacional, 2016). Several factors interact in the production of the agricultural sector, which are the essential elements necessary to produce goods. These factors include land, labor, capital, technology, organization and inputs. Agricultural inputs comprise all the products and resources needed to carry out agricultural and livestock activities, such as fertilizers, pesticides and phytosanitary products, seeds, animal feed, veterinary drugs, equipment and tools, construction materials, biological products, technology and software, and genetic material. These inputs have a direct impact on productivity and competitiveness due to their incidence on production costs, entailing risks that affect the efficiency and profitability of agricultural activity and, therefore, the producer's income (FAO, 2022).

Due to the importance of the agricultural sector and the need to ensure food security, the national government has given importance to agricultural inputs by creating law 2183 of January 6, 2022, which establishes the national system of agricultural inputs, establishes the national policy of agricultural inputs, and creates the fund for access to agricultural inputs. On the other hand, according to the Ministry of Agriculture and Rural Development (MADR), fertilizers represent 55% of the sales of inputs demanded by the agricultural sector, pesticides 27%, veterinary drugs 13% and biological products 5%.

In recent decades, Colombia has promoted its integration into the global economic and trade landscape. These include free trade zones and common markets. It develops these free trade zones through Free Trade Agreements (FTAs). However, empirical evidence shows that this openness has had mixed impacts. Apparently, openness and trade issues through multilateralism and free trade agreements (FTAs) have provided many positive opportunities to boost the country's economic development. For example, Colombia has maintained good trade relations with the European Union, the Andean Community, Mercosur, and others.

The problems associated with the costs of agricultural inputs can be categorized into three groups: i) the influence of the international market, ii) domestic marketing, and iii) use and application (Ministerio de Agricultura y Desarrollo Rural, 2018). Since this research focuses on the analysis of imports, the influence of the international market will be analyzed in depth, which has a direct impact on the formation of national prices of the main inputs, given that Colombia does not produce the so-called simple fertilizers: Urea, source of Nitrogen, Diammonium Phosphate (DAP) source of Phosphorus and Potassium Chloride (KCL) source of Potassium. In the case of pesticides, active ingredients are the main raw material for their manufacture, and 98% are imported. In Colombia, the local industry primarily relies on imports of active ingredients for the manufacture of pesticides for the domestic market and for export. Veterinary drugs and biological products are industries that also have a significant imported component in their cost structures, since research and development activities are centralized in multinational companies, directly at the level of their parent companies.

Recent research demonstrates that machine learning (ML) methods offer a powerful alternative to conventional techniques for analyzing global trade patterns (Batarseh and Yang, 2017; Batarseh et al., 2019, 2021; Gopinath et al., 2021). These approaches enable the identification of complex patterns in import dynamics that can directly inform public policy formulation.

Studies on Colombia's imports have primarily employed econometric, statistical, and descriptive approaches. Gómez-Sánchez and Salazar-Villano (2014) developed an import demand model using cointegration analysis, while Rangel Vargas et al. (2019) identified Gross Domestic Product and the Real Exchange Rate as key determinants of import behavior. Research on trade agreements has yielded mixed findings: Trochez González et al. (2018) found limited effects of the U.S. FTA on corn prices, whereas Vargas-Chaves (2023) documented significant impacts on seed certification systems that affected crop diversity. These studies collectively highlight internal challenges in logistics infrastructure and technological capacity that constrain Colombia's trade performance (Cruz Negrete, 2018; Piedrahita et al., 2022)

The strategic importance of agricultural inputs is underscored by recent global disruptions.(Quitzow, Balmaceda and Goldthau, 2025) documented how the Ukraine conflict triggered fertilizer price volatility, revealing the vulnerability of import-dependent regions like Latin America. Meanwhile, international standards from Codex Alimentarius, IPPC, and WOAH establish critical frameworks governing inputs from seeds to veterinary products (FAO, 2024; IPPC, 2024).

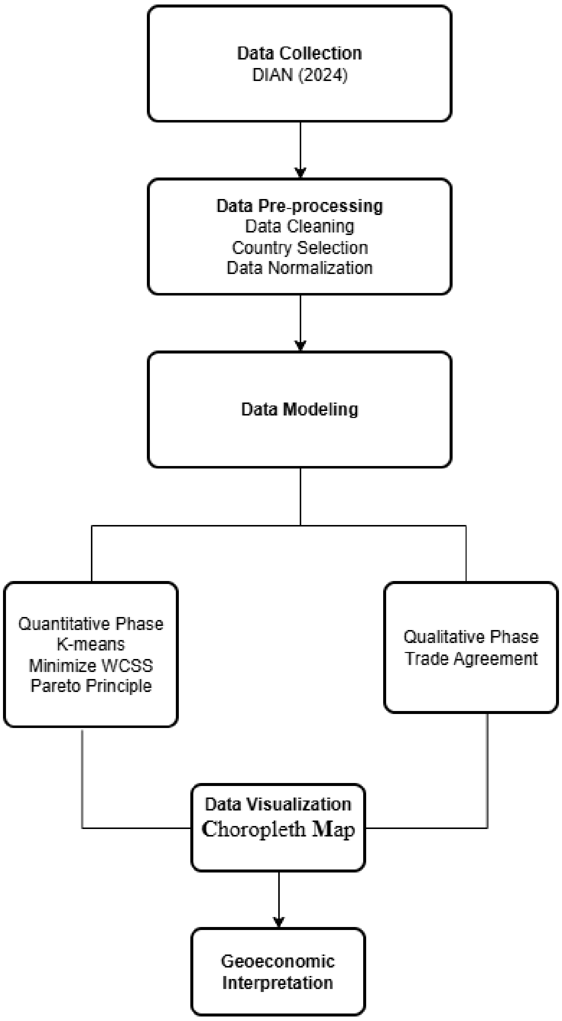
ML techniques have been widely applied across agricultural domains, including yield prediction, disease detection, and resource management (Storm, Baylis and Heckelei, 2020; Benos et al., 2021). In trade analysis specifically, researchers have employed diverse approaches: Batarseh et al. (Batarseh et al., 2019, 2021) used k-means clustering and boosting algorithms for commodity trade forecasting, while Zhang et al. (2025) applied unsupervised learning to analyze China's agricultural import channels. Advanced methods such as LSTM networks (Qin, Wu and Chen, 2025) and ensemble models (Arora, Sarkar and Ponmagal, 2025) have demonstrated superior performance in predicting trade flows and supporting decision-making.

This study aims to analyze geoeconomic patterns in Colombian agricultural input imports through an integrated approach that combines machine learning clustering with trade policy analysis. Specifically, the research seeks to: 1) What are the geoeconomic patterns in Colombian imports of agricultural inputs, considering both value (CIF) and volume (gross weight)?; 2) What factors explain the composition and evolution of these clusters, and how effective are they? ; and 3) How can these patterns inform public policies to reduce strategic vulnerability and promote supplier diversification?

By applying k-means clustering to CIF value and gross weight data from 2005-2024, this research provides a novel methodology for identifying trading partners and patterns that can inform strategic decision-making in agricultural trade policy.

Materials and methods

The present research employs a mixed methodology. The subsequent quantitative phase employs the K-means algorithm to cluster countries according to their import profiles. The results are presented on a choropleth map, a geographical representation of population density. In the subsequent phase, these patterns are interpreted in the context of trade agreements, thereby facilitating the attainment of a comprehensive geoeconomic understanding (see Figure 1).



Source: Prepared by authors

Figure 1: Proposed methodology.

Data collection

The data set under consideration encompasses import data from 2001 to 2024, as provided by the National Directorate of Taxes and Customs (DIAN). DIAN supplies information in accordance with the Harmonized Commodity System, version 2022. Data preparation involves the process of data loading, processing and cleaning. The Pareto principle was used to identify the countries that concentrated on the highest value of imports, thus allowing the analysis to focus on the most relevant actors. Given that this study focuses on agricultural inputs, 4-digit HS tariff headings were considered at the tariff heading level and are shown in Table A1. To generate an analysis in common terms, the tariff headings were grouped into input categories, according to information from technical and specialized documents. The table 1 below relates each category to the tariff items considered in this study.

Tariff item	Category
3101,3102,3103,3104,3105,	Fertilizers
1201,1202,1204,1205,1206,1207,1209	Seeds
2309,1214	Animal feed
3004,3002,2937,8414	Veterinary medicines
8701,8432,8433,8201,8424	Equipment & Tools
8806, 9015,9025, 9026, 8523,4911,9032,8543	Technology and software
3101,3808	Biological products
1209	Genetic material
9406, 7308, 7314	Construction Material

Source: Prepared by authors

Table 1: Tariff item of each category.

For the preparation of data for the descriptive analysis, variables selected are shown in Table 2.

Denotation	Description and Measurement
Tariff item	is a code in the customs tariff schedule that identifies a specific product and determines the duties, taxes, and regulations that apply to it in international trade.
CIF	Agricultural inputs import value of products exchanged between nations. It is expressed in monetary terms, miles US Dollars
Gross Weight	The weight of the goods including packaging, in tons
Origin country	country of origin of the goods, i.e. where they are produced, grown, manufactured, extracted, or processed.
Tariff	Tariff duty according to the customs tariff.
Trade agreement	An agreement code so that the importer receives preferential treatment.

Source: Prepared by authors

Table 2: Variables.

Data pre-processing

Subsequently, data preparation involved a three-stage preprocessing pipeline:

1. Data cleaning: Records with missing or inconsistent values in critical fields e.g., CIF value, gross weight, or country of origin were removed to ensure data integrity.

2. Country selection: To focus the analysis on the most economically significant trading partners, the Pareto principle (80/20 rule) was applied. Countries accounting for the top 80% of the cumulative CIF value of imports for each agricultural input category were selected for the cluster analysis. This step reduces computational complexity while ensuring the analysis captures the dominant patterns that are most relevant for policy formulation.

3. Data normalization: Prior to clustering, the selected variables: CIF value ins USD and Gross Weight in tons were standardized using z-score normalization. This ensures that both variables contribute equally to the distance calculations in the k-means algorithm, preventing the model from being biased by the different scales of the features. The formula for z-score normalization is as follows:

$$\boldsymbol{Z} = \frac{\boldsymbol{X} - \boldsymbol{\mu}}{\boldsymbol{\sigma}} \quad (1)$$

Where X denotes the original value of the feature, Z signifies the standardized value, μ represents the mean of the feature across the dataset, and σ indicates the standard deviation of the feature across the dataset.

Data modeling

The term "Machine Learning" originated from A.L. Samuel in his paper "Some Studies in Machine Learning Using the Game of Checkers" (Samuel, 1959). Machine Learning is defined as deriving patterns learned from data via interpreting the data through unknown inputs. Machine learning is part of artificial intelligence and statistics, and machine learning algorithm processes a sizeable amount of information which for the human brain is a natural occurrence (Samuel, 1959; Simon et al., 2022). ML techniques often encompass four paradigms- descriptive, diagnostic, predictive, and prescriptive and the focus of this study is in the descriptive and predictive domain. Two techniques are used in the descriptive domain: data visualization and data analysis. Data visualization produces graphical images of data or concepts, which helps decision making. Data analytics consists of common statistical techniques, including mean, media, standard deviation, range, stem, and histogram and advanced data mining techniques used to describe hidden patterns in the data (Liu et al., 2023).

To classify countries of origin according to their import characteristics, we applied a non-hierarchical exploratory clustering technique, specifically the K-means algorithm. The classification was based on a two-dimensional feature space comprising the total CIF value (in thousands of USD) and the total gross weight (in tons) for each country. Prior to clustering, a preliminary correlation analysis was performed, revealing that CIF value and Gross Weight are only weakly correlated. This low correlation indicates that each variable contributes distinct information to the clustering process and avoids redundancy in the formation of groups. Therefore, both variables were retained to capture meaningful variation in import patterns. This unsupervised statistical method is effective for segmenting the data into homogeneous groups, allowing the identification of intrinsic patterns and similarities in agricultural input trade flows that are not immediately apparent through descriptive analysis alone. (Batarseh et al., 2021; Zhang et al., 2025). The analysis was conducted in Python.

It is important to clarify that K-means always relies on two complementary steps: (1) assigning each observation to the nearest cluster center using Euclidean distance, and (2) updating each centroid as the mean of all observations assigned to it. Thus, the centroid expression shown in Equation 2 and the Euclidean distance expression in Equation 3 represent two essential components of the same algorithmic process, not separate methodologies.

To determine the optimal number of clusters, we employ the elbow method, which evaluates the relationship between the Within-Cluster Sum of Squares (WCSS) and the number of clusters. As the number of clusters increases, the WCSS decreases; however, beyond a certain point, the rate of improvement becomes marginal. This inflection point or "elbow" is considered the optimal number of clusters. The WCSS is computed as:

$$\boldsymbol{WCSS}\ (\boldsymbol{k}) = \sum_{\boldsymbol{i=1}}^{\boldsymbol{k}} \sum_{\boldsymbol{x} \in \boldsymbol{C_i}} |\boldsymbol{x} - \boldsymbol{\mu_i}|^{\boldsymbol{2}} \quad (2)$$

Here, k represents the number of clusters, C_i denotes the set of points in cluster, x stands for a data point and μ_i signifies the centroid of cluster i. This centroid formula reflects the updating step of the K-means algorithm.

To formalize the clustering process, let a set of observations x_1, x_2,…,x_n, denote Colombia's agricultural import records from different countries. The K-means algorithm partitions the n observations into k clusters by minimizing the WCSS. Each iteration consists of two steps: (i) assigning each observation to the nearest centroid using Euclidean distance, and (ii) recalculating each centroid as the mean of the points assigned to it.

The assignment step of the K-means algorithm relies on Euclidean distance. For each data point x_p, we compute its Euclidean distance to all centroids and assign it to the nearest one:

$$\boldsymbol{Distance}\ (\boldsymbol{x_i}, \boldsymbol{\mu_j}) = |\boldsymbol{x_i} - \boldsymbol{\mu_j}| = \sqrt{\sum_{d=1}^{D} (\boldsymbol{X_{id}} - \boldsymbol{\mu_{jd}})^2} \quad (3)$$

Where D is the dimensionality of the data point. This step ensures that each observation is grouped with the most similar centroid in terms of Euclidean proximity.

Data visualization

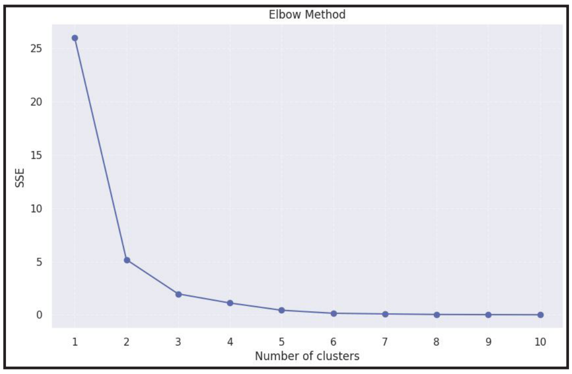
In data visualization, choropleth map used to show the temporal evolution of clusters with their respective tariff labels and trade agreements and CIF dispersion vs. Weight .

Geoconomic interpretation

Cluster analysis is a more advanced statistical technique than traditional descriptive statistics. It involves the grouping of countries according to their strategic import patterns (i.e. high, medium, or low), thus allowing for the identification of critical dependencies and opportunities for diversification. The core value of the model is the integration of quantitative results with qualitative variables, such as trade agreements and tariff rates, thereby facilitating a causal interpretation of patterns. This approach has the capacity to transform trade data into an actionable diagnosis for public policy, revealing not only the identity of the suppliers but also the reasons for their predominance and the means of mitigating strategic risks.

Results and discussion

The application of the k-means algorithm with k = 3, validated using the elbow method (see the Figure 1), reveals a consistent structure in most input categories. The cluster centroids for the fertiliser category in the 2020-2024 period (see the Figure 2) demonstrate a clear separation between groups (see the Table 2).



Source: Prepared by authors

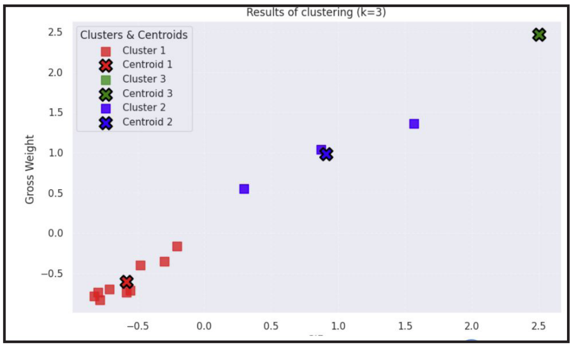
Figure 2: Elbow method result.

	CIF (miles US dollars)	Gross Weight (tons)
High Import	1067590.18	2236684.32
Middle import	588619.52	1296045.47
Low import	139108.06	291556.63

Source: Prepared by authors

Table 3: Cluster centroids.

Figure 3 presents the distribution of countries across the three clusters generated by the K-means algorithm, based on standardized CIF value and Gross Weight. A clear separation between the clusters is observed, particularly between Cluster 1 and Cluster 3, indicating substantial differences in the import characteristics of these country groups. Cluster 1 is composed of countries with relatively low CIF values and low gross weight, forming a compact group near the origin. Cluster 2 contains countries with moderate values in both dimensions, while Cluster 3 represents the country with the highest CIF value and gross weight in the dataset. It is important to note that Cluster 3 consists of a single country Russia. This explains why, in Figure 3, the cluster is represented by a single point whose location coincides with its centroid. The centroids displayed in Figure 3 reflect the average position of each cluster in the standardized feature space, and their separation visually confirms the heterogeneity between the groups. Furthermore, the three clusters capture 92.4% of the variance in the two-variable data structure, indicating that the clustering solution provides a robust representation of the underlying import patterns.



Source: Prepared by authors

Figure 3: Visualization of fertilizer clusters (2020-2024).

This section presents the core findings of the cluster analysis, organized by input category. Table 4 provides a synthesized overview of the main trends and economic insights for all categories between 2005 and 2024. For readers interested in the detailed year-by-year cluster composition, including country-specific percentages for CIF value and gross weight, Main Trade Agreement, Average tariff the complete results are available in Appendix Tables A2 through A9.

To complement the analysis, a comparative performance analysis was carried out by trade block for agricultural inputs imported into Colombia for all the periods analyzed. Table 5 shows those belonging to cluster 1, i.e., those with a high level of imports. For more information on the percentage of countries belonging to each block or country participating in the category according to the cluster analysis classification, see Table A10.

The disparity in cluster 1 participation among economic blocs could be associated with differences in their productive structures, comparative advantages, and trade strategies. Mercosur and the Andean Community show declining or marginal participation, while China and the US consolidate their presence. The Barranquilla Free Trade Zone has potential in biological products, but its irregularity suggests challenges in sustainability or competitiveness. Regarding the impact of trade agreements, the US takes advantage of its FTAs to diversify exports. In contrast, blocks such as CARICOM or the Pacific Alliance do not register activity, possibly because they prioritize other sectors. Brazil and Mexico, with equipment and tools, could strengthen their integration into regional value chains, especially in agricultural technology.

Category	Main Trend (2005-2024)	Key Pattern & Periods	Economic Insight
Fertilizers	Concentration	RUS/USA dominance (>60% CIF) all periods. Peak RUS (59%) in 2020-24 despite sanctions.	Price/logistics > tariff advantages. High strategic vulnerability.
Seeds	Concentration & Reset	USA dominance, interrupted by BOL/ARG (2005-14), then USA regained >80% share.	Structural competitiveness outweighs FTAs—limited long-term diversification.
Animal feed	Stability	USA stable leader (55-58% CIF). BRA grew in Cluster 2 (24%→34%) despite high tariffs.	FTA consolidates leader; competitive advantages (proximity/quality) enable challengers.
Veterinary medicines	Diversification & Value Shift	Shift from multi-country (ARG, BRA, MEX) to USA/CHN focus. CIF stable, but weight fell from 73% to 24%	Transition to high-value products from key partners, with Mexico dominating bulk imports.
Equipment & Tools	Regional Diversification	MEX/BRA dominance (2005-14: ~80% CIF) → CHN/BRA/USA shared leadership (2020-24: ~41% each).	Regional agreements initially dominated, but Asian competition fragmented the market.
Technology and software	Full Transition	USA leader (2005-2019) → CHN leader (2020-2024: 65% CIF).	Cost competitiveness and scale displace traditional partners, regardless of FTAs.
Biological products	Asian Consolidation	CHN increased dominance (52%→65% CIF). ZFBa/USA presence declined (36%→26%).	Absolute price competitiveness overcomes lack of trade agreements.
Genetic material	Absolute Concentration	Only RUS/USA suppliers throughout all periods. No cluster analysis possible.	Maximum dependency risk. Critical vulnerability for food security.
Construction Material	Asian Dominance	CHN increased share (52%→59% CIF) despite high tariffs (7.98%). EU/USA secondary role.	Bulk commodity imports where price competitiveness dominates all other factors.

Source: Prepared by authors

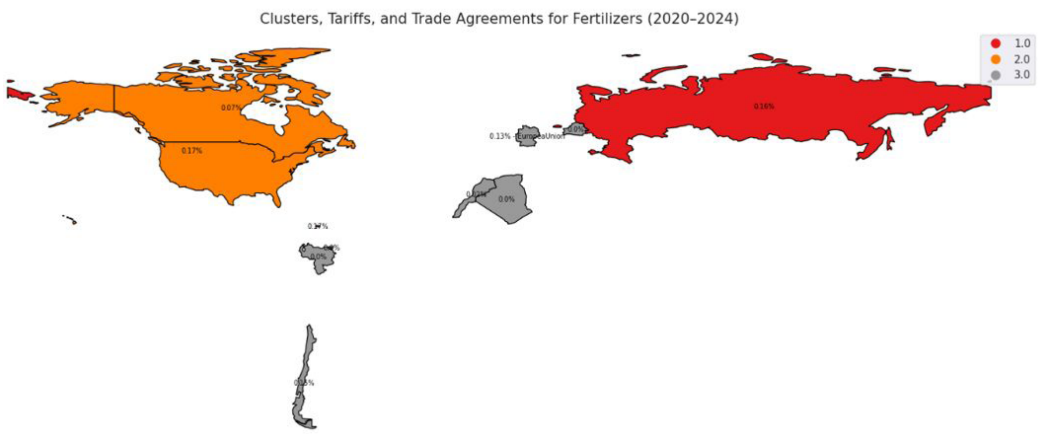
Table 4: Trends of agricultural input imports.

Trade Bloc	Agreement in force	Category in Cluster 1			
		2005-2009	2010-2014	2015-2019	2020-2024
European Union	EU AC (2013)	NA	-	-	
Andean Community	Agreement (1969)	Construction material (VEN) -20%	-	-	-
Mercosur	Agreement (1991)	Veterinary medicines (ARG, BRA) -50%	Equipment and tools (BRA) -25%	-	-
Pacific Alliance	Agreement (2016)	-	-	-	-
CARICOM	Cartagena Agreement (1992)	-	-	-	-
China	No FTA (Negotiation in Progress)	Technology and software, Biological products	Biological products, Construction material	Biological products, Construction material	Biological products, Construction material, Equipment and tools
Russia	No FTA	Fertilizers	Fertilizers	Fertilizers	-
México	ECA (1993)	Equipment and tools	-	Equipment and tools	-
Brazil	ECA 72 G (2017)	-	-	Equipment and tools	-
United States	FTA con EE.UU. (Effective from 2012)	Fertilizers, Seed Technology and software	Fertilizers, Seeds Technology and Software, Animal feed	Fertilizers, Seeds Technology and software, Animal feed, Euipment and tools	Seeds, Animal feed
Canada	FTA with Canada (20119	-	-	-	-
India	No FTA	-	Construction material	-	-
Barranquilla Free Trade Zone	Free Zone Regime	Technology and software, Biological products	-	Biological products	-

Note: Although Mexico, the US, and Canada have a treaty between Mexico, the United States, and Canada that replaced the North American Free Trade Agreement (NAFTA) as of July 1, 2020, there is no direct trade agreement between the USMCA as a bloc. However, Colombia has bilateral agreements with each of the three members of the USMCA, which is why each country is shown separately. The situation is similar with Brazil, given that it belongs to Mercosur and ALADI, depending on the input, it falls under one or the other. In cases where no bloc or agreement had been created, it was designated as NA, not applicable. Acronyms: ECA-Economic Complementation Agreement, FTA-Free Trade Agreement.
Source: Prepared by authors

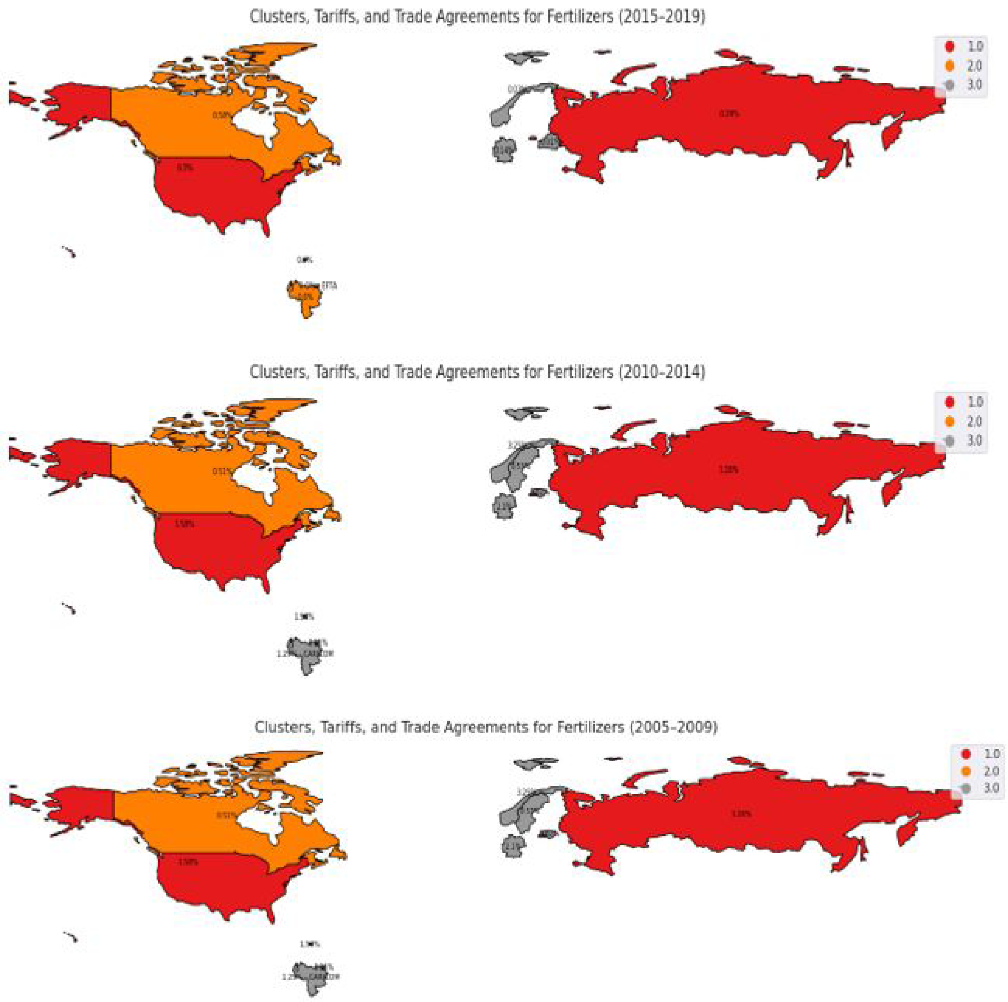
Table 5: Product categories by trade bloc and period (2006–2024), for Cluster 1.

Figure 4 show clusters, tariffs, and trade agreements for fertilizers for the periods 2005–2009, 2010–2014, 2015–2019, and 2020–2024. The figure is highly relevant because it reveals the underlying structure of the global fertilizer market.



Source: Prepared by authors

Figure 4: Choropleth map showing clusters, tariffs, and trade agreements for fertilizers for the periods 2005–2009, 2010–2014, 2015–2019, and 2020–2024. (To be continued).



Note: It was developed based on the results of the cluster and the complementary analysis of the average tariff of each country in each cluster. See A2, A3, A4, and A5

Source: Prepared by authors

Figure 4: Choropleth map showing clusters, tariffs, and trade agreements for fertilizers for the periods 2005–2009, 2010–2014, 2015–2019, and 2020–2024. (Continuation).

The main objective of this study is to analyse the clusters applied to Colombian agricultural imports between 2005 and 2024. To this end, an exhaustive review of the relevant scientific and trade policy literature was carried out, allowing five main patterns to be identified. These patterns are presented and discussed below in the context of economic and trade policy literature.

The first finding reveals a high level of dependence on a small number of suppliers for essential resources. Russia and the United States consistently accounted for over 60% of the CIF value and gross weight of fertilizers (Cluster 1), despite not having a bilateral free trade agreement (FTA). This suggests that economies of scale and logistics costs outweigh tariff advantages, which corroborates the findings of Quitzow et al. (2025) Latin American countries suffer from high levels of import dependency, which exposes them to external supply shocks, a vulnerability that has been exacerbated by the increase in fertilizer prices following the war in Ukraine. Similarly, the United States regained its leadership in seeds (80% of CIF) after 2015, despite competing with Andean Community and Mercosur countries that had tariff preferences. This suggests that the structural advantages of competitiveness, which Baier and Regmi (2023) identified as a key factor in successful FTAs, can sometimes operate independently of them.

A second pattern is the reconfiguration of supply chains, with China's rise being particularly notable. Despite not having an FTA, this country has achieved a dominant position in technology and software (65% CIF, 78% weight) and biological products. Its overall competitiveness, encompassing both value and volume, challenges traditional gravitational models that favour proximity and trade agreements (Zhang et al., 2025). At the same time, the veterinary medicine sector is transitioning towards higher-value products. The divergence between stable CIF and a sharp drop in gross weight suggests an upgrading process in the import basket. This is consistent with the hypothesis that trade integration can encourage specialisation in higher-value segments (Storm, Baylis and Heckelei, 2020).

The third pattern reveals contrasting sectoral dynamics. While the FTA with the US consolidated its stable leadership in the animal feed sector (Cluster 1, 55-58% CIF), regional agreements lost relevance in the equipment and tools sector due to growing market fragmentation. This reflects the theory of sectoral heterogeneity, whereby the effectiveness of trade policies is influenced by the inherent characteristics of products and markets (Batarseh et al., 2021).

A fourth pattern that was identified was the consistent underutilisation of trading partners with which existing agreements were in place. Despite having low preferential tariffs (e.g. 0.13% for the EU), countries in Cluster 3, which include members of the European Union and CARICOM, maintained marginal shares (e.g. 8% for fertilisers from the EU). The extant evidence suggests that the formal existence of an FTA is a necessary but not sufficient condition for boosting trade flows, thus supporting the theory that non-tariff barriers and transaction costs may persist even after tariff liberalization (Piñeiro et al., 2023).

Finally, the fifth pattern demonstrates the remarkable resilience of suppliers without trade agreements. In the context of trade negotiations, China has exhibited a capacity to preserve or augment its market share in various sectors, a feat further compounded by its ability to do so despite facing substantially higher tariffs than competitors with free trade agreements (FTAs). A similar resilience has been demonstrated by Brazil in the domain of animal feed, underscoring the country's capacity to maintain or increase its market share in the face of competitive tariff environments. This finding suggests that significant competitive advantages, such as geographic proximity, productive complementarity, or differentiated quality, have the capacity to offset and even surpass the disadvantages associated with tariffs. This expands the conventional understanding of the determinants of international trade.

Public policy implications for the agricultural sector in Colombia

Cluster analysis reveals distinct strategic patterns in Colombia's agricultural input imports that demand targeted policy responses. These empirical findings provide a critical evidence base for the National Agricultural Innovation System (SNIA), established in (2017) as Colombia's multi-level governance framework for coordinating science, technology, and innovation in agriculture. The SNIA's structure comprising subsystems for Research and Technological Development, Agricultural Extension, and Education and Training offers the institutional "how" to transform these diagnostic insights into concrete state action. Since agricultural innovation is inextricably linked to input supply chain efficiency, the following recommendations are designed to leverage the SNIA's architecture to reduce vulnerability, capitalize on diversification opportunities, and strengthen sectoral resilience.

The analysis identifies extreme import concentration in genetically sensitive materials (exclusive dependence on Russia and the United States) and a persistently limited supplier base for fertilizers (Cluster 1 > 60% of CIF value and gross weight). This high dependency creates significant vulnerability to geopolitical and market disruptions. To address this strategic risk, a dual approach leveraging the SNIA is essential, combining immediate commercial diversification with a long-term strategy for national input development. The Ministry of Commerce, Industry, and Tourism, in coordination with the SNIA's technical bodies, should implement a targeted diversification program. This program must actively promote new commercial partnerships with competitively proven suppliers from Cluster 2, such as Canada and China for fertilizers. These countries have demonstrated reliable supply capacity without preferential trade agreements, offering a viable pathway to immediately mitigate supply chain risk. Concurrently, the Subsystem of Research and Technological Development of the SNIA must be strengthened to orchestrate a long-term solution. This involves: Directing the research agendas of Agrosavia and partner universities towards the development and domestic production of alternative fertilizers and bio-inputs and securing public investment and international cooperation funding specifically for the research, registration, and scaling of these nationally produced inputs, reducing the legal and financial barriers to their adoption. To ensure the efficacy of both strategies, the Subsystem of Agricultural Extension must be activated. The Departmental Agricultural Extension Plans (PDEA) should incorporate training programs on the efficient use of both newly diversified imports and domestic alternatives. This includes promoting regenerative agriculture practices that reduce the overall dependency on synthetic fertilizers, thereby building systemic resilience at the farm level.

Veterinary medicines show a marked transition towards high-value products (stable CIF value but gross weight plummeting from 73% to 24%), indicating a market shift from bulk commodities to specialized ingredients and finished products. This divergence between value and volume metrics reveals a segmented market requiring distinct policy approach. SNIA provides the ideal framework to navigate this dual market structure. A segmented strategy should be implemented through its respective subsystems to simultaneously build technological sovereignty and guarantee the supply of essential medicines. For High-Value products, Cluster 1-USA/China, The Subsystem of Research and Technological Development, led by Agrosavia and Colciencias, must prioritize veterinary pharmacology and biotechnology. This involves: Fostering public-private partnerships and technology transfer alliances for the local development and production of Active Pharmaceutical Ingredients (APIs) and creating specialized research groups and grant lines focused on advanced veterinary therapies, vaccines, and diagnostics to capture value in this high-margin segment and reduce import dependency. For Bulk Essential Medicines, Cluster 2-Mexico, The Subsystem of Agricultural Extension and trade authorities should work in concert to ensure supply chain security for cost-effective, essential veterinary products. Strengthen trade facilitation measures and logistical corridors with key Cluster 2 suppliers like Mexico. Integrate into the Departmental Agricultural Extension Plans (PDEA) training programs on the rational use of these bulk imported medicines, ensuring their effective and accessible application by livestock producers

China has achieved dominant positions in technology and biological products, with 65% CIF and 78% gross weight respectively, without free trade agreements, demonstrating unprecedented price competitiveness. Considering this reality and the urgent need to adapt agri-food systems to climate change, it is recommended that existing technical cooperation platforms are utilised. Import policies should be coordinated with initiatives such as AgriLAC Resiliente CGIAR, It operates in Colombia and seeks to increase the resilience and sustainability of agri-food systems. The strategy must be segmented. For technologically complex inputs, where China has structural advantages, technical cooperation agreements should be prioritized, making use of CGIAR initiatives in genetic improvement, plant health and agronomy instead of traditional, tariff-focused negotiations. For biological products, implement quality assurance protocols that ensure price competitiveness does not compromise national biosecurity or climate adaptation, in line with CGIAR's Germplasm Bank initiatives and phytosanitary standards. This approach would enable Chinese imports to enhance the immediate competitiveness and long-term resilience of the Colombian agricultural sector simultaneously. It is recommended that the SNIA strengthens its measures relating to science, technology and innovation by creating specialised committees on disruptive technologies, such as precision agriculture and biotechnology, to identify opportunities for South-South collaboration with China and other leaders beyond free trade agreements (FTAs). The SNIA should also guide the user registration and classification process in a coordinated manner to identify level 3 and 4 producers who are ready to adopt advanced technologies, connecting them with Chinese suppliers or equivalent national developments.

The United States maintains stable leadership in animal feed imports (Cluster 1, 55-58% CIF), effectively utilizing preferences under the bilateral free trade agreement. However, the concurrent competitiveness of non-FTA partners despite tariff disadvantages points to untapped opportunities for complementary sourcing strategies. Maximize tariff-rate quotas and preferential access under the US-Colombia FTA for compound feed ingredients. Concurrently, develop specialized logistics corridors to facilitate imports from Brazil (Cluster 2), which has maintained competitive supply despite facing tariffs of 13-18%, suggesting strong inherent advantages in product quality or geographic proximity. A pragmatic innovation policy within the SNIA should move beyond a singular focus on FTAs by pursuing a dual strategy of strategic R&D alliances and producer association. This involves: Promoting strategic R&D partnerships with resilient suppliers, such as Colombia-Brazil technical cooperation in animal nutrition or Colombia-China collaboration in digital agriculture, to leverage complementary strengths and build technological capacity. Strengthening producer associativity as a key social capability, where the Departmental Agricultural Extension Plans (PDEAs) prioritize the development of cooperatives and associations. This enables Colombian producers to achieve the economies of scale necessary to compete with major suppliers, improve their bargaining power, and access quality inputs at competitive prices, thereby enhancing overall sector resilience

Cluster 3 suppliers remain consistently marginalized across multiple input categories despite favorable trade agreements. For instance, the European Union maintains only 8% market share in fertilizer imports despite the EU-Colombia Trade Agreement, while CARICOM members show minimal participation despite the Cartagena Agreement. This persistent underutilization despite generally low tariff barriers (e.g., 0.13% average tariff for EU fertilizers) suggests that addressing this gap requires moving beyond tariff reduction to actively bridge existing market disconnections. Cluster 3 suppliers remain consistently marginalized across multiple input categories despite favorable trade agreements. For instance, the European Union maintains only 8% market share in fertilizer imports despite the EU-Colombia Trade Agreement, while CARICOM members show minimal participation despite the Cartagena Agreement. This persistent underutilization despite generally low tariff barriers (e.g., 0.13% average tariff for EU fertilizers) suggests that addressing this gap requires moving beyond tariff reduction to actively bridge existing market disconnections

Finally, a Pragmatic Innovation Policy within the SNIA implies not focusing exclusively on FTAs, but promoting strategic R&D alliances with resilient suppliers, such as the Colombia-Brazil technical cooperation in animal feed or the Colombia-China technical cooperation in digital agriculture; and, complementarily, it is necessary to foster associativity as a key social capacity, so that the PDEAs prioritize the strengthening of cooperatives and associations that allow Colombian producers to achieve the necessary scale to compete with countries like Brazil, negotiate better, and access quality inputs at competitive prices.

Conclusion

This study demonstrates that cluster analysis provides a powerful tool for diagnosing strategic patterns in Colombia's agricultural input imports, revealing significant disparities in country participation across the three identified clusters. These variations are associated with differences in productive structures, comparative advantages, and commercial strategies, while the persistent dominance of certain suppliers even in the absence of trade agreements highlights how price and logistical competitiveness can outweigh tariff advantages.

However, several limitations must be acknowledged. The analysis relied on data aggregated at the 4-digit HS code level, which may mask product-specific dynamics within broader categories. Furthermore, the study did not account for non-tariff measures which constitute significant barriers in agricultural trade. The k-means methodology itself, while effective for identifying patterns, does not establish causal relationships.

Notwithstanding these limitations, the findings offer actionable insights. The Barranquilla Free Trade Zone emerges as a strategic platform to enhance competitiveness through economic and technological incentives. Future research should incorporate disaggregated data and analyze non-tariff barriers, particularly for clusters with high supplier concentration. Additional studies could also quantitatively assess the impact of the Barranquilla Free Trade Zone on specific value chains and examine the role of FTAs in export diversification through detailed case studies

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Appendix

Tariff item	Description
3101	Animal or vegetable fertilisers, whether or not mixed together or chemically treated; fertilisers produced by the mixing or chemical treatment of animal or vegetable products.
3102	Mineral or chemical fertilisers, nitrogenous.
3103	Mineral or chemical fertilisers, phosphatic.
3104	Mineral or chemical fertilisers, potassic.
3105	Mineral or chemical fertilisers containing two or three of the fertilising elements nitrogen, phosphorus and potassium; other fertilisers; goods of this Chapter in tablets or similar forms or in packages of a gross weight not exceeding 10 kg.
3808	Insecticides, rodenticides, fungicides, herbicides, anti-sprouting products and plant-growth regulators, disinfectants and similar products, put up in forms or packings for retail sale or as preparations or articles (for example, sulphur-treated bands, wicks and candles, and fly-papers).
1201	Soya beans, whether or not broken.
1202	Ground-nuts, not roasted or otherwise cooked, whether or not shelled or broken.
1204	Linseed, whether or not broken.
1205	Rape or colza seeds, whether or not broken.
1206	Sunflower seeds, whether or not broken.
1207	Other oil seeds and oleaginous fruits, whether or not broken.
1209	Seeds, fruit and spores, of a kind used for sowing.
2309	Preparations of a kind used in animal feeding.
1214	Swedes, mangolds, fodder roots, hay, lucerne (alfalfa), clover, sainfoin, forage kale, lupines, vetches and similar forage products, whether or not in the form of pellets.
3004	Medicaments (excluding goods of heading 30.02, 30.05 or 30.06) consisting of mixed or unmixed products for therapeutic or prophylactic uses, put up in measured doses (including those in the form of transdermal administration systems) or in forms or packings for retail sale.
3002	Human blood; animal blood prepared for therapeutic, prophylactic or diagnostic uses; antisera, other blood fractions and immunological products, whether or not modified or obtained by means of biotechnological processes; vaccines, toxins, cultures of micro-organisms (excluding yeasts) and similar products; cell cultures, whether or not modified.
2937	Hormones, prostaglandins, thromboxanes and leukotrienes, natural or reproduced by synthesis; derivatives and structural analogues thereof, including chain modified polypeptides, used primarily as hormones.
8414	Air or vacuum pumps, air or other gas compressors and fans; ventilating or recycling hoods incorporating a fan, whether or not fitted with filters; gas-tight biological safety cabinets, whether or not fitted with filters.
8701	Tractors (other than tractors of heading 87.09).
8432	Agricultural, horticultural or forestry machinery for soil preparation or cultivation; lawn or sports-ground rollers.
8433	Harvesting or threshing machinery, including straw or fodder balers; grass or hay mowers; machines for cleaning, sorting or grading eggs, fruit or other agricultural produce, other than machinery of heading 84.37.
8201	Hand tools, the following : spades, shovels, mattocks, picks, hoes, forks and rakes; axes, bill hooks and similar hewing tools; secateurs and pruners of any kind; scythes, sickles, hay knives, hedge shears, timber wedges and other tools of a kind used in agriculture, horticulture or forestry.
8424	Mechanical appliances (whether or not hand-operated) for projecting, dispersing or spraying liquids or powders; fire extinguishers, whether or not charged; spray guns and similar appliances; steam or sand blasting machines and similar jet projecting machines.
9406	Furniture; bedding, mattresses, mattress supports, cushions and similar stuffed furnishings; luminaires and lighting fittings, not elsewhere specified or included; illuminated signs, illuminated name-plates and the like; prefabricated buildings
7314	Cloth (including endless bands), grill, netting and fencing, of iron or steel wire; expanded metal of iron or steel.
7308	Structures (excluding prefabricated buildings of heading 94.06) and parts of structures (for example, bridges and bridge-sections, lock-gates, towers, lattice masts, roofs, roofing frame-works, doors and windows and their frames and thresholds for doors, shutters, balustrades, pillars and columns), of iron or steel; plates, rods, angles, shapes, sections, tubes and the like, prepared for use in structures, of iron or steel.
8806	Structures (excluding prefabricated buildings of heading 94.06) and parts of structures (for example, bridges and bridge-sections, lock-gates, towers, lattice masts, roofs, roofing frame-works, doors and windows and their frames and thresholds for doors, shutters, balustrades, pillars and columns), of iron or steel; plates, rods, angles, shapes, sections, tubes and the like, prepared for use in structures, of iron or steel.
9026	Instruments and apparatus for measuring or checking the flow, level, pressure or other variables of liquids or gases (for example, flow meters, level gauges, manometers, heat meters), excluding instruments and apparatus of heading 90.14, 90.15, 90.28 or 90.32.
9025	Hydrometers and similar floating instruments, thermometers, pyrometers, barometers, hygrometers and psychrometers, recording or not, and any combination of these instruments.
9015	Surveying (including photogrammetrical surveying), hydrographic, oceanographic, hydrological, meteorological or geophysical instruments and appliances, excluding compasses; rangefinders.
8523	Discs, tapes, solid-state non-volatile storage devices, «smart cards» and other media for the recording of sound or of other phenomena, whether or not recorded, including matrices and masters for the production of discs, but excluding products of Chapter 37.
4911	Other printed matter, including printed pictures and photographs.
9032	Other printed matter, including printed pictures and photographs.
8543	Electrical machines and apparatus, having individual functions, not specified or included elsewhere in this Chapter.

Source: SA-version 2022

Table A1: Tariff items for agricultural input..

Category	Cluster	Details	2005-2009	2010-2014	2015-2019	2020-2024
Fertilizers	1	Countries	RUS, USA	USA, RUS	RUS, USA	RUS
		% CIF	64%	64%	62%	59%
		% Gross Weight	59%	61%	60%	58%
		Main Trade Agreement	-	-	-	-
		Average tariff	3.35%	1.43%	0.29%	-
	2	Countries	CAN, VEN	CAN	VEN, CHN, CAN	CAN, CHN, USA
		% CIF	27%	11%	26%	33%
		% Gross Weight	29%	11%	27%	34%
		Main Trade Agreement	Comunidad Andina	-	-	-
		Average tariff	2.27%	0.51%	0.48%	-
	3	Countries	CHN, DEUMAR, NLD, TTO, NOR, LTU, SWE, VGB	VEN, TTO, SWE, NLD, NOR, LTU, CHN, DEU	TTO, NOR BLR, DEU	DEU, DZA, BLR, CHL, FIN, MAR, NLD, TTO, VEN
		% CIF	10%	10%	12%	8%
		% Gross Weight	11%	10%	13%	8%
		Main Trade Agreement	Agreement Caricom	Agreement Caricom	ALC. cn Noruega	AC. con UE
		Average tariff	3.23%	1.18%	0.04%	0.1282
Seeds	1	Countries	USA	USA	-	-
		% CIF	73%	40%	-	-
		% Gross Weight	73%	47%	-	-
		Main Trade Agreement	-	FTA. con EEUU	-	-
		Average tariff	6.67%	3.15%	-	-
	2	Countries	BOL	BOL	-	-
		% CIF	19%	40%	-	-
		% Gross Weight	19%	23%	-	-
		Main Trade Agreement	Comunidad Andina	Comunidad Andina	-	-
		Average tariff	0.28%	0.40%	-	-
	3	Countries	ARG	ARG	-	-
		% CIF	8%	20%	-	-
		% Gross Weight	8%	30%	-	-
		Main Trade Agreement	Mercosur	Mercosur	-	-
		Average tariff	5.19%	2.58%	-	-

Source: Prepared by authors

Table A2: Fertilizers and seeds.

Category	Cluster	Details	2005-2009	2010-2014	2015-2019	2020-2024
Fertilizers	1	Countries	-	USA	USA	USA
		% CIF	-	55%	56%	58%
		% Gross Weight	-	57%	57%	62%
		Main Trade Agreement	-	FTA. con EEUU	-	FTA. con EEUU
		Average tariff	-	6.20 %	0.72%	0.44
	2	Countries	-	CHN, PER	BRA	BRA
		% CIF	-	29%	24%	34%
		% Gross Weight	-	32%	18%	30%
		Main Trade Agreement	-	Comunidad Andina	-	ECA 72 G Brasil Mercosur
		Average tariff	-	4.83%	18.22%	13.19%
	3	Countries	-	BRA, ARG	PER, CHN	PER, CHN, ECU, MEX
		% CIF	-	16%	13%	7%
		% Gross Weight	-	11%	16%	8%
		Main Trade Agreement	-	Mercosur	-	Agreement de Cartagena Alianza Pacífico
		Average tariff	-	5.23%	6.37	1.19%
Seeds	1	Countries	ARG, BRA, USA, MEX	DEU, USA	DEU, USA	USA, CHN
		% CIF	49%	71%	70%	64%
		% Gross Weight	73%	24%	23%	24%
		Main Trade Agreement	Mercosur Ac -Mexico	-	AC. con UE	FTA. con EEUU
		Average tariff	4.76 %	3.85	1.66	2.39
	2	Countries	DEU	MEX, CHN	MEX, CHN	MEX
		% CIF	41%	17%	17%	23%
		% Gross Weight	11%	59%	60%	69%
		Main Trade Agreement	-	Ac -Mexico Comunidad Andina	Ac -Mexico	Ac -Mexico
		Average tariff	7.16 %	3.29	2.20	0.84
	3	Countries	CAN, NLD	ARG, BRA, CAN, ESP, IND	BRA	BRA, NLD, ESP
		% CIF	10%	12%	14%	13%
		% Gross Weight	15%	17%	16%	7%
		Main Trade Agreement	-	Mercosur	214 ECA 72 G Brasil	214 ECA 72 G Brasil AC. con UE
		Average tariff	6.74%	3.44	0.94	0.99

Source: Prepared by authors

Table A3: Animal feed and veterinary medicines.

Category	Cluster	Details	2005-2009	2010-2014	2015-2019	2020-2024
Equipment and Tools	1	Countries	MEX	BRA	MEX, USA, BRA	CHN
		% CIF	77%	79%	48%	41%
		% Gross Weight	75%	80%	26%	64%
		Main Trade Agreement	-	Mercosur	Ac -Mexico, FTA. con EEUU 214 ECA 72 G Brasil	-
		Average tariff	4.97 %	1.94%	2.21	4.52
	2	Countries	USA	USA	CHN	BRA, MEX
		% CIF	13%	13%	39%	41%
		% Gross Weight	11%	11%	65%	24%
		Main Trade Agreement	-	-	-	-
		Average tariff	9.75%	5.57%	3.30%	2.62%
	3	Countries	BRA	MEX	JPN	USA
		% CIF	10%	8%	13%	18%
		% Gross Weight	13%	9%	9%	12%
		Main Trade Agreement	Mercosur	Ac -Mexico	-	Ac -Mexico
		Average tariff	6.70	1.94	2.50	3.36
Technology and software	1	Countries	USA	USA	USA	CHN
		% CIF	76%	62%	60%	65%
		% Gross Weight	38%	24%	73%	78%
		Main Trade Agreement	-	-	FTA. con EEUU	-
		Average tariff	8.18 %	5.34 %	0.72%	2.28%
	2	Countries	CHN, PER	CHN	CHN	USA
		% CIF	12%	28%	31%	26%
		% Gross Weight	47%	51%	19%	14%
		Main Trade Agreement	-	-	-	FTA. con EEUU
		Average tariff	7.60%	4.88%	18.22%	1.95%
	3	Countries	MEX, CN-TW, BRA, DEU	PER, MEX, CN-TW	PER, MEX, CN-TW, DEU	PER, MEX, CN-TW, BRA
		% CIF	12%	10%	9%	8%
		% Gross Weight	15%	26%	8%	8%
		Main Trade Agreement	Comunidad Andina	Comunidad Andina	AC. con UE	-
		Average tariff	8.22%	4.04%	6.37%	2.03%

Source: Prepared by authors

Table A4: Equipment and Tools and Technology and software.

Category	Cluster	Details	2005-2009	2010-2014	2015-2019	2020-2024
Equipment and Tools	1	Countries	CHN, ZFBa	CHN	CHN	CHN
		% CIF	52%	56%	60%	65%
		% Gross Weight	63%	71%	73%	78%
		Main Trade Agreement	-	-	-	-
		Average tariff	8.22 %	3.70 %	1.66%	2.90%
	2	Countries	DEU, BRA, USA	ZFBa, USA	ZFBa, USA	ZFBa, USA
		% CIF	36%	33%	31%	26%
		% Gross Weight	19%	20%	19%	14%
		Main Trade Agreement	Mercosur	-	FTA. con EEUU	FTA. con EEUU
		Average tariff	6.42%	3.29	0.45%	2.16%
	3	Countries	BEL, ECU, IND, VEN	MEX, IND, BRA, ARG, DEU	MEX, IND, BRA, DEU	DEU, IND, MEX
		% CIF	12%	11%	9%	8%
		% Gross Weight	18%	8%	8%	8%
		Main Trade Agreement	Comunidad Andina	Ac -Mexico Mercosur	Ac -Mexico Mercosur AC. con UE	Ac -Mexico C. con UE
		Average tariff	4.26%	2.72%	0.55%	2.15%
Technology and software	1	Countries	VEN	CHN	CHN, IND	CHN
		% CIF	52	49%	60%	59%
		% Gross Weight	72	64%	73%	66%
		Main Trade Agreement	Comunidad Andina	-	-	-
		Average tariff	4.19%	7.33%	7.31%	7.98%
	2	Countries	CHN, USA	USA, ESP	ESP	ESP, IND
		% CIF	39%	37%	43%	35%
		% Gross Weight	24%	28%	50%	29%
		Main Trade Agreement	-	-	AC. con UE	AC. con UE
		Average tariff	13.82%	7.33%	4.10 %	5.08
	3	Countries	CAN, ESP, MYS	ITA, ARE, DEU	MEX, USA, DEU	MEX, PER, ECU, BRA
		% CIF	9%	14%	44%	6%
		% Gross Weight	4%	8%	44%	6%
		Main Trade Agreement	-	-	Ac -Mexico FTA. con EEUU	Ac -Mexico Comunidad Andina Alianza Pacífico
		Average tariff	13.03%	7.43%	4.71%	2.15%

Source: Prepared by authors

Table A5: Biological products and construction material.

Tables A6, A7, A8, and A9 show the distribution of the main supplier countries of agricultural inputs, grouped by market share clusters, for the periods 2005–2009, 2010–2014, 2015–2019, and 2020–2024. The percentages corresponding to the CIF value and gross weight of imports are shown, as well as the main trade agreement in force with each country and the tariff applied.

Category	Cluster	Countries	% CIF	% Gross Weight	Trade Agreements	Tariff of each country
Fertilizers	1	RUS	20%	19%	-	3.1
		USA	27%	24%		3.6
	2	CAN	11%	12%	Agreement de Cartagena	2.35
		VEN	9%	9%		2.21
	3	CHN	3%	2%	Agreement Caricom	4.29
		DEU	5%	7%		4.59
		MAR	3%	7%		1.35
		NLD	4%	4%		4.53
		TTO	5%	5%		0.23
		NOR	4%	3%		6.65
		LTU	3%	3%		2.63
		SWE	5%	4%		1.63
		VGB	1%	1%		3.19
Seeds	1	USA	92.81%	96.34%	-	6.67
	2	BOL	6.95%	3.57%	Agreement de Cartagena	0.28
	3	ARG	0.24%	0.09%	Mercosur	5.19
Veterinary medicines	1	ARG	8%	20%	Mercosur México-Colombia	5.79
		BRA	14%	24%		3.8
		USA	40%	18%		6.45
		MEX	12%	26%		3
	2	DEU	18%	4%	-	7.16
	3	CAN	3%	6%	-	7.16
		NLD	5%	4%		6.34
Equipment and Tools	1	MEX	77%	75%	-	4.97
	2	USA	13%	11%	-	9.75
	3	BRA	10%	13%	Mercosur	6.7
Technology and software	1	USA	52%	20%	-	8.19
	2	CHN	10%	27%	-	9.5
		PER	7%	22%		5.71
	3	BRA	6%	8%	-	7.22
		CN-TW	3%	11%		9.72
		MEX	13%	5%		7.36
		DEU	10%	7%		8.6
Biological products	1	CHN	21%	28%	-	6.58
		ZFBa	19%	22%		6.48
	2	DEU	12%	4%	Mercosur	6.52
		BRA	12%	7%		6.15
		USA	18%	13%		6.61
	3	BEL	3%	4%	Agreement de Cartagena	7.34
		ECU	3%	6%		0.23
		IND	4%	6%		7.22
		VEN	8%	12%		2.28
Construction Material	1	VEN	33%	54%	Agreement de Cartagena	4.19
	2	CHN USA	16%	20%	-	12.65
			34%	16%		15
	3	CAN	6%	2%	-	13.64
		ESP	7%	6%		12.9
		MYS	5%	2%		12.56
Animal Feed	NA	NA	NA	NA	NA	NA
Genetic material	NA	NA	NA	NA	NA	NA

Source: Prepared by authors

Table A6: Participation of countries supplying agricultural inputs is according to CIF value, gross weight and applied tariff 2005-2009.

Category	Cluster	Countries	% CIF	% Gross Weight	Trade Agreements	Tariff of each country
Fertilizers	1	USA	27%	24%	-	1.58
		RUS	24%	24%		1.28
	2	CAN	11%	11%	-	0.51
	3	VEN	7%	7%	Agreement Caricom	1.29
		TTO	5%	5%		0.11
		SWE	3%	3%		0.53
		NLD	3%	4%		2.64
		NOR	3%	4%		3.25
		LTU	6%	6%		0.82
		CHN	7%	8%		1.93
		DEU	5%	5%		2.1
Seeds	1	USA	40%	47%	FTA. con EEUU	3.15
	2	BOL	40%	23%	Agreement de Cartagena	0.41
	3	ARG	20%	30%	Mercosur	2.58
Veterinary medicines	1	DEU	24%	4%	-	4.26
		USA	36%	16%		3.44
	2	MEX	9%	29%	México con cod. Agreement 21 1 Agreement de Cartagena	1.73
		CHN	5%	18%		4.87
	3	ARG	4%	11%	Mercosur	2.75
		BRA	8%	14%		1.49
		CAN	4%	3%		4.45
		ESP	5%	2%		4.53
		IND	4%	3%		4
Equipment and Tools	1	BRA	79%	80%	Mercosur	2.24
	2	USA	13%	11%	-	5.58
	3	MEX	8%	9%	México con cod. Agreement 21	1.95
Technology and software	1	USA	52%	24%	-	5.34
	2	CHN	24%	34%	-	4.88
	3	PER	6%	23%	1 Agreement de Cartagena	2.98
		MEX	14%	5%		3.8
		CN-TW	4%	23%		5.35
Biological products	1	CHN	31%	46%	-	3.71
	2	ZFBa	18%	16%	-	3.55
		USA	19%	10%		3.04
	3	MEX	3%	4%	México con cod. Agreement 21 Mercosur	0.98
		IND	6%	9%		3.88
		BRA	10%	5%		2.13
		ARG	3%	5%		3.4
		DEU	10%	4%		3.21
Construction Material	1	CHN	30%	45%	-	7.81
	2	USA	26%	18%	-	7.49
		ESP	19%	21%		7.19
	3	ITA	11%	6%	-	7.31
		ARE	7%	6%		8.13
		DEU	7%	5%		6.87
Animal Feed	1	USA	38%	40%	FTA. con EEUU - cód Agreement 097-Grav cupos	6.2
	2	CHN	23%	18%	Agreement de Cartagena	9.5
		PER	17%	26%		0.17
	3	BRA	10%	6%	Mercosur	5.83
		ARG	12%	9%		4.64
Genetic material	NA	NA	NA	NA	NA	NA

Source: Prepared by authors

Table A7: Participation of countries supplying agricultural inputs is according to CIF value, gross weight and applied tariff 2010-2014.

Category	Cluster	Count-ries	% CIF	% Gross Weight	Trade Agreements	Tariff of each country
Fertilizers	1	RUS	28%	28%	-	0.29
		USA	24%	21%		0.3
	2	VEN	8%	9%	-	0
		CHN	13%	14%		0.86
		CAN	10%	11%		0.58
	3	TTO	5%	5%	ALC. cn Noruega	0
		NOR	3%	3%		0.03
		BLR	4%	4%		0.01
		DEU	5%	4%		0.14
Veterinary medicines	1	DEU	39%	20%	AC. con UE	1.78
		USA	36%	5%		1.55
	2	MEX	11%	41%	México con cod. Agreement 21	0.98
		CHN	7%	25%		3.44
	3	BRA	7%	%	214 ECA 72 G Brasil	0.94
Equipment and Tools	1	MEX	26%	17%	México con cod. Agreement 21 FTA. con EEUU 214 ECA 72 G Brasil	1.89
		USA	23%	13%		3.14
		BRA	24%	21%		1.62
	2	CHN	20%	43%	-	3.3
	3	JPN	7%	6%	-	2.51
Technology and software	1	USA	35%	9%	FTA. con EEUU	2.73
	2	CHN	32%	46%	-	2.98
	3	PER	6%	18%	AC. con UE	2.26
		MEX	14%	9%		2.2
		CN-TW	3%	15%		3.3
		DEU	10%	4%		2.65
Biological products	1	CHN	38%	51%	-	1.66
	2	USA	21%	9%	FTA. con EEUU	0.24
		ZFBa	17%	18%		0.67
	3	MEX	4%	7%	México con cod. Agreement 21 Mercosur AC. con UE	0.7
		IND	5%	7%		0.62
		BRA	5%	4%		0.6
		DEU	8%	3%		0.28
Construction Material	1	CHN	26%	38%	-	7.61
		IND	28%	30%		7.02
	2	ESP	23%	19%	AC. con UE	4.1
	3	MEX	6%	4%	México con cod. Agreement 21 FTA. con EEUU	2.07
		USA	10%	4%		4.46
		DEU	8%	4%		4.25
Animal	1	USA	56%	57%	-	0.72
Feed	2	BRA	21%	16%	-	18.22
	3	PER	8%	13%	-	0.73
		CHN	15%	14%		12.02
Seeds	NA	NA	NA	NA	NA	NA
Genetic material	NA	NA	NA	NA	NA	NA

Source: Prepared by authors

Table A8: Participation of countries supplying agricultural inputs is according to CIF value, gross weight and applied tariff 2015-2019.

Category	Cluster	Countries	% CIF	% Gross Weight	Trade Agreements	Tariff of each country
Fertilizers	1	RUS	10%	12%	-	0.16
	2	CAN	4%	3%	-	0.07
		CHN	2%	2%	-	0.45
		USA	2%	3%	-	0.17
	3	DEU	5%	5%	124 AC. con UE - cód Agreement	0.13
		DZA	2%	2%	-	0
		BLR	4%	5%	-	0
		CHL	3%	2%	-	0.15
		FIN	6%	6%	-	0
		MAR	2%	2%	-	2
		NLD	14%	15%	124 AC. con UE - cód Agreement	8
		TTO	19%	18%	-	0
		VEN	26%	26%	-	0
Animal feed	1	USA	48%	49%	FTA. con EEUU - cód Agreement 096- general	0.44
	2	BRA	28%	24%	214 ECA 72 G Brasil Brasil con Código 014 (MERCOSUR)	13.19
	3	PER	4%	7%	1 Agreement de Cartagena Alianza Pacífico - México Cód. 152	1.19%
		CHN	8%	9%		
		ECU	5%	5%		
		MEX	7%	5%		
Veterinary medicines	1	USA CHN	13%	7%	FTA. con EEUU - cód Agreement 096- general	2.39
	2	MEX	23%	69%	México con cod. Agreement 21	0.84
	3	BRA	64%	24%	214 ECA 72 G Brasil 124 AC. con UE - cód Agreement 124 -general	0.99
		NLD				
		ESP				
Equipment and Tools	1	CHN	18%	12%	-	4.52
	2	BRA	41%	24%	-	2.62
		MEX				
	3	USA	41%	64%	México con cod. Agreement 21	3.36
Technology and software	1	CHN	51%	74%	-	2.28
	2	USA	41%	13%	-	1.95
	3	BRA	4%	7%	FTA. con EEUU - cód Agreement 096-general	2.03
		CN-TW	4%	4%		
		MEX	10%	10%		
		PER	4%	21%		
Biological products	1	CHN	46%	59%	-	2.9
	2	ZFBa	15%	15%	FTA. con EEUU - cód Agreement 096-general	2.16
		USA	22%	6%		
	3	DEU	6%	5%	México con cod. Agreement 21 AC. con UE - cód Agreement 124 - general	2.15
		IND	7%	8%		
		MEX	5%	7%		
Construction Material	1	CHN	38%	45%	-	7.98
	2	ESP	25%	14%	AC. con UE - cód Agreement 124 -genera	5.08
		IND	21%	26%		
	3	MEX	6%	4%	México con cod. Agreement 21 1 Agreement de Cartagena Alianza Pacífico - México Cód. 152	2.15
		PER	4%	4%		
		ECU	3%	4%		
		BRA	4%	3%		

Source: Prepared by authors

Table A9: Participation of countries supplying agricultural inputs is according to CIF value, gross weight and applied tariff 2020-2024.

Cluster	Trade Bloc	2005-2009	2010-2014	2015-2019	2020-2024
Cluster 1	Comunidad Andina (CAN)	X Construction Material (VEN) 1/5=0.2=20%	-	-	-
	Alianza del Pacífico	-	-	-	-
	Caricom	-	-	-	-
	Mercosur	Veterinary Medicines (ARG, BRA) 50%	Equipment and Tools (BRA) 25%	-	-
	Unión Europea	-	-	-	-
	T-MEC	It did not exist	It did not exist	It did not exist	-
	USA	Fertilizers	Fertilizers	Fertilizers	-
		Seeds	Seeds	Seeds	Seeds
		Technology and software	Animal Feed Technology and software	Animal Feed Equipment and Tools Technology and software	Animal Feed
	MEX	Equipment and Tools		Equipment and Tools	
	RUS	Fertilizers	Fertilizers	Fertilizers	-
	CAN				
	VEN				
	CHN	Technology and software	Biological products	Biological products	Equipment and Tools
		Biological products	Construction Material	Construction Material	Biological products Construction Material
	BRA			Equipment and Tools	
	ZFBa	Technology and software Biological products		Biological products	
	IND		Construction Material		
Cluster 2	Comunidad Andina	-	Animal Feed (PER) 1/4=25%	-	-
	Alianza del Pacífico	-	-	-	Animal Feed (MEX)
	Caricom				
	Mercosur	Biological products (BRA) =1/5=20%	Animal Feed (BRA,ARG) =2/5=40%	-	-
	Unión	Technology and software (DEU)=1/26=3.84%	Construction Material (ESP)		Construction Material (ESP)
	Europea	Biological products (DEU)=1/26=3.84%	1/27=3.70%		1/26=3.84%
	USA	Equipment and Tools Technology and software Biological products Construction Material	Equipment and Tools Biolo-gical products Construction Material		
	MEX	-	-	-	Equipment and Tools
	RUS				
	CAN	Fertilizers	Fertilizers	Fertilizers	Fertilizers
	VEN	-	-	Fertilizers	
	CHN	Technology and software Construction Material	Animal Feed Technology and software	Fertilizers Equipment and Tools	Fertilizers
	BRA	Technology and software	-	-	Equipment and Tools
	ZFBa		Biological products		
	ESP		Construction Material		
	IND				Construction Material

Source: Prepared by authors

Table A10: Classification of products by trade level and tariff condition in selected trade blocs and countries (2005–2024) according to K-means analysis (to be continued).

Cluster	Trade Bloc	2005-2009	2010-2014	2015-2019	2020-2024
Cluster 3	Comunidad Andina	Technology and software (ECU) =1/4=25% Technology and software (PER) =1/4=25% Biological products (ECU) =1/4=25%	Technology and software (PER) =1/4=25%	Animal Feed (PER) 1/4=25%	Animal Feed (PER, ECU) 1/4=25% Construction Material (PER, ECU) 2/4=50%
	Alianza del Pacífico				Construction Material
	Caricom	TTO	TTO	TTO	TTO
	Mercosur	Equipment and Tools (BRA) =1/5=20% Technology and software (BRA) =1/5=20%	Veterinary Medicines (AR-G,BRA) =2/5=40% Biological products (ARG, BRA) =2/5=40%	Biological products (BRA) ==1/5=20%	
	Unión Europea	Fertilizers (DEU, NLD, LTU, SWE) 4/26=15.38% Technology and software (BEL)=1/26=3.84% Biological products (BEL)=1/26=3.84%	Fertilizers (DEU,NLD,LTU,SWE) 4/27=14.81% Biological products (DEU)=1/27=3.70% Construction Material (DEU, ITA)=2/27=7.40% Construction Material (DEU)=1/27=3.70%	Fertilizers (DEU)=1/27=3.70% Biological products (DEU)=1/27=3.70% Construction Material (DEU)=1/27=3.70%	Fertilizers (DEU,NLD,FIN) 3/26=11.53% Biological products (DEU) 1/26=3.84%
	USA	Biological products (BEL)=1/26=3.84%	Construction Material	Construction Material	Equipment and Tools
	MEX	Technology and software	Equipment and Tools Biological products Construction Material	Construction Material	Biological products Construction Material
	RUS	-	-	-	-
	CAN	Construction Material			
	BRA	-	-	Veterinary Medicines	Veterinary Medicines Construction Material
	VEN	Biological products	Fertilizers	-	Fertilizers
	CHN	Fertilizers	Fertilizers Animal Feed	Animal Feed	Animal Feed
	MAR	Fertilizers	-	-	Fertilizers
	NOR	Fertilizers	Fertilizers	Fertilizers	Fertilizers
	VGB	Fertilizers	-	-	-
	MAR	-	-	-	Fertilizers
	CHL	-	-	-	Fertilizers
	CHN	-	-	Equipment and Tools	-
	CN-TW	Technology and software	-	-	-
	IND	Biological products	Biological products	-	Biological products
	ESP	Construction Material	-	-	-
	ARE		Construction Material	-	-

Source: Prepared by authors

Table A10: Classification of products by trade level and tariff condition in selected trade blocs and countries (2005–2024) according to K-means analysis (Continuation).

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International Trade in the Face of War: Agricultural Trade Relations of Ukraine and the EU Countries

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Abstract

The outbreak of war in Ukraine in 2022 significantly reshaped agricultural trade dynamics between Ukraine and the European Union (EU). The main goal of this study is to examine the factors associated with increased exports of Ukrainian agricultural products to EU countries in light of the complex situation that includes the outbreak of war, trade liberalization, and provisional trade bans. The study employs a gravity model to analyze Ukrainian imports of selected agricultural products to EU countries, using monthly data from 2020 to 2023. The Poisson Pseudo-Maximum Likelihood model with high-dimensional fixed effects is utilized. EU countries that are more geographically distant significantly increased their imports of Ukrainian agricultural products, driven by a higher market absorption capacity and robust infrastructure, challenging the traditional assumptions of gravity models. Meanwhile, Ukraine's neighboring countries played a crucial role in absorbing Ukrainian exports due to logistical advantages, regulatory support, and the suspension of tariffs. However, the main effect of trade intensification for these countries was primarily observed in the first year of the war. This study makes a novel contribution by examining the cumulative effects of distance, war, and liberalization on trade volumes, marking the first such analysis in the context of EU-Ukraine relations. The use of monthly data enables us to accurately capture short-term changes in trade, both before and after the onset of the war, offering new insights into how crises reshape trade patterns.

Keywords

Gravity model, international trade, war, agriculture, Ukraine.

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Introduction

The European Union (EU) countries are significant buyers of agri-food products from Ukraine. Since the outbreak of war in Ukraine in 2022, the role of Ukraine's neighboring countries in receiving these products has increased significantly. In 2016, when the Deep and Comprehensive Free Trade Area (DCFTA) (L 161/2014, n.d.), entered into force –introducing the gradual reduction and elimination of tariffs on trade between the EU and Ukraine, while maintaining tariff-rate quotas for selected agricultural products, including cereals (notably wheat, maize and barley), sugar, meat, or eggs. In that year, Ukraine's neighboring countries imported 14% of the value of Ukrainian agricultural exports to the EU (Eurostat, 2024). Following Russia's full-scale invasion in 2022, the EU introduced extraordinary Autonomous Trade Measures (ATMs), temporarily suspending TRQs applicable under the DCFTA framework, thereby allowing duty-free and quota-free imports during the period of application of these measures. In 2022, this share increased to 40% (Eurostat, 2024).

However, the war in Ukraine has severely destabilized the market for agri-food products, leading to the highest increase in food prices since 1990 (Abay et al., 2023). It has been a major challenge for Ukraine to find alternative transportation routes for agri-food products due to problems with access to Ukrainian Black Sea ports (Varynskyi et al., 2023). One alternative was to export goods by road and rail, enabling far more agri-food products from Ukraine to reach neighboring countries. This shift translated into a marked reconfiguration of the territorial structure of Ukraine's exports to the EU: neighboring Member States increasingly served not only as immediate destination markets but also as the main entry and redistribution hubs for further shipments into the Single Market. This was possible, among other things, thanks to the EU regulation on the so-called solidarity corridors, which allowed preferential exports of Ukrainian agricultural goods to EU countries without customs duties and quota limits (Bodnar et al., 2024). From June 2022, the European Union liberalized trade with Ukraine and suspended previously existing quotas (PE/21/2022/REV/1, 2022). These measures have contributed to a partial solution to Ukraine's problems with access to global markets, but at the same time, have introduced tensions in European markets.

In Ukraine's neighboring countries, especially Poland, Romania, and Hungary, an excessive influx of certain products was observed, including cereals and oilseed crops (Bulkowska and Bazhenova, 2023; Sterie et al., 2022), resulting in price drops in local agricultural markets and caused dissatisfaction among local farmers (Beluhova-Uzunova et al., 2024; Ostashko, 2023). In response to pressure from farmers, Poland, Hungary, Slovakia, Romania, and Bulgaria initially imposed temporary restrictions on imports of Ukrainian agricultural products to protect their internal market. In Commission Implementing Regulation (EU) 2023/903 of May 2 2023, the European Commission decided to restrict direct imports of certain goods to Ukraine's neighboring countries but allowed their transit to other European Union countries. Due to storage difficulties and weakened profitability of producers, the import restrictions mainly covered wheat, corn, rapeseed, and sunflower seeds (2023/903, 2023).

The issue of excessive inflow of agricultural products from Ukraine to neighboring countries such as Poland, Hungary, and Romania can be explained by the assumptions of the gravity model in international trade. Although the liberalization of trade in agri-food products with Ukraine was introduced at the level of the entire European Union, the countries directly bordering Ukraine felt the most substantial influx of these goods. The gravity model assumes that the shorter the distance between two countries, the greater the trade flow between them should be (De Benedictis and Taglioni, 2011). In practice, Regional Trade Agreements (RTAs) also contribute to increased trade to a greater extent, the shorter the distance between signatory countries (Freeman and Lewis, 2021). Lower transportation costs and easier logistics encourage manufacturers to export their goods to geographically close markets (Giuliano et al., 2014). In the case of agricultural exports from Ukraine, neighboring EU countries may have become an economically advantageous destination, as proximity to the border allowed for quick and relatively cheap transportation of agricultural products, which was necessary when the war broke out. However, the trade situation since the outbreak of the war in Ukraine has been changing dynamically and has been influenced by many factors of different natures. Therefore, a detailed empirical analysis of the topic is needed to draw appropriate conclusions.

The main question is whether the distance remains the primary determinant of trade development between the EU and Ukraine or is more strongly influenced by other factors, such as the war or trade measures introduced in recent years (trade liberalization or partial import restrictions). Therefore, the main goal of this article is to examine the extent to which different factors were associated with increased exports of Ukrainian agricultural products to EU countries, given the extraordinary circumstances. The objective will be achieved using gravity models for selected agricultural products. The analysis focused on the import of major crops and oilseeds, as these were among the most frequently exported agricultural products from Ukraine (Ministry of Agrarian Policy and Food of Ukraine, 2024).

The novelty of the article lies in at least two areas. Firstly, the study employs a gravity model that considers the cumulative impact of war and liberalization processes on trade, going beyond classical determinants, such as distance or GDP previously analyzed in this setup. Secondly, the original contribution is employing monthly data for 2020-2023 to model trade between the EU and Ukraine, allowing us to accurately capture short-term changes in trade, both in the period before the war and after it began. To the best of our knowledge, the study represents one of the first attempts to combine the cumulative effects of distance, war, and liberalization on trade volumes, and it is the first one in the context of UE-Ukraine relations.

The rest of the article is broken down as follows: the next section provides literature review focusing on the EU-Ukraine trade relations. The following part describes the data and research methods used. Afterwards, the research results and their discussion is presented. The last part summarizes the research carried out and contains policy recommendations.

Literature review

In the context of agri-food trade between Ukraine and the European Union, research focuses mainly on two aspects: the impact of trade liberalization resulting from the DCFTA (Frey and Olekseyuk, 2014; Nekhay et al., 2021; Ostashko et al., 2022; Rau, 2014; Tuliakov et al., 2023; Rabinovych, 2024) and the effects of the ongoing Russian-Ukrainian war (Borin et al., 2022; Bulkowska and Bazhenova, 2023; Jagtap et al., 2022; Mbah and Wasum, 2022; Prohorovs, 2022; Steinbach, 2023).

One of the early studies on the potential impact of DCFTA by Nekhay et al. (2012), using the AGLINK-COSIMO model, assessed the consequences of removing tariffs on 14 major agricultural products, such as wheat, oilseeds, and dairy products. The results indicated significant benefits for both sides - farmers' revenues in Ukraine increased by €393 million, and farmers in the EU by €860 million. However, the effects varied by product. According to the forecast, Ukraine would gain primarily in the grains and oilseeds sector but would face challenges adjusting to EU sanitary and quality standards. The potential benefits and challenges of Ukraine's agricultural market liberalization in the context of the DCFTA were also studied by Yatsenko et al. (2017), who noted increased export opportunities and a more significant role for processed food exports to the European market. Moreover, Cherevko (2017) emphasizes the agri-food sector's export potential but also highlights structural weaknesses that could hinder competitiveness in the EU market.

Cramon-Taubadel et al. (2010), analyzing a potential free trade agreement between Ukraine and the EU and its effects on agriculture, assuming a 50% reduction in tariffs, found mutual benefits from liberalization. The results underscored an increase in the productivity of Ukrainian agriculture and a better ability to cope with competition that followed. Grain production and exports, mainly wheat, were also forecast to increase. In turn, Ostashko et al. (2022) reported a 10.3% increase in agricultural exports from Ukraine to the EU over the first five years after the implementation of the DCFTA. In addition, Tuliakov et al. (2023) indicate that, between 2013 and 2021, trade turnover between the EU and Ukraine increased by an average of 60%. Beyond the growth in trade volume, the DCFTA served primarily as an engine of internal reforms in Ukraine in 2014–2019, forcing changes in technical barriers to trade (TBT) and competition policy, as emphasized by Rabinovych (2024). While these results underscore the clear benefits of trade liberalization between Ukraine and the EU, the war has created new challenges, particularly in transportation and logistics, limiting the full potential of trade integration. Shnyrkov and Chugaiev (2023) noted that the importance of exports of grains, vegetable oils, and other agri-food products has increased. Exports of processed products also increased, suggesting Ukraine's shift from raw material exports to more advanced agri-food products. However, the latest research documents a shift: from full wartime liberalization in 2022 toward selective EU protectionism (Butenko et al., 2025). Since June 2024, the EU has gradually reinstated tariffs and quotas on selected sensitive agricultural products from Ukraine, partially modifying the ATMs (Sirenko and Mikuliak, 2025).

In recent years, Ukraine has benefited from agricultural exports to the EU but has seen a lot of market disruption due to the war. Despite these difficulties, trade integration between Ukraine and the EU is progressing, and the agri-food sector remains a key area of cooperation between partners. The Russian-Ukrainian war, especially its development in 2022, has significantly affected international trade, including the agri-food sector. Shnyrkov and Chugaiev (2023) note that, despite maritime blockades and logistical disruptions, Ukraine has been able to maintain exports to the EU, with grain and vegetable oil exports growing in importance in particular. In the face of these challenges, the EU has become Ukraine's leading trading partner, especially in agricultural products. Moreover, the EU's decisions to suspend tariffs and import quotas on agricultural products from Ukraine have allowed for the maintenance of high levels of exports despite the difficulties associated with the ongoing war.

The literature indicates that trade liberalization has a positive impact on trade. National governments can unilaterally reduce tariffs or introduce preferential reductions for selected trading partners. Both of these approaches result in the creation of trade, as the elimination of trade barriers means that domestic suppliers are often abandoned in favor of more efficiently produced goods from partner countries (Kandogan, 2009). A free trade agreement, or a common border between countries, significantly promotes trade. Additionally, the liberalization and removal of tariff barriers create positive trade effects not only for countries in the resulting free trade zone but also for countries outside the bloc (Yang and Martinez-Zarzoso, 2014).

Despite many positive aspects of trade liberalization, negative ones can also be observed. From the EU's perspective, trade liberalization with Ukraine has disrupted European markets. As Butenko et al. (2025) indicate, the number of notifications concerning sanitary and phytosanitary (SPS) measures for products from Ukraine increased by 18% during 2024, suggesting stricter controls and a perceived need to protect the market. The findings of (Butenko et al., 2025) also point to hidden trade costs stemming from the fact that a one–standard deviation increase in SPS intensity (measured as the logarithm of the number of notifications) translates into a 3.5–4.0% increase in trade costs, which in practice may offset the benefits of zero tariffs. In addition, looking at the effects of liberalization after 2022, sudden price and supply fluctuations triggered tendencies to protect producers and populations at the expense of global food trade stability, resulting in a negative outcome (Kutsmus et al., 2024).

In light of trade theory, trade is significantly affected by the distance between countries and the size of their economies, as measured by GDP (Chaney, 2018). Karemera et al. (1999), while studying the effect of distance on trade in the Pacific region, found that countries closer to each other were more likely to trade due to lower transportation costs, cultural proximity, and similarities in consumption patterns. Their findings confirm that shorter distances between member countries favor trade in integrated regions, such as ASEAN, where trade agreements exist. Thus, in the context of trade liberalization, a small distance can strengthen economic integration by facilitating the exchange of goods between geographically close countries. In turn, Jagdambe and Kannan (2020) used a gravity model to analyze agricultural trade between India and ASEAN (AIFTA). The study covered 50 countries and five major trade agreements (including AIFTA, NAFTA, MERCOSUR, and the EU) from 2005 to 2014. Their results also indicate that a greater distance between countries results in lower trade flows, as it increases transaction costs. At the same time, geographic proximity and a common border are drivers of trade. The closer the countries are, the lower the costs of trade, which promotes increased exchanges between them.

Conversely, war tends to act as a brake on trade by tightening controls, protectionism, and breaking supply chains. On the other hand, post-conflict efforts to rebuild and stabilize the economy sometimes emerge, which can foster openness to trade and new economic alliances (Barbieri and Levy, 1999; Martin et al., 2008; Taylor and Glick, 2005). Such cases occurred, for instance, after World War II, when the creation of institutions such as the General Agreement on Tariffs and Trade (GATT) fostered greater economic openness (Irwin, 1994; McKenzie, 2020).

However, the literature does not currently provide studies considering the simultaneous effects of geographic distance and armed conflict on trade volumes. Separate studies show that distance and war can significantly impact trade, but their cumulative impact remains unknown. With global crises such as the war in Ukraine, the role of distance and armed conflict is becoming increasingly complex. Understanding their collective impact on trade is key to formulating policies promoting trade stability. Our study fills an existing research gap by analyzing the cumulative effects of geographic distance and armed conflict on trade volumes between the EU and Ukraine.

Materials and methods

We constructed our gravity models based on panel data for 27 EU countries regarding import volumes from Ukraine, considering 39 crop and oilseed products, as these are among Ukraine's most exported agricultural products. We use monthly data for the period 2020-2023 to evaluate the change between years without war (2020-2021) and with war (2022-2023).

Trade data was retrieved from the Comext-EUROSTAT database (EUROSTAT, 2024) using the 8-digit level disaggregation of the Harmonized Commodity Description and Coding System (HS). A complete list of products used is given in the supplementary files (S1). We employed the monthly data on imports in kilograms from Ukraine to EU-27 countries as a dependent variable. Such an approach is chosen as it provides a more accurate assessment of trade flows, as it is not influenced by price changes or exchange rate variations as in the case of monetary trade values (Lewis, 2017).

The great circle distance between the capitals of EU countries and the Ukrainian capital was employed to estimate the geographic distance. This approach, while straightforward, is widely used in gravity models as a reliable proxy for spatial interaction in trade analysis (Head and Mayer, 2014). Following the tradition of gravity models, the distance and the GDP were used as independent variables in their logarithmic form (Anderson and van Wincoop, 2003). The data on nominal quarterly GDP in USD retrieved from the EUROSTAT database were used (Eurostat, 2025). The quarterly GDP data were linearly interpolated to get a monthly representation of the GDP.

The rest of the variables are binary, indicating a war at Ukraine's territory, shared border, trade ban to countries bordering Ukraine for certain products, and two variables regarding tariff-rate quotas (TRQs). The complete list of variables is given in Table 1. In the case of the war dummy, we decided that the trade had been affected since March 2022, as the war started on the 20th of February, but its major part was not affected. The trade ban variable was set to 1 (signifying trade restrictions but possible transit) from March 2023 for Bulgaria, Hungary, Poland, Romania, and Slovakia. The ban included specific products from barley, rape, sunflower, and wheat products.

To account for the fact that the war could have affected trade asymmetrically across importers, we include interaction term between the war dummy and share border. This variable equals 1 for border countries (e.g., Poland, Hungary, Slovakia, Romania) in the war months and 0 otherwise. The interaction tests whether imports to neighboring countries increased specifically because they were neighbors during wartime (e.g., due to logistical re-routing and land transport advantages), rather than due to war or border proximity alone. The interaction coefficient therefore captures how much larger (or smaller) the war effect is for bordering countries compared to non-border countries.

We decided to account for TRQs employing two variables, one indicating if TRQs exist as a trade barrier and the second indicating if TRQs for a certain period are exceeded. Together, these variables account for a dual effect of TRQs on trade. First, within the quota, TRQs restrict trade by capping the number of imports eligible for lower tariffs (Bureau et al., 2019) (in the case of imports of analyzed products from Ukraine to the EU, the tariff within the quota is 0). Second, once the TRQ threshold is exceeded, higher out-of-quota tariffs can significantly deter additional trade (Muchopa, 2021). The information about existing TRQs between Ukraine and the EU and their exceedance was retrieved directly from DCFTA and special regulations on trade, effectively abolishing TRQs from June 2022.

The gravity model framework employed in this study underwent rigorous pre-validation steps to ensure the robustness of the results. This included stationarity testing, multicollinearity diagnostics, and a strategy to address seasonality and zero trade flows in the dependent variable.

Seasonality is a well-documented characteristic of agricultural trade flows, driven by factors such as harvest cycles, climatic conditions, and shifting demand patterns (Cipollina and Salvatici, 2010). To address this, monthly dummies are included in the gravity model to control for unobserved, time-specific effects that could bias the estimation results

Variables	Type	Description	Symbol
Dependent variable			
Import quantity	continuous	Quantities in kg	QUANTITY_IN_KG
Independent variables			
Nominal GDP	continuous	Logarithmic form	ln_GDP
Distance	continuous	Great circle distance between capitals Logarithmic form	ln_Distance
War dummy	binary	War (1) No war (0), war from March 2022	wardummy
Shared border	binary	Shared border (1) No border (0)	Shared_border
Trade ban	binary	Trade ban (1), No trade ban (0), ban for selected products from May 2023	ban
Tariff-rate quota (TRQs)	binary	TRQs exist as a trade barrier (1), TRQs do not exist as a trade barrier (0)	TRQs
Tariff-rate quota exceeded	binary	TRQ is exceeded (1), TRQ is not exceeded (0)	TRQ_exceeded
War dummy x Shared border	Interaction (binary)	Interaction term between the war dummy and the shared border	int_war_border

Source: Own compilation.

Table 1: Variables used in gravity models.

(Serlenga and Shin, 2007). Monthly dummies effectively capture variations in trade flows that arise from agricultural seasonality, ensuring that these time-specific factors do not confound the estimated coefficients (Heerman and Sheldon, 2018).

Multicollinearity was assessed using the Variance Inflation Factor (VIF), which measures what portion of the variance of the estimator is caused by the correlation of the variables in the model, according to the formula (James et al., 2021):

$$VIF = \frac{1}{1 - R_j^2} \tag{1}$$

where:

VIF - variance inflation factor;

R^2 - coefficient of determination;

j - independent variable.

The average VIF value is well below the commonly used thresholds of 10 or 4 more strictly (O'brien, 2007), with the highest observed VIF being 5.63 for the variable TRQs (Table 2). The mean VIF was consistently low across specifications, ranging from 1.17 to 2.13, indicating an absence of significant multicollinearity. Consequently, all variables were retained in the model without the need for adjustment.

Variables	**VIF**	**1/VIF**
TRQs	5.63	0.1777
wardummy	5.43	0.1843
month_dummy5	1.94	0.5154
month_dummy3	1.94	0.5161
month_dummy4	1.94	0.5161
month_dummy10	1.86	0.5386
month_dummy9	1.86	0.5387
month_dummy11	1.86	0.5387
month_dummy8	1.86	0.5387
month_dummy12	1.86	0.5387
month_dummy7	1.86	0.5387
month_dummy6	1.86	0.5387
month_dummy2	1.83	0.5455
ln_Distance	1.42	0.7061
shared_border	1.38	0.7250
ln_GDP	1.10	0.9130
ban	1.08	0.9230
TRQ_exceeded	1.02	0.9817
Mean VIF	2.09	

Source: Own compilation.

Table 2: Results of the variance inflation factor (VIF) for variables used in models.

To avoid spurious regressions, we tested GDP for stationarity. The Levin-Lin-Chu unit root test was applied to the logarithm of GDP across panels (Levin et al., 2002). The results strongly rejected the null hypothesis of non-stationarity, confirming that the data is stationary (adjusted t* = −44.6884, p<0.001).

Our import data (dependent variable) contains numerous zero trade flows, which pose challenges for traditional estimation techniques like Ordinary Least Squares (OLS). Log-linearizing the gravity model excludes zero flows or requires arbitrary adjustments, introducing biases (Martin and Pham, 2020). Additionally, OLS is inconsistent under heteroskedasticity, which is pervasive in trade data (Sukanuntathum, 2012). To address these issues, alternative methods like Poisson Pseudo-Maximum Likelihood (PPML) have been proposed to ensure robustness against both zero flows and heteroskedasticity (Santos Silva and Tenreyro, 2006). The PPML estimator addresses these issues by directly estimating trade flows in levels, making it robust to heteroskedasticity and capable of handling zero trade values without transformations (Santos Silva and Tenreyro, 2011). Furthermore, PPML ensures interpretable coefficients as elasticities and is robust to non-stationary dependent variables (Fally, 2015). The PPML estimator maximizes the following pseudo-log-likelihood function:

$$\mathcal{L}(\beta) = \sum_{ijt} [Trade_{ijt}\, ln(\hat{Trade}_{ijt}) - \hat{Trade}_{ijt}] \tag{2}$$

where:

$\hat{Trade}_{ijt} = exp(X'_{ijt}\beta)$ represents the predicted trade flow in the model. It is derived by exponentiating a linear combination of the explanatory variables (X_{ijt}) and their corresponding coefficients (β). This functional form ensures that the predicted trade flow remains strictly positive, aligning with trade data's non-negative nature (Santos Silva and Tenreyro, 2006).

Tradeijt is observed trade flow (can be zero or positive).

To estimate β, the PPML estimator solves the following first-order conditions:

$$\sum_{ijt} [Trade_{ijt} - \hat{Trade}_{ijt}]\, X_{ijt} = 0 \tag{3}$$

This condition ensures that the weighted residuals sum to zero, where the weights depend on the predicted trade flows. Unlike log-linearized

OLS models, PPML works directly with trade flows in levels. The logarithm of zero is undefined, but PPML avoids this issue because it does not require a log transformation of the dependent variable.

The PPML estimator was selected as the best fit for our models. However, we also employed high-dimensional fixed effects (HDFE) since the HDFE framework provides a computationally efficient way to incorporate fixed effects, controlling for unobserved heterogeneity without explicitly generating dummy variables (Correia et al., 2020). Instead of estimating the fixed effects directly, the HDFE transforms the data by de-meaning it within each group to "absorb" the fixed effects. We employed the product fixed effects for our models to account for unobservable, time-invariant characteristics specific to each product. Fixed effects for countries or time were excluded to prevent key variables, such as ln_Distance, wardummy, and shared_border, from being dropped due to collinearity. These variables are constant across specific dimensions (e.g., ln_Distance and shared_border within countries) or vary only by time (wardummy), making them absorbed when corresponding fixed effects are included. The models avoid such issues by focusing on product-level fixed effects, allowing these critical explanatory variables to remain in the analysis. Our approach is consistent with the recommendation to select fixed effects strategically, ensuring that they do not absorb the variation of interest in the independent variables (Head and Mayer, 2014). Using product fixed effects captures essential heterogeneity across product categories while preserving the explanatory power of variables like distance, which are central to the gravity framework.

Lastly, we applied cluster-robust standard errors for each country-product pair, which ensures robust inference by addressing within-cluster correlation specific to each country-product combination. Clustering at the country-product level accounts for shared shocks or dependencies within each product-country combination over time, ensuring robust statistical inference. This step complements the use of product fixed effects by addressing correlated errors that fixed effects alone cannot handle (Cameron and Miller, 2015). Therefore, our first model was specified as follows:

$$E(Trade_{ijt}) = \exp(\beta_0 + \beta_1 \ln(GDP_{it}) + \\ + \beta_2 \ln(Distance_{ij}) + \beta_3 Ban_{ijt} + \beta_4 TRQs_{ijt} + \\ + \beta_5 Wardummy_t + \beta_6 Shared_{Border_{ij}} + \\ + \beta_7 TRQ_{Exceeded_{ijt}} + \\ + \sum_{m=2}^{12} \delta_m MonthDummy_m + \gamma_p) \quad (4)$$

where:

$Trade_{ijt}$ represents trade flows in kilograms between Ukraine (i) and importer j at time t;

δ_m represents coefficients for the monthly dummy variables, explicitly included to capture time effects for months $m = 2,\ldots,12$ (the first month serves as the reference category);

γ_p represents product fixed effects, absorbed using HDFE.

We also specified the second model, which additionally includes the interaction term between the war dummy and the shared border. Such a solution was chosen based on the data observation, showing a significant increase in imports into countries bordering Ukraine immediately after the start of the war compared to other EU countries. Therefore, the second model was specified as:

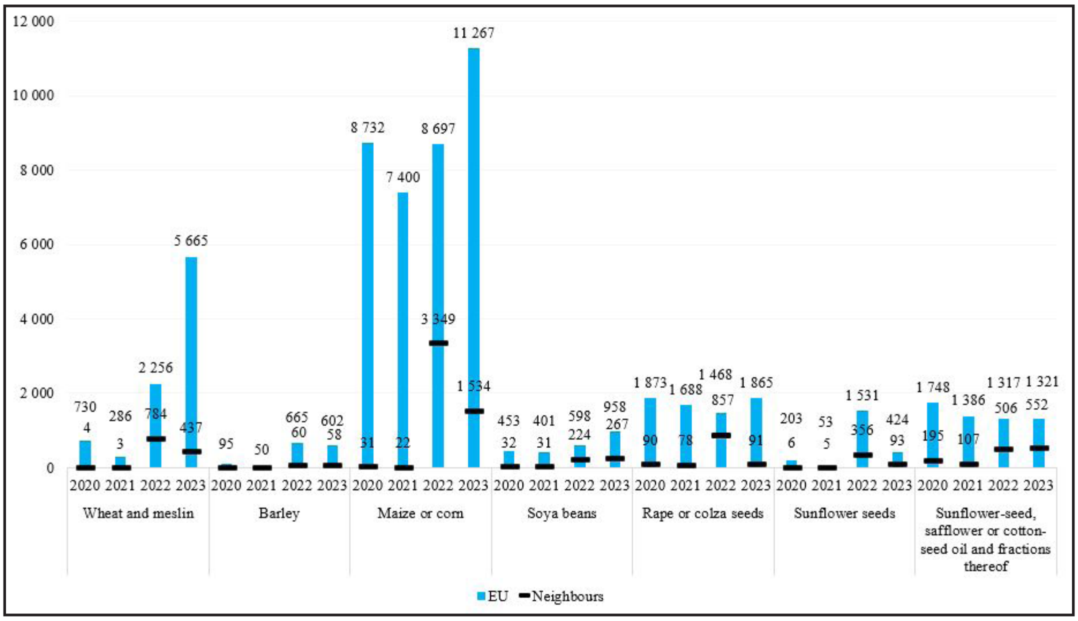
$$E(Trade_{ijt}) = \exp(\beta_0 + \beta_1 \ln(GDP_{it}) + \\ + \beta_2 \ln(Distance_{ij}) + \beta_3 Ban_{ijt} + \\ + \beta_4 TRQs_{ijt} + \beta_5 Wardummy_t + \\ + \beta_6 Shared_{Border_{ij}} + \beta_7 TRQ_{Exceeded_{ijt}} + \\ + \beta_8 \left(\mathrm{Wardummy_t} \times \mathrm{Shared_{Border_{ij}}}\right) + \\ + \sum_{m=2}^{12} \delta_m MonthDummy_m + \gamma_p) \quad (5)$$

The study is based on the gravity model, which emphasizes the importance of geographical proximity as a key factor influencing trade flows. However, it does not directly account for the relationship between distance and transport costs, which may be affected by factors such as infrastructure quality, trade agreements, or geopolitical barriers (Brancaccio et al., 2020; Clarifying Trade Costs, 2009). Although the study discusses the dynamics of trade between Ukraine and the EU under conditions of war and trade liberalization, it does not include precise estimates of transport costs. This limitation arises from the difficulty in distinguishing which products were transported by land and which by sea, depending on the country. Another obstacle was the lack of comprehensive data on the modes of transport used, which ultimately impacted costs. This limitation prevented the consideration of differences in the cost structure associated with maritime and land transport and the inclusion of variations in sea and land distances between Ukraine and EU countries. However, such an approach is commonly applied in different studies (e.g., Arvis et al., 2016; Fang and Shakur, 2018).

Results and discussion

In 2022, the onset of the war in Ukraine led to a notable increase in the inflow of agricultural products into the EU market. This growth was driven by multiple factors, including the EU's solidarity corridors, which facilitated the preferential export of Ukrainian agricultural goods, the suspension of tariffs and quotas, and the need to find alternative transport routes due to the blockade of Black Sea ports (Bulkowska and Bazhenova, 2023).

The most significant increase in imports was observed in the countries bordering Ukraine (Poland, Hungary, Slovakia, Romania) (Figure 1). This is directly in line with the gravity theory developed in the past (e.g., Anderson, 1979; Bergstrand, 1985; Deardorff, 1998) and more recently (e.g., Allen et al., 2014; Eaton et al., 2016). Due to geographical proximity and the possibility of land transport, these countries became natural recipients of products such as wheat, corn, rapeseed, and oilseeds, which were particularly significant for Ukraine's exports. Corn imports to neighboring countries increased more than 150-fold when comparing 2021 to 2022. However, the substantial growth of imports, or even the import dependency ratio, as measured by the share of imports from Ukraine in overall imports of individual countries, may not accurately reflect the trade-related consequences of trade shifts for agricultural markets and food security if imports constitute a small share of domestic supply. Therefore, the ratio of imports to domestic production is a more relevant measure for recognizing import dependence. Before the Russia-Ukraine war, the share of corn imports from Ukraine to Central and Eastern European Countries was marginal (less than 0.5%), but during the war, it increased, reaching almost 16.5% before import bans were introduced in May 2023. A similar trend, though to a lesser extent, was also observed in the case of wheat, where the share of Ukrainian imports in the domestic production of EU countries increased from around 0% to 3% (EUROSTAT, 2024). Ukraine has been an important wheat supplier to EU countries during the analyzed period. In total, 2023 wheat imports from Ukraine accounted for around 50-60% of total EU wheat imports, whereas before the war began, in 2021, they accounted for around 10%. The critical importance of grain and oilseed



Source: Own calculations based on COMEXT-Eurostat data

Figure 1: Imports of agricultural products from Ukraine to Ukraine's neighbors and other EU countries in 2020-2023 (mln of tons).

imports from Ukraine to various world subregions, including European countries, has already been discussed by Hamulczuk et al. (2023). Based on the share of imports from Ukraine in domestic use, they showed that the most import-dependent regions, such as Northern Africa and Western Asia, might have experienced the suspension of grain deliveries from Ukraine the most. Still, at the same time, due to the high import-dependency ratio, Southern and Western European countries could also be threatened.

Despite the significant growth in the inflow of agricultural products to Ukraine's neighboring countries, the data also indicate an increase in the flow of Ukrainian products to more distant EU states. A detailed analysis of the data revealed a rise in imports, both in terms of quantity and value, to countries such as Germany, Italy, and Spain. This growth was slower than that observed in Ukraine's neighbors, which resulted from higher transportation costs and limited availability of Ukrainian products in the early stages of the conflict. Nevertheless, the visible growth in imports to these countries suggests the potential for further trade diversification within the EU. The identified trends confirm that transportation costs dependent on the distance between countries limit agricultural exports. Such regularity is in line with analyses by, Jayasinghe and Sarker (2008), focusing on agri-food trade in NAFTA countries and with the study by Hatab et al. (2010), who analyzed the main factors affecting Egypt's agricultural exports to major trading partners from 1994 to 2008. However, transportation costs are not the only factors determining the value of bilateral trade flows. Our observations might settle that, as previously shown by Paiva (2005), Hatab et al. (2010), and Melece and Hazners (2014), GDP per capita in trading partner countries and agriculture's contribution to GDP in exporting countries are also critical for shaping mutual agri-food trade flows.

In 2023, a continued increase in the inflow of agricultural products to EU countries can be observed. However, for countries neighboring Ukraine, the effects of temporary import restrictions introduced by Poland, Hungary, Slovakia, Romania, and Bulgaria on products such as wheat, corn, rapeseed, and sunflower seeds are evident. In the case of corn, this decline was more than twofold, dropping from nearly 3.5 billion tons in 2022 to 1.5 billion tons in 2023. As for Ukraine's neighboring countries, their share of Ukraine's agri-food imports was 17% in 2021, 40% in 2022, and 29% in 2023. These results highlight the dynamic nature of agricultural trade between Ukraine and the EU, shaped by both geopolitical factors and market adjustments. Those trade drivers often result from trade liberalization, and their impact on bilateral trade has already been investigated (e.g., Huchet, Mouël and Vijil 2016; Matkovski, Lovre and Zekic 2017). It results from their estimations employing a gravity model that the trade liberalization has positive effects on the intensification of trade flows between the signatories of the trade agreement at the expense of countries not involved in the preferential trade area, which usually are located at a greater distance.

The gravity models were constructed to assess whether distance remains the primary determinant of trade development between the EU and Ukraine in the context of war and the implemented trade measures, such as trade liberalization or partial import restrictions. The results of both models are given in Table 3. In the case of the first model, the coefficient for ln_GDP is 0.6537 ($p = 0.000$), indicating a statistically significant relationship between the economic size of EU countries and the volume of agricultural imports from Ukraine. A 1% increase in GDP is associated with an approximate 0.65% increase in trade flows. However, an unusual positive coefficient (1.7760) ($p = 0.000$) was observed for ln_Distance. This suggests that the greater the distance between Ukraine and an EU country, the higher the exports from Ukraine. This could be attributed to the fact that wealthier EU countries (e.g., Germany, Spain, Italy) located farther from Ukraine have a greater capacity to absorb imports. Higher transport costs may be mitigated by the short distances within the EU and higher demand in countries with developed infrastructure (Persyn et al., 2022). However, this contradicts the classical assumptions of the theory concerning gravity models (Tinbergen, 1962). Nevertheless, it should be noted that under wartime conditions and constrained access to the Black Sea, geographic distance need not constitute an adequate proxy for trade costs, as the capacity of alternative transport corridors and importers' logistical capabilities become pivotal determinants of flows. Accordingly, the positive coefficient on ln_Distance may also reflect destination selection and the concentration of exports in countries able to effectively coordinate imports via the EU's transit and port infrastructure.

Variable	Model 1	Model 2
ln_GDP	0.6537*** (0.1201)	0.6495*** (0.1201)
ln_Distance	1.7760*** (0.4478)	1.7791*** (0.4462)
ban	-2.5848*** (0.3906)	-3.1787*** (0.3646)
TRQs	-0.8326 (1.1938)	-1.0227 (1.1999)
wardummy	0.6568** (0.264)	0.2752 (0.2821)
shared_border	2.2118*** (0.4787)	-0.1273 (0.6635)
TRQ_exceeded	0.9782 (1.1714)	1.1368 (1.1701)
int_war_border		3.0762*** (0.4681)
month_dummies2	-0.1393** (0.0542)	-0.1394** (0.0542)
month_dummies3	-0.5384*** (0.1156)	-0.5433*** (0.1124)
month_dummies4	-0.7385*** (0.1145)	-0.7443*** (0.1127)
month_dummies5	-0.7760*** (0.1087)	-0.7327*** (0.1019)
month_dummies6	-0.8645*** (0.1304)	-0.8265*** (0.1329)
month_dummies7	-0.8880*** (0.1636)	-0.8418*** (0.1687)
month_dummies8	-0.7295*** (0.2386)	-0.6916*** (0.243)
month_dummies9	-0.5006* (0.287)	-0.4627 (0.2901)
month_dummies10	-0.3367 (0.2254)	-0.2987 (0.2274)
month_dummies11	-0.0788 (0.1283)	-0.0411 (0.1308)
month_dummies12	-0.0887 (0.0939)	-0.0513 (0.0954)
_cons	-3.8665 (4.1228)	-3.6415 (4.1246)
Parameters	19	20
Observations	37 584	37 584
Country_Product clusters	783	783
Absorbed Product FE	Yes	Yes
Pseudo R-squared	0.6495	0.6723

Note: *** p < 0.01, ** p < 0.05, * p < 0.1 (robust standard errors in parentheses)
Source: own computation in the STATA 15, based on COMEXT-Eurostat and World Bank data.

Table 3: Gravity model on Ukraine-EU selected agricultural products imports (PPML estimation with HDFE for products).

Variables such as TRQ (p = 0.486) and TRQ_exceeded (p = 0.404) were found to be not statistically significant in the model. The import ban on specific agricultural products from Ukraine to EU countries proved statistically significant. The coefficient for the ban is -2.5848 (p = 0.000), meaning that the ban has caused a significant reduction in imports from Ukraine. The model results also indicate a statistically significant impact of the war on the increase in the volume of agricultural imports to the EU (coefficient = 0.6568, p = 0.013). Additionally, the shared border was significant, with a coefficient of 2.2118 (p = 0.000), suggesting that being a neighbor of Ukraine positively influences imports of agricultural products.

On the one hand, our results show that the role of distance contradicts the assumptions of the theory on gravity models, indicating that the greater the distance between countries, the higher the trade volume. On the other hand, the coefficient for the shared bordered variable suggests that geographical proximity matters and increases trade. A particular dichotomy of our results becomes evident. A detailed analysis of the data revealed that the most significant inflow of agricultural products to countries neighboring Ukraine occurred in the first months following the outbreak of the war. Therefore, we decided to include an additional variable, int_war_border, into the model, which accounts for the interaction between war and a shared border. This resulted in the shared border variable no longer being statistically significant (p = 0.848). War is also no longer statistically significant (p = 0.329), whereas the interaction between the border and war became substantial and positively correlated with trade volume. The coefficient for int_war_border is 3.0762 (p = 0.000). The insignificance of wardummy and shared_border and the significance of the interaction term (int_war_border) indicate that the combined effect of war and proximity to Ukraine is more important than their individual effects. This finding highlights the conditional nature of the relationship, which is an essential insight for understanding trade dynamics in the context of war.

The impact of conflicts on trade flows has attracted the attention of scholars for decades; however, the research results remain ambiguous. Karlsson & Hedberg (2021) showed that in the nineteenth century, the negative influence of war on trade was noted only in relations between war-involved economies, while trade between war-embroiled countries and third countries was either unaffected or even increased during wartime. As far as twentieth-century wars were concerned, they reduced trade between the parties to the conflict and between countries directly involved in it and countries neutral to the conflict. The war-related impacts on trade in third countries were also confirmed by Krpec and Hodulak (2019). A valuable analysis of the effects of conflicts on trade in 1979-2000 was delivered by Marano et al. (2013). Similarly to the studies mentioned above, they proved that conflicts negatively affect both countries that directly experience war disruptions and neighboring countries. Moreover, their findings indicate that trade is more negatively impacted by conflict in the exporter's territory than in the importer's territory. Using the gravity approach, Kamin (2022) also found that the conflict types and their unique characteristics are essential in determining the extent and direction of their impact on trade. It means that the war-related trade impact on a specific economy depends on whether the conflict is interstate or intrastate and whether both trading partners are in conflict. Similarly to our study, Kamin (2022) proved that the distance between trading partners does not have a leading impact on bilateral trade during the war. This clearly shows that the assumptions of classical gravity theory indicating that trade intensifies between countries close to each other could remain invalid in the face of sudden and exceptional circumstances, such as armed conflicts, including the war between Russia and Ukraine, and its impact on EU-Ukraine agri-food trade.

The results for other variables, such as ln_GDP, ln_Distance, and ban, are consistent with the baseline model (Table 3), indicating their stability as determinants of trade. In the case of the ban, the coefficient decreased to -3.1787, suggesting an even more negative impact on the volume of trade. The presence of seasonality in trade, represented by the month_dummies variables, is also consistent across both models, which is a standard phenomenon for agricultural products. However, the extended model provides a better understanding of trade mechanisms during the war and the structure and significance of traditional determinants of international trade.

Conclusions

In the presence of war and trade liberalization, which changed the trade situation between Ukraine and the EU, the study found that neighboring countries became a natural center for absorbing Ukrainian products due to their geographical proximity and the availability of transportation infrastructure. Nevertheless, the excessive inflow of these products created tensions in local markets, necessitating protectionist measures. At the same time, the visible growth in imports to distant countries suggests that the EU has the potential for further diversification and internal trade development in response to potential future crises.

The analysis results indicate that distance does not always act as a limiting factor for trade, contrary to the assumptions of the classical gravity model. The findings suggest that geographical proximity plays a particularly significant role in the initial phase of a crisis. However, the negative impact of distance on trade may diminish in the case of countries with high GDP and well-developed trade infrastructure. The EU countries that do not share a border with Ukraine and are located farther away increased their share in importing Ukrainian products. From 2023 onward, the increased inflow of Ukrainian goods to more distant EU countries was also influenced by the import bans introduced by some of Ukraine's neighboring Member States. Simultaneously, the pivotal role of border countries in handling Ukrainian exports highlights the importance of a shared border under crisis conditions. The study found that the traditional relationship between distance and trade volume can be disrupted in crises, especially when other factors, such as trade regulations and infrastructure, play a significant role.

In addition to the dynamic growth in trade, the war introduced significant challenges, such as the need to create new transport routes, which affected costs and the direction of trade flows. The study's findings emphasize the necessity of EU actions to support an even distribution of the import burden among member states, which could reduce economic and social tensions. In the long term, the EU faces the challenge of developing mechanisms that ensure the effective distribution of agricultural products within the Union.

The development of logistical infrastructure, particularly in regions bordering Ukraine, could help minimize economic tensions. Investments in efficient transportation systems and initiatives to strengthen local markets could help mitigate inequalities and support long-term stability at both regional and EU levels. We recommend introducing joint management systems for surplus goods, such as shared warehouses. Additionally, it would be essential to undertake investments to expand logistical infrastructure and support the flow of goods to reduce pressure on local markets.

The study addresses a research gap concerning the simultaneous impact of distance and armed conflicts on international trade. Previous literature has examined these factors separately, whereas the conducted analysis integrates their cumulative effects, highlighting the conditional nature of their influence on trade. The results indicating atypical behavior in the gravity model suggest the need for further research on the impact of conflicts and crises on international trade and the resilience of markets to these crises. Future studies should also include an analysis of transport cost structures and preferred transport routes. These analyses could help better adapt trade policies to potential crises.

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Monetary Conditions and Firm Performance in Czech Agriculture: Evidence from Firm-Level Panel Data

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Abstract

The aim of this paper is to examine how monetary conditions are associated with firm performance in the Czech agricultural sector. Using a balanced panel of 167 firms observed over the effective estimation period 2016-2024, the paper estimates static firm fixed-effects models for three complementary outcomes: return on equity (ROE), year-on-year log sales growth and cash flow to assets. The objective is to assess whether tighter monetary conditions were linked to weaker profitability, slower expansion and lower internal financing capacity in the broad agricultural economy. The results indicate that higher interest rates are associated with lower ROE, weaker sales growth and lower cash flow to assets, while higher real rates are negatively associated with ROE and internal liquidity. Exchange-rate appreciation is positively associated with sales growth and cash-flow capacity, which suggests that, in this sector, the imported-input cost channel may dominate the conventional export-price competitiveness channel.

Keywords

Monetary policy, interest rate, exchange rate, firm performance, agriculture, Czech Republic.

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Introduction

Monetary policy affects firms through several interconnected channels. Changes in policy rates alter the cost of external finance and the opportunity cost of internal funds; they also interact with bank balance sheets, risk-taking incentives, expectations and asset prices. In the canonical transmission literature, firm outcomes respond not only through the traditional interest-rate channel but also through credit frictions and balance-sheet amplification (Bernanke, 2022; Borio and Zhu, 2012). These mechanisms are unlikely to be uniform across firms. Theory and evidence suggest that balance-sheet strength, dependence on external finance, collateral, firm size and sectoral business models condition how the same macroeconomic impulse is transmitted into profitability and growth (Bruno and Shin, 2015). This heterogeneity is central for an agricultural-economics perspective because sectoral composition affects both financing structures and exposure to input-cost shocks.

In small open economies, the exchange-rate channel adds another layer of heterogeneity. Exchange-rate movements reshape the relative price of exports and imported inputs, and the net firm-level effect depends on invoicing, import intensity, pricing power, productivity and the composition of revenues and costs (Galí and Monacelli, 2005; Campa and Goldberg, 2005; Berman et al., 2012; Amiti et al., 2014; Aman et al., 2022). For some firms, appreciation weakens external competitiveness; for others, it lowers the cost of imported energy, feed, fertilisers, machinery and intermediate inputs. This ambiguity is exactly why sector-specific evidence matters.

Agriculture provides a particularly informative setting for studying such heterogeneity. Firms in this broad sector combine biological production cycles, weather exposure, uneven bargaining power, seasonal working-capital needs and sensitivity to transport, fuel and imported inputs, which makes their margins and liquidity sensitive to both input-cost and financing shocks (Pokrivčák and Tóth, 2022; Khafagy and Vigani, 2023; Ölkers and Musshoff, 2024). In addition, the capital structure of agricultural firms is shaped by land, buildings, machinery, biological assets and inventories that are asset-heavy, sector-specific and often imperfectly liquid. These assets can support collateralised borrowing, but they also create high fixed costs, long investment horizons and exposure to valuation changes, making leverage and the cost of debt central to profitability and financial resilience (Pokharel et al., 2019; Toušek et al., 2025). As a result, interest-rate increases may affect agricultural firms not only through the price of new credit, but also through refinancing conditions, working-capital pressure and the opportunity cost of maintaining liquidity buffers (Yeager and Barnard, 2014; Ölkers and Musshoff, 2024).

Existing agricultural finance research supports this concern. Evidence from the United States shows that financial stress in agricultural cooperatives is closely linked to low profitability, leverage and the interest-rate environment (Pokharel et al., 2019). Farm-management case research similarly indicates that liquidity buffers become more valuable when net farm incomes weaken and interest rates rise (Yeager and Barnard, 2014). Recent Czech evidence also suggests that leverage and the cost of debt remain central drivers of financial outcomes in agricultural firms once balance-sheet composition and biological assets are taken into account (Toušek et al., 2025).

The Czech Republic is an especially relevant case because the estimation period 2016-2024 combines years of near-zero interest rates, pandemic disruption, the aftermath of the Czech National Bank (CNB) exchange-rate commitment, the energy shock and a rapid tightening cycle. Czech macroeconomic research has documented important changes in the domestic transmission mechanism and the balance-sheet implications of exchange-rate policy, while price studies show that pass-through remains an important feature of the small open economy environment (Brůna, 2010; Franta et al., 2014; Hájek and Horváth, 2016; Franta et al., 2022). Yet firm-level sector evidence for the broad agricultural economy remains scarce. A further motivation is conceptual. In this paper, competitiveness is treated as a multidimensional firm concept rather than as a single trade indicator. This is why the analysis considers profitability, expansion and internally generated funds simultaneously; taken together, these outcomes capture whether firms can maintain accounting profitability, grow and finance adaptation under changing macroeconomic conditions. At the same time, because they are accounting-based measures, they have to be interpreted with the caution emphasised in the earnings-quality literature (Dechow et al., 2010).

The objective of this paper is to examine how monetary conditions are associated with three complementary dimensions of firm performance in the Czech NACE section A - agriculture, forestry and fishing: profitability, sales growth and internal liquidity. The paper uses a balanced panel of 167 firms observed over the effective estimation period 2016-2024 and estimates static firm fixed-effects models for ROE, year-on-year log sales growth and the cash flow to assets ratio. The focus on this sector reflects both the substantive relevance of the sector and the need to retain a sample large enough for credible sector-level inference.

The contribution of the paper is threefold. First, it provides sector-specific evidence for Czech agriculture within a firm-level panel framework. Second, it brings together the interest rate, exchange rate and real interest rate perspectives within one sector-specific design. Third, it connects macroeconomic financial transmission to firm-level outcomes that matter directly for resilience and competitiveness in the agricultural economy.

Literature review

Monetary transmission from macro policy to firm outcomes

The broader macroeconomic literature treats monetary policy as a central determinant of aggregate demand, inflation and financing conditions, but the firm-level route of transmission is increasingly understood as a macro-financial process rather than a single mechanical interest-rate effect. In the New Keynesian tradition, policy influences output and prices through intertemporal substitution, expectations management and the credibility of the nominal anchor (Carlin and Soskice, 2015; Mishkin, 2022). Central banking research then adds institutional design, communication and credibility as key elements of the transmission environment (Blinder et al., 2008; Bernanke, 2022).

A related insight of the post-crisis literature is that the financial cycle modifies the strength of transmission and may generate outcomes that cannot be understood from the policy rate alone. When leverage, liquidity and balance-sheet valuations move strongly, monetary policy can affect risk appetite and external finance premia in ways that alter firm outcomes even before standard investment responses fully materialise (Borio and Zhu, 2012; Borio, 2014; Bruno and Shin, 2015). This broader perspective is especially useful for reading the examined period, which includes both accommodative conditions and a sharp tightening phase.

Interest-rate and credit channel

The interest-rate and credit channel is the most direct benchmark for the present analysis. Bernanke (2022) shows how monetary tightening affects credit conditions through banks and the cost of finance. This logic is extended by emphasising agency costs, borrower balance sheets and the financial accelerator. In this framework, weaker net worth raises the external finance premium, reducing investment and amplifying the real effects of shocks.

At the firm level, the empirical implications are clear: firms that are more dependent on external finance, hold weaker collateral, or face tighter liquidity constraints should react more strongly to monetary tightening. This logic is reinforced by the financing-constraints literature and by evidence on small-firm cyclicality and bank-lending transmission. Recession and credit-crunch evidence further suggests that the effect of tighter conditions is not limited to investment, but can also compress profitability, working capital and survival margins (Claessens et al., 2008; Bianchi, 2011).

Exchange-rate channel in a small open economy

For a small open economy, the exchange rate is not a side issue but a core transmission channel. The classic open-economy framework predicts that monetary policy affects output partly through the exchange rate and trade competitiveness. Later models formalise how exchange-rate movements enter domestic demand, pricing and inflation dynamics in an economy with incomplete pass-through and sectoral heterogeneity (Galí and Monacelli, 2005; Campa and Goldberg, 2005).

The firm-level trade literature makes this channel more nuanced. Exchange-rate movements do not affect all firms alike because exporters, importers and two-way traders differ in market structure, mark-ups, import intensity and productivity. More productive firms may absorb part of the shock in margins; input-intensive firms may benefit from appreciation even if export competitiveness weakens; and heterogeneous-firm selection can reshape sector aggregates (Berman et al., 2012; Amiti et al., 2014). This matters for section A because agricultural, forestry and fishing firms often combine domestic production with imported inputs and equipment.

Internal finance, liquidity and resilience in agriculture

A complementary strand of literature links monetary conditions to internal finance and resilience. Cash flow, retained earnings and liquidity buffers can determine whether firms are able to maintain investment, working capital and adaptation expenditures during periods of tighter financing conditions. This perspective is closely connected to the financial accelerator, but it also highlights the role of self-financing and balance-sheet resilience in day-to-day business operation (Dechow et al., 2010).

This issue is particularly relevant in agriculture and related sectors. Agri-food firms often face financing gaps despite being economically viable, because investments are lumpy, collateral can be imperfect, and project horizons may be long relative to loan structures (Pokrivčák and Tóth, 2022). Recent evidence links external finance to agricultural productivity growth (Khafagy and Vigani, 2023) and shows that agricultural loan demand responds to interest rates, macroeconomic conditions and agricultural cycles (Ölkers and Musshoff, 2024). Cooperative studies also underline that low profitability, leverage and high interest rates can jointly create financial stress, while liquidity management may be crucial for repayment capacity under adverse scenarios (Pokharel et al., 2019; Yeager and Barnard, 2014).

Agricultural firms, profitability and balance-sheet composition

The agricultural-finance literature also points to the importance of firm structure. Recent Czech evidence suggests that the cost of debt in agricultural firms depends strongly on leverage, while profitability is shaped by balance-sheet composition and asset tangibility (Toušek et al., 2025). Related studies in agricultural and agri-food industries show that profitability depends on working capital, asset structure, capital intensity and financial development, all of which can affect how macroeconomic tightening translates into firm outcomes (Setianto et al., 2022; Beyer and Hinke, 2020; Mijic and Jaksic, 2017). In agriculture, this transmission is likely to be shaped by a distinctive asset base: land-related assets, machinery, biological assets and inventories make balance sheets comparatively asset-intensive, while the liquidity of these assets may be limited in periods of stress. The same asset structure can improve collateral capacity in normal times but can also make profitability and refinancing more sensitive to interest-rate changes when debt service costs rise.

These insights reinforce the relevance of using more than one dependent variable. Profitability alone may miss whether a macroeconomic shock works primarily through accounting profitability, revenue growth or the internal generation of funds; because these three dimensions need not move together, a single ratio can understate firm-level exposure. A multidimensional outcome set is therefore useful when the objective is to connect macro-financial tightening to firm resilience rather than to a single accounting ratio.

Czech evidence and the research gap

The Czech literature provides an important macro background, but it leaves a sector-level micro gap. Brůna (2010) discusses liquidity management and monetary-policy implementation in the Czech banking environment. Franta et al. (2014) examine changes in the Czech monetary transmission mechanism, while Hájek and Horváth (2016) show that exchange-rate pass-through remains relevant in the Czech Republic. Franta et al. (2022) further demonstrate that the legacy of exchange-rate policy has material balance-sheet implications in a small open economy. Together, these studies confirm that monetary conditions matter in the Czech setting, but they do not directly show how such conditions are reflected in firm-level agricultural outcomes.

What is still missing in the literature is sector-specific firm-level evidence for the broad agricultural economy in the Czech Republic. Existing work either stays at the macro level, focuses on prices and pass-through, or analyses agricultural firms through different accounting questions rather than through the lens of monetary transmission. The present paper addresses this gap by bringing a Czech agricultural sector panel into a fixed-effects framework that jointly tests rate, exchange-rate and real-rate conditions against profitability, sales growth and cash-flow capacity.

Materials and methods

Data sources and sample construction

The empirical analysis combines firm-level accounting data from Orbis with annual macroeconomic indicators from the Czech Statistical Office and the Czech National Bank databases. The underlying firm panel covers 2015-2024 and is constructed as a balanced panel of Czech-resident firms. Because sales growth and exchange-rate changes are measured in year-on-year differences, the effective estimation period in the static specifications runs from 2016 to 2024. The sector sample used in this paper consists of 167 firms classified under CZ-NACE Section A, corresponding to NACE Rev. 2 Section A: Agriculture, forestry and fishing, including divisions 01-03.

Constructing the dataset as a balanced panel improves the consistency of the longitudinal analysis by ensuring that each firm is observed across the full study period. This restriction is analytically useful, but it also narrows the empirical coverage of the sample. In particular, it excludes firms with interrupted reporting records, firms entering the sector during the period, and firms exiting before the end of the examined period. As a consequence, the sample is likely to over-represent firms with greater organisational stability and more regular reporting practices. The balanced-panel structure should therefore be understood as a deliberate methodological trade-off: it strengthens comparability over time, but it does not constitute a complete census of all firms operating in the sector in each year.

Model specification

Firm performance is captured by three dependent variables. The first is return on equity (ROE), used as an equity-scaled measure of accounting profitability. The second is year-on-year log sales growth, defined as the change in the natural logarithm of operating revenue and used to capture expansion in market activity. The third is cash flow to assets, defined as operating cash flow relative to total assets and used to proxy internal financing capacity and operational resilience. This outcome set reflects a multidimensional view of competitiveness at the firm level rather than a single export-based measure. Because all three outcomes are accounting-based, they are interpreted with caution and not as comprehensive measures of welfare or technical efficiency.

The key macroeconomic variables are the year-end CNB two-week repo rate, the annual log change in the CNB nominal effective exchange-rate index (NEER), and the real policy rate defined as the repo rate minus annual CPI inflation. The exchange-rate variable is multiplied by 100, so a positive value corresponds to an appreciation of the koruna. Additional controls include annual CPI inflation, year-on-year growth of the M2 broad-money aggregate, the Czech Statistical Office business/economic-sentiment confidence indicator, and firm size measured by the logarithm of total assets. In the real-rate specification, the real rate replaces the separate nominal-rate and inflation terms to avoid double counting.

The use of ROE rather than a ROA-based profitability measure deserves comment, because interest rates affect firm performance partly through financial leverage and the cost of debt. By construction, ROE is sensitive to capital structure: for a given level of operating performance, higher leverage mechanically raises ROE in favourable years and depresses it when financing costs rise. This mechanical sensitivity is precisely why the coefficient is not interpreted as a pure operating-profitability effect. ROE is retained because it is widely reported in the agricultural-finance literature and because the equity-holder perspective is relevant when monetary tightening works through leverage, refinancing and the cost of debt. At the same time, ROE is complemented by cash flow to assets, which is asset-scaled and less directly affected by equity scaling, and the consistency of signs across these outcomes is treated as evidence that the results are not driven solely by the mechanical leverage component of ROE. A fuller ROA/leverage comparison is left for future work because consistently reported operating-profit and liability items are not available in the present extract.

Firm performance is modelled with a static firm fixed-effects specification. For firm *i* in year *t*, each outcome is related to a single monetary variable and a vector of controls according to:

$$y_{it} = \alpha_i + \beta\, MP_t + \gamma' X_{it} + \varepsilon_{it} \qquad (1)$$

where y_{it} denotes the relevant firm outcome, α_i captures unobserved time-invariant firm heterogeneity, MP_t denotes the selected monetary variable, X_{it} contains the macroeconomic controls and the firm-size control, β is the coefficient of interest, and ε_{it} is the idiosyncratic error term. Standard errors are clustered at the firm level, and the significance of the monetary coefficients is cross-checked with Driscoll-Kraay standard errors that are robust to heteroskedasticity, serial correlation and cross-sectional dependence.

For each of the three dependent variables, equation (1) is estimated in three separate versions that differ only in the monetary variable MP_t: (a) a repo-rate model, in which MP_t is the CNB two-week repo rate; (b) a real-rate model, in which MP_t is the real repo rate (the repo rate minus CPI inflation), with the separate inflation control omitted to avoid double counting; and (c) an exchange-rate model, in which MP_t is the annual log change in the nominal effective exchange rate. This design yields nine estimated equations in total (three outcomes × three monetary variables). The three monetary variables are treated as complementary rather than competing: the repo rate captures nominal financing pressure, the real rate captures monetary tightness net of inflation, and the exchange rate captures external input-cost and competitiveness conditions.

The coefficients are interpreted with deliberate caution. Because the monetary variables are common to all firms in a given year, the coefficient β is identified only from variation over time across a relatively short horizon. The estimates should therefore be read as conditional within-firm associations that are consistent with standard transmission mechanisms, not as structural causal multipliers; the identification concerns this raises are discussed in detail in the Limitations subsection.

Table 1 summarises the construction and interpretation of all variables used in the estimations, grouped into dependent

Group	Variable	Construction / definition	Interpretation
Dependent	ROE	ROE (%); Orbis ratio defined as profit/loss before tax divided by book equity; winsorised at the 1st and 99th percentiles	Profitability (equity-scaled; sensitive to leverage)
	Δln Sales	Δln Sales = ln(operating revenuet) - ln(operating revenuet-1); winsorised at the 1st and 99th percentiles	Firm expansion / turnover dynamics
	CF/Assets	CF/Assets = operating cash flow, measured as net income plus depreciation and amortisation, divided by total assets; winsorised at the 1st and 99th percentiles	Internal financing capacity and operational resilience (asset-scaled)
Monetary	Repo rate	Year-end value of the CNB two-week repo rate, in percent	Nominal monetary-policy stance
	Real repo rate	Real repo rate = year-end CNB two-week repo rate minus annual CPI inflation, in percentage points	Real monetary tightness
	Δln NEER	100 × [ln(NEERt) - ln(NEERt-1)], based on the CNB nominal effective exchange-rate index; positive values denote koruna appreciation	Exchange-rate / imported-input cost and competitiveness conditions
Controls	CPI inflation	Annual average CPI inflation rate, in percent, from the Czech Statistical Office	Price environment
	M2 growth	Year-on-year growth of the M2 broad-money aggregate, in percent	Macro-financial environment
	Business confidence	Annual average of the Czech Statistical Office business/economic-sentiment confidence indicator	Expectations / demand environment
	ln Assets	Natural logarithm of total assets from Orbis	Firm-size control

Source: Own processing

Table 1: Variable construction and interpretation.

variables, the main monetary (explanatory) variables, and control variables. The set of outcomes deliberately combines a profitability indicator, a growth indicator and an internal-finance indicator, so that the empirical results can speak to several dimensions of firm resilience at once rather than to a single accounting ratio.

Sample composition and descriptive statistics

An important descriptive feature of the sample is that this section is agriculture-dominant even though the paper keeps the formal section-A label throughout. More than 92% of firms and observations come from NACE division 01, while division 02 represents a smaller forestry-and-logging segment and division 03 is only marginally represented. This composition justifies two statements at once: first, the broad sectoral label remains factually correct; second, the results are likely to reflect the economics of agriculture much more than the economics of fishing.

The sample is also informative about firm size. Using the size classification in the underlying dataset, 152 of the 167 firms (91.0%) are small, 15 (9.0%) are medium-sized and none are large, so the panel is dominated by small and medium-sized enterprises. Size dispersion is nonetheless considerable: the logarithm of total assets has a mean of 15.09 and ranges from 12.02 to 18.26 (Table 3), so even within a predominantly small-firm sample the largest balance sheets are several hundred times larger than the smallest. Information on financial leverage is not available in a sufficiently consistent form in the current data extract, which contains turnover, cash-flow information, total assets and profitability indicators but does not include reliable liability items across the full balanced panel. The role of indebtedness is therefore noted as a limitation and a priority for future data collection rather than quantified here.

Given the accounting nature of the data, key ratio variables are winsorised at the 1st and 99th percentiles. This is especially important for ROE because accounting profitability can become mechanically volatile when equity is low. Winsorisation does not solve all measurement problems, but it reduces the influence of extreme observations without removing the within-sample variation that the fixed-effects design needs. The descriptive statistics confirm that the resulting sample still exhibits substantial dispersion, especially in profitability and sales growth.

Because the fixed-effects estimator exploits only within-firm variation, Table 4 decomposes

NACE division	Firms	Firm share (%)	Observations	Obs. share (%)
01 Agriculture	154	92.2	1386	92.2
02 Forestry and logging	12	7.2	108	7.2
03 Fishing and aquaculture	1	0.6	9	0.6

Source: Own processing based on the section A estimation sample

Table 2: Composition of the section A sample by NACE division.

Variable	N	Mean	Std. dev.	Min	Median	Max
ROE, winsorised	1503	7.843	18.763	-220.105	6.736	111.973
Δln Sales, winsorised	1502	0.073	0.330	-0.773	0.042	2.969
CF/Assets, winsorised	1503	0.107	0.079	-0.489	0.098	0.584
ln Assets	1503	15.093	1.012	12.021	15.055	18.255
Repo rate	1503	2.894	2.509	0.050	2.000	7.000
CPI inflation	1503	4.811	4.518	0.700	2.800	15.100
M2 growth	1503	7.414	1.620	4.964	7.013	10.671
Business confidence	1503	98.743	5.699	88.903	96.527	106.436
Δln NEER	1503	1.207	2.578	-2.357	0.482	6.322
Real repo rate	1503	-1.917	2.680	-8.100	-0.800	1.600

Source: Own processing based on Orbis and CZSO data

Table 3: Descriptive statistics of the sample.

Variable	Overall SD	Between-firm SD	Within-firm SD	Within share (%)
ROE	18.763	11.141	15.097	64.7
Δln Sales	0.330	0.102	0.314	90.5
CF/Assets	0.079	0.055	0.056	50.9

Source: Own processing based on the estimation sample

Table 4: Within-firm variation in the dependent variables.

the dispersion of each dependent variable into a between-firm and a within-firm component. The within-firm component dominates for all three outcomes, accounting for about 65% of the total variance of ROE, 91% for sales growth and 51% for cash flow to assets. This is informative for interpreting the modest within R^2 reported below: the limited explanatory power does not stem from a lack of within-firm variation—there is substantial year-to-year movement within firms—but rather from the limited explanatory reach of macroeconomic regressors that are common to all firms in a given year.

Annual macroeconomic context

The macroeconomic environment changed sharply over the estimation period. The annual values in Table 5 show three distinct phases: a low-rate period in 2016–2020, an abrupt tightening and inflation episode in 2021–2023, and the return to a positive real repo rate in 2024. This chronology matters for interpretation because the estimated firm-level coefficients combine these different regimes into one within-sample relationship (Figure 1).

Model selection, diagnostic tests and inference

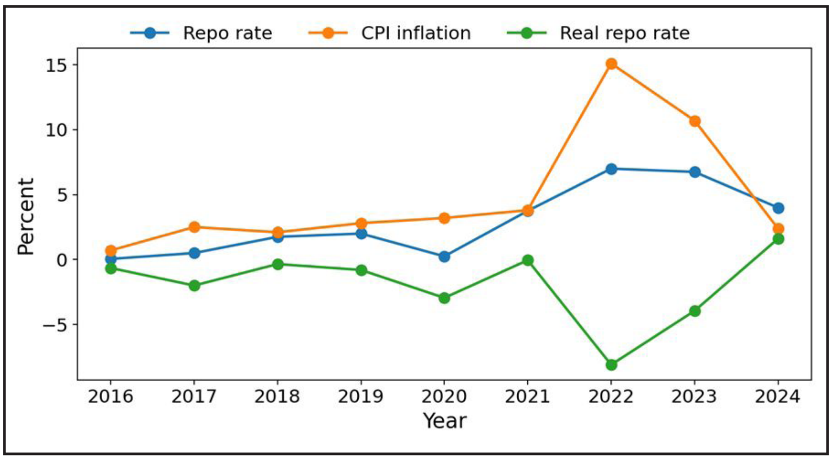
The baseline estimator is the firm fixed-effects model. This choice is motivated primarily by the research question, which focuses on within-firm associations after removing time-invariant heterogeneity in the business model, accounting practice and risk profile. Fixed and random effects were compared using Hausman tests for all nine baseline equations. The evidence is mixed: the null of no systematic FE–RE difference is rejected only in the real-rate sales-growth equation ($p = 0.016$), while the remaining equations do not reject the null. Because the FE and RE monetary coefficients are quantitatively very similar and because FE remains consistent under possible correlation between firm-specific heterogeneity and the regressors, FE is retained as the conservative baseline estimator.

Residual diagnostics were then performed for the FE equations. Wooldridge tests do not

Year	Repo rate	CPI inflation	Real repo rate	M2 growth	Business confidence	Δln NEER
2016	0.05	0.70	-0.65	6.57	103.90	0.48
2017	0.50	2.50	-2.00	8.58	105.13	6.32
2018	1.75	2.10	-0.35	5.64	106.44	-0.28
2019	2.00	2.80	-0.80	7.01	102.83	0.80
2020	0.25	3.20	-2.95	10.67	88.90	-1.13
2021	3.75	3.80	-0.05	6.99	96.53	3.03
2022	7.00	15.10	-8.10	4.96	95.99	3.99
2023	6.75	10.70	-3.95	8.58	93.21	-0.01
2024	4.00	2.40	1.60	7.73	95.75	-2.36

Source: Own processing based on CNB and CZSO indicators assigned to firm-year observations

Table 5: Annual macroeconomic context in the estimation period.



Source: Own processing based on annual CNB and CZSO data

Figure 1: Czech monetary environment in 2016–2024.

indicate first-order serial correlation in the ROE equations ($p \approx 0.40$), but they do indicate serial correlation in the sales-growth and cash-flow equations ($p < 0.001$). Modified Wald tests reject homoskedasticity in all nine equations ($p < 0.001$). Pesaran CD statistics additionally point to cross-sectional dependence in most specifications, which is unsurprising because the key macroeconomic variables are common within each year. The main tables therefore report firm-clustered robust standard errors, and the statistical significance of the main monetary coefficients is cross-checked using Driscoll–Kraay standard errors robust to heteroskedasticity, serial correlation and cross-sectional dependence. The main tables (Table 6 and Table 7) therefore report firm-clustered robust standard errors.

Results and discussion

Table 7 and Figure 2 summarize the main monetary coefficients for the three outcomes. The overall pattern is coherent across specifications: tighter monetary conditions are associated with weaker firm outcomes in section A. The clearest result is the nominal interest-rate channel. A one-percentage-point increase in the CNB repo rate is associated with a decline in ROE of about 1.69 percentage points, an approximately 4.2% decline in the level of sales and a decline in cash flow to assets of about 0.0077, which equals roughly 7.2% of the sample mean of 0.107. Relative to the descriptive means reported above, these are economically meaningful associations rather than merely statistically significant signs. Because the monetary variables vary only over time, these estimates cannot fully separate the effect of monetary conditions from other macroeconomic developments that co-moved over the period, such as inflation, energy prices and the broader business cycle; the patterns below are therefore described as associations and are revisited in the Limitations subsection.

Diagnostic and robustness checks support the substantive reading of Table 7. When inference is re-estimated with Driscoll–Kraay standard errors robust to heteroskedasticity, serial correlation and cross-sectional dependence, the repo-rate coefficients remain negative and statistically

Outcome	Specification	Hausman p	Wooldridge p	Wald p
ROE	Exchange-rate	1.000	0.399	<0.001
ROE	Repo-rate	0.911	0.406	<0.001
ROE	Real-rate	0.999	0.403	<0.001
Δln Sales	Exchange-rate	0.105	<0.001	<0.001
Δln Sales	Repo-rate	0.863	<0.001	<0.001
Δln Sales	Real-rate	0.016	<0.001	<0.001
CF/Assets	Exchange-rate	0.824	<0.001	<0.001
CF/Assets	Repo-rate	1.000	<0.001	<0.001
CF/Assets	Real-rate	0.806	<0.001	<0.001

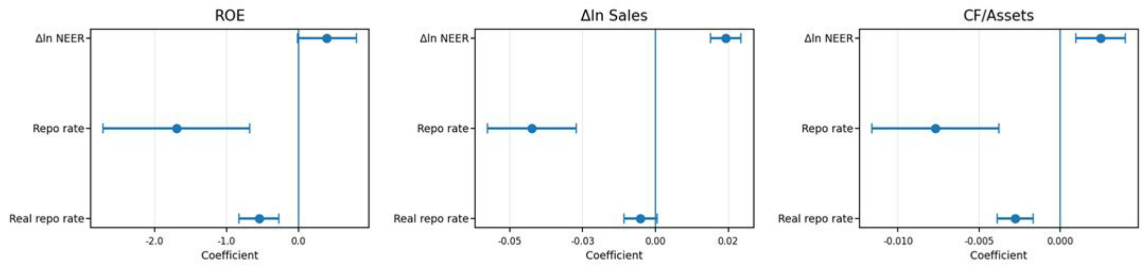
Note: Hausman compares fixed and random effects; Wooldridge tests first-order serial correlation; modified Wald tests groupwise heteroskedasticity
Source: Own processing

Table 6: Model selection and diagnostic tests.

Monetary variable	Specification	ROE	Δln Sales	CF/Assets
Δln NEER	Exchange-rate	0.3978* (0.2095) within R^2 = 0.010	0.0241*** (0.0027) within R^2 = 0.071	0.0025*** (0.0008) within R^2 = 0.025
Repo rate	Repo-rate	-1.6933*** (0.5200) within R^2 = 0.021	-0.0424*** (0.0077) within R^2 = 0.069	-0.0077*** (0.0020) within R^2 = 0.038
Real repo rate	Real-rate	-0.5465*** (0.1402) within R^2 = 0.013	-0.0051* (0.0029) within R^2 = 0.049	-0.0028*** (0.0006) within R^2 = 0.027
Observations		1503	1502	1503
Firms		167	167	167

Notes: Coefficients shown with firm-clustered robust standard errors in parentheses; *, ** and *** denote significance at the 10%, 5% and 1% levels. Within R^2, the number of observations and the number of firms are reported in the lower panel
Source: Own processing.

Table 7: Main fixed-effects estimates for monetary variables.



Source: Own processing

Figure 2: Main monetary coefficients with 95% confidence intervals.

significant for ROE, sales growth and cash flow to assets. The real-rate coefficients remain negative and significant for ROE and cash flow to assets, while the sales-growth effect becomes weaker. In the exchange-rate specification, the positive coefficients for sales growth and cash flow to assets remain significant, whereas the positive ROE coefficient becomes statistically weak. This pattern indicates that the main conclusions are not an artefact of one particular error structure.

The profitability result is economically meaningful. The sample mean of winsorised ROE is 7.84%, so the repo-rate coefficient corresponds to a sizeable fraction of average profitability. This does not imply that every firm loses profitability mechanically when the policy rate rises. Rather, it indicates that within the observed macroeconomic environment, years with tighter nominal monetary conditions were years in which the same firms tended to exhibit lower accounting profitability. For a sector that often operates with limited profitability buffers and considerable working-capital needs, such a relationship is entirely plausible.

The sales-growth equation points to a similarly clear pattern. Because the dependent variable is defined as a log-difference, the repo-rate coefficient of -0.0424 should be interpreted as a change in the level of sales rather than as a coefficient in ordinary percentage points. In this specification, a one-percentage-point increase in the repo rate is associated with about a 4.2% decline in sales using the log approximation. Relative to an average winsorised sales-growth rate of 0.073, the estimated association is not trivial. It suggests that monetary tightening matters not only through financing costs but also through the expansion channel, either because credit becomes more expensive, because customers weaken demand, or because cost pressure constrains the ability of firms to maintain volumes and pricing.

The exchange-rate specification delivers a more selective but highly informative result. A one-unit increase in the exchange-rate variable-interpretable approximately as a 1% appreciation because the variable is scaled as 100 x Δln(NEER) is associated with higher sales growth and higher cash flow to assets. Because the sales-growth outcome is a log-difference, the estimated coefficient of 0.0241 corresponds to about a 2.4% increase in sales. The cash-flow coefficient of 0.0025 represents about 2.3% of the sample mean CF/Assets ratio of 0.107. The coefficient on ROE is positive as well, but only marginally significant. Taken together, this pattern is consistent with a sector in which the cost-of-imported-inputs channel was quantitatively important during the analysed period. A standard export-competitiveness story would predict that appreciation weakens domestic producers by making their output relatively more expensive abroad. Yet many firms in this sector also depend on imported inputs, machinery, fuel, fertilisers, chemicals and feed. If imported-input costs respond more quickly or more strongly than export revenues, appreciation can improve operating conditions even when it does not uniformly improve bottom-line profitability. The present estimates are consistent with such a mechanism. They suggest that currency exposure in the agricultural sector should not be viewed only through export competitiveness, but also through the domestic-currency cost of imported production inputs.

The real-rate specification provides a separate reading of monetary tightness after inflation is netted out. A one-percentage-point increase in the real policy rate is associated with a decline in ROE of about 0.55 percentage points and a decline in cash flow to assets of about 0.0028, which represents roughly 2.6% of the sample mean CF/Assets ratio of 0.107. The sales-growth coefficient of -0.0051 corresponds to an approximately 0.5% decline in sales when converted from the log-difference specification. This pattern confirms the nominal-rate result in a more conservative form: the relationship is not only a feature of high nominal rates, but also of tighter real monetary conditions once inflation dynamics are taken into account.

Cash flow to assets deserves special attention because it is the outcome most directly linked to internal resilience. The mean of the winsorised ratio is about 0.107, so the repo-rate coefficient of -0.0077 corresponds to a weakening equal to roughly 7.2% of average internal funding capacity in the sample. The real-rate coefficient of -0.0028 points in the same direction and represents about 2.6% of the same mean. In practice, this matters because internally generated funds help finance working capital, maintenance investment, adaptation and short-term liquidity needs. In sectors exposed to weather risk, biological cycles or volatile input prices, lower internal funding can be an important transmission margin even when firms do not undertake large balance-sheet expansions.

The control variables provide additional context. In the exchange-rate specification, CPI inflation, M2 growth and business confidence are all negatively associated with sales growth, suggesting that the exchange-rate result is not simply picking up a generic macro boom. In the repo-rate specification, CPI inflation enters positively in the ROE and cash-flow equations, which is plausible in a period when nominal price increases may have temporarily supported revenues in some firms even as tighter policy worked in the opposite direction. The confidence indicator is generally weak or negative in these short-horizon regressions, which again reinforces the need for cautious interpretation when macro variables move together over a limited number of years.

A useful way to read the three specifications jointly is to think in terms of complementary rather than competing channels. The repo-rate model captures nominal financing pressure, the exchange-rate model captures external cost conditions, and the real-rate model captures monetary tightness after accounting for inflation. The fact that the signs are broadly consistent across profitability, growth and cash-flow outcomes strengthens the case that the results reflect a genuine sectoral pattern rather than a random correlation attached to one isolated dependent variable.

Reading across the three monetary variables reinforces this picture in a systematic way. For profitability, the repo-rate, real-rate and exchange-rate specifications imply, respectively, a decline of about 1.69 percentage points of ROE per one-percentage-point increase in the nominal rate, a decline of about 0.55 percentage points per one-point increase in the real rate, and a small positive but only marginally significant association with appreciation. For sales growth, the same ordering holds when coefficients are converted from log differences into approximate percentage changes in sales levels: the repo-rate coefficient (-0.0424) implies about a 4.2% decline in sales, the real-rate coefficient (-0.0051) implies about a 0.5% decline, and the appreciation coefficient (0.0241) implies about a 2.4% increase. For cash flow to assets, the repo-rate, real-rate and exchange-rate coefficients correspond, respectively, to about -7.2%, -2.6% and +2.3% of the sample mean CF/Assets ratio of 0.107. The real-rate column thus consistently confirms the nominal-rate results once inflation is netted out, while being quantitatively smaller, which is what one would expect when a single composite tightness measure replaces the separate nominal-rate and inflation terms.

Relation to previous literature

The negative repo-rate and real-rate coefficients align well with the rate and credit-channel literature. In the standard transmission view, tighter policy raises financing costs and weakens borrower balance sheets; with agency frictions, this also widens the external finance premium and amplifies the real effect of the shock (Kashyap and Stein, 2000). The present results do not identify exogenous policy shocks, but the sign pattern is consistent with this mechanism: tighter monetary conditions are associated with lower profitability and weaker internal financing capacity in this sector.

The exchange-rate result also fits the open-economy firm literature once input-cost exposure is taken seriously. A standard export story would predict that appreciation harms sales, yet incomplete pass-through and import-intensive production can reverse this effect when cheaper imported inputs and capital goods support margins and demand conditions (Campa and Goldberg, 2005; Amiti et al., 2014; Aman et al., 2022). For the agricultural sector, where production often combines domestic raw production with imported machinery, feed, fertilisers, fuel and other tradable inputs, the positive association between appreciation, sales growth and cash-flow capacity is therefore economically plausible.

Finally, the cash-flow results speak directly to the agricultural-finance literature. They resonate with work showing financing gaps in agri-food sectors, the importance of leverage and the cost of debt in agricultural firms, and the stabilising role of liquidity when financial conditions become less favourable (Pokrivčák and Tóth, 2022; Khafagy and Vigani, 2023; Toušek et al., 2025; Yeager and Barnard, 2014). In this sense, the article contributes not only to monetary-transmission research but also to the literature on farm and agri-food resilience under changing macro-financial regimes.

The appendix tables report the full regression output for transparency. They show that the main message does not depend on suppressing inconvenient control coefficients. At the same time, the supplementary tables also make clear why the paper avoids causal language. The within R^2 values are modest, the time dimension is short, and the macro variables are common within each year. These are normal features of a sector-level accounting panel, but they set clear limits on what the design can identify. The paper therefore contributes primarily by documenting a robust empirical pattern: the agricultural sector appears systematically exposed to tighter monetary conditions, and the exchange-rate channel in this sector appears to be shaped importantly by input-cost considerations.

From a practical point of view, the results have implications for both firms and policy monitoring. For firms, they underline the importance of working-capital management, maturity management and active monitoring of interest-rate and exchange-rate exposure. For policy analysis, they suggest that aggregate monetary tightening can redistribute pressure across sectors in ways that are not visible in headline macro indicators alone. Even if the central bank targets price stability at the aggregate level, the real-economy burden of tightening may be concentrated in sectors whose margins, financing structure and import dependence make them especially sensitive to changing monetary conditions.

Managerial and policy implications

A useful implication of the results is that monetary transmission into the agricultural sector should be thought of as a risk-management problem as much as a macroeconomic one. When rates rise sharply, the effect is not limited to the accounting cost of debt. Tighter policy can alter customer demand, inventory financing, maintenance planning and the timing of investment. For managers, this means that interest-rate exposure should be monitored together with working-capital discipline and liquidity buffers rather than being treated as a narrow treasury issue.

The exchange-rate results point to a similar broadening of perspective. For many firms in the agricultural sector, the currency channel is not only about export revenues but also about the domestic cost of imported inputs. This implies that exchange-rate management should be linked to procurement strategy, budgeting and margin monitoring. In years of appreciation, the gain may arrive more through cheaper inputs and improved cash generation than through visibly stronger accounting profitability. That distinction is economically important because it changes where managers should look for early warning signals.

For policy monitoring, the findings suggest that a central bank or a macroprudential authority can benefit from watching sectoral firm indicators alongside aggregate macro variables. The Czech National Bank sets policy for the economy as a whole, but the real-economy burden of tightening is unlikely to be evenly distributed. This sector may react through profitability, liquidity and internal cash generation before this becomes obvious in aggregate business statistics. Even without claiming causal identification, firm-level sector evidence can therefore serve as a useful complement to standard macro monitoring.

Limitations of the empirical design

Several features of the design limit what the estimates can identify and should be kept in mind when reading the results. First, the key explanatory variables- the repo rate, the real rate and the exchange-rate change are macroeconomic and therefore common to all firms within each year. Identification consequently rests entirely on variation over a relatively short period (2016-2024), which makes it difficult to separate the influence of monetary conditions from other macroeconomic developments that co-moved over the same window, including inflation dynamics, energy-price shocks and broader business-cycle fluctuations. Second, the policy rate is itself endogenous to macroeconomic conditions: it responds to inflation and activity, so the estimated coefficients may partly capture these broader dynamics rather than the isolated effect of monetary policy. For both reasons, the relationships are interpreted as conditional associations rather than as causal policy multipliers, and a full two-way fixed-effects baseline is infeasible because year effects would absorb the common monetary regressors in this single-section design.

Third, although the specification includes several macroeconomic controls, it remains relatively parsimonious given the complexity of the factors that shape firm performance in agriculture. Some potentially relevant time-varying factors—notably input and energy prices, weather and other sector-specific shocks—are not fully captured and may be correlated with both monetary conditions and firm outcomes. Fourth, the balanced-panel construction, while strengthening longitudinal comparability, may bias the sample toward more stable and more formalised firms and under-represent entrants and exiters, so the estimates are most representative of established firms. Finally, the outcome variables are accounting-based and therefore subject to the measurement and earnings-quality caveats discussed earlier. These limitations do not overturn the central finding: a coherent, robust association between tighter monetary conditions and weaker firm outcomes—but they delimit its interpretation and point to natural extensions, such as linking outcomes to firm-level exposure measures (leverage, debt maturity or trade intensity) that would help move from association toward identification.

Conclusion

This paper examined how monetary conditions were associated with firm performance in the Czech agricultural sector, that is, agriculture, forestry and fishing, during 2016–2024. Using a balanced firm-level panel and static fixed-effects models, it showed a consistent pattern: tighter monetary conditions were associated with lower profitability, slower sales growth and weaker internal financing capacity. The nominal repo rate produced the clearest and most uniform negative pattern across the three dependent variables. The real-rate specification reinforced the interpretation that tighter real monetary conditions constrained profitability and cash generation. Exchange-rate appreciation, by contrast, was positively associated with sales growth and cash flow to assets.

The findings suggest that the broad agricultural economy should not be viewed as insulated from monetary conditions. On the contrary, the sector appears materially exposed to both financing costs and exchange-rate-induced changes in input prices. This matters for managers because internal liquidity, refinancing discipline and currency-aware cost planning become more important during tightening episodes. It also matters for policy discussion because aggregate monetary indicators may hide a non-trivial redistribution of financial stress across sectors.

The paper remains cautious about interpretation. The macroeconomic variables are common across firms within each year and the time dimension is short, so the coefficients should be read as conditional associations rather than as causal policy multipliers. The balanced-panel design may also bias the sample toward more stable firms. Even with these limitations, however, the evidence is informative. It indicates that this sector was among the parts of the Czech economy in which monetary tightening was visible at the level of firm accounting outcomes. That is already a useful result for agricultural economics, for corporate risk management, and for future research that aims to connect monetary transmission more directly to firm-level exposure measures such as leverage, maturity structure or trade intensity. Because the key monetary regressors are common within year, a full two-way fixed-effects baseline would absorb the monetary variables themselves in this single-section design; robustness is therefore based on model diagnostics and alternative inference rather than on a year-fixed-effects baseline.

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Appendix: Supplementary regression output

The following Tables A1 - A4 report the full coefficients for the three baseline specifications. They are included for transparency and to show how the main monetary coefficients sit within the broader set of controls.

Variable	ROE	Δln Sales	CF/Assets
Δln NEER	0.3978* (0.2095)	0.0241*** (0.0027)	0.0025*** (0.0008)
CPI inflation	-0.0259 (0.1696)	-0.0147*** (0.0028)	-0.0002 (0.0006)
M2 growth	-0.7275* (0.4228)	-0.0579*** (0.0073)	-0.0036** (0.0017)
Business confidence	-0.0567 (0.1634)	-0.0114*** (0.0024)	-0.0007 (0.0006)
ln(Assets)	-1.8920 (3.3187)	-0.1333** (0.0675)	-0.0218 (0.0167)
Observations	1503	1502	1503
Firms	167	167	167
Within R^2	0.010	0.071	0.025

Note: Coefficients shown with firm-clustered robust standard errors in parentheses
Source: Own processing

Table A1: Exchange-rate specification – full coefficients.

Variable	ROE	Δln Sales	CF/Assets
Repo rate	-1.6933*** (0.5200)	-0.0424*** (0.0077)	-0.0077*** (0.0020)
CPI inflation	0.7163*** (0.1621)	0.0106*** (0.0030)	0.0035*** (0.0007)
M2 growth	-1.2114*** (0.4444)	-0.0591*** (0.0085)	-0.0053*** (0.0016)
Business confidence	-0.0711 (0.1124)	-0.0059*** (0.0021)	-0.0005 (0.0004)
ln(Assets)	1.1747 (3.9485)	-0.0656 (0.0719)	-0.0083 (0.0194)
Observations	1503	1502	1503
Firms	167	167	167
Within R^2	0.021	0.069	0.038

Note: Coefficients shown with firm-clustered robust standard errors in parentheses
Source: Own processing

Table A2: Repo-rate specification – full coefficients.

Variable	ROE	Δln Sales	CF/Assets
Real repo rate	-0.5465*** (0.1402)	-0.0051* (0.0029)	-0.0028*** (0.0006)
M2 growth	-0.3020 (0.2949)	-0.0295*** (0.0058)	-0.0014 (0.0014)
Business confidence	0.1704 (0.1257)	0.0020 (0.0021)	0.0006 (0.0006)
ln(Assets)	-1.5234 (3.2701)	-0.1532** (0.0669)	-0.0198 (0.0164)
Observations	1503	1502	1503
Firms	167	167	167
Within R^2	0.013	0.049	0.027

Note: Coefficients shown with firm-clustered robust standard errors in parentheses
Source: Own processing

Table A3: Real-rate specification – full coefficients.

Year	Mean ROE	Mean Δln Sales	Mean CF/Assets	Repo rate	Real repo rate	Δln NEER
2016	9.059	0.301	0.116	0.050	-0.650	0.482
2017	8.690	0.096	0.112	0.500	-2.000	6.322
2018	9.728	0.052	0.111	1.750	-0.350	-0.275
2019	7.785	0.021	0.106	2.000	-0.800	0.804
2020	8.032	-0.013	0.108	0.250	-2.950	-1.129
2021	7.200	0.137	0.107	3.750	-0.050	3.035
2022	11.763	0.155	0.124	7.000	-8.100	3.991
2023	4.228	-0.059	0.091	6.750	-3.950	-0.009
2024	4.108	-0.030	0.085	4.000	1.600	-2.357

Source: Own processing

Table A4: Annual sample means of firm outcomes and monetary variables.

The annual means in Table A4 are not used for identification, but they provide an intuitive bridge between the macroeconomic chronology and the firm-level outcomes. They show, for example, that profitability and internal cash-flow capacity were visibly weaker at the end of the sample than in the earlier low-rate years, while sales growth also turned negative in 2023–2024.

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The Role of ICT in Advancing Farmer Welfare: A Systematic Literature Review of Multidimensional Outcomes

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Abstract

Existing studies on the role of Information and Communication Technology (ICT) in agriculture often reduce farmer welfare to economic outcomes, overlooking its social, psychological, and environmental dimensions. This narrow perspective limits a comprehensive understanding of how ICT contributes to rural development. To address this gap, this study systematically reviews peer-reviewed articles published between 2014 and 2024 using the PRISMA protocol. The results map the types of ICT interventions, welfare indicators, and pathways through which ICT influences farmer welfare. The findings show that ICT adoption through mobile communication, digital platforms, and internet-based services enhances not only income and productivity but also social capital, livelihood assets, and subjective well-being. These positive outcomes are more pronounced when ICT adoption is accompanied by extension services, credit access, and capacity-building programs. However, the analysis reveals that infrastructural limitations, digital illiteracy, and financial barriers hinder ICT's full potential, especially among marginalized farmers. The evidence also shows regional imbalances, with research concentrated in a few countries, limiting generalization. By developing a conceptual framework, this review advances a multidimensional understanding of ICT's role in improving farmer welfare. The results provide actionable insights for policymakers and development practitioners to design inclusive and context-sensitive ICT interventions for sustainable rural transformation.

Keywords

Information and communication technology, ICT, farmer welfare, rural development, systematic literature review, digital agriculture, livelihood resilience.

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Introduction

In the paradox of the 21st century, despite humanity's unparalleled agricultural productivity, millions of rural farmers, the essential stewards of global food systems, remain ensnared in cycles of poverty, food insecurity, and social vulnerability. This contradiction represents not just an economic challenge but also a humanitarian disaster that jeopardises the stability of rural communities, the resilience of food systems, and the achievement of global development objectives (Peng et al., 2023; Thanh and Ancev, 2021). The evidence consistently indicates that farmer welfare is not merely an ancillary issue, but rather a fundamental determinant of food security, rural development, and poverty alleviation (Hossain et al., 2024). Alarmingly, smallholder farmers, despite contributing significantly to food production in developing regions, often face fragile livelihoods, inadequate access to markets, and limited policy support, which perpetuate multidimensional poverty and undermine sustainable development (Lopez-Ridaura et al., 2018; Nehring et al., 2017). In the absence of intentional and efficient actions, the global objective of achieving food security and alleviating rural poverty would remain an elusive goal.

Amidst the enduring rural poverty and food insecurity, the swift and revolutionary incorporation of Information and Communication Technology (ICT) into agriculture presents a positive change with extensive consequences. Farmers are increasingly employing various ICT tools, such as mobile applications, remote sensing, geographic information systems (GIS), big data analytics, and artificial intelligence, to enhance production, lower input costs, and facilitate informed decision-making (El Bilali and Allahyari, 2018). These technologies have transformed conventional farming methods by enabling precision agriculture, facilitating real-time weather forecasts, monitoring soil and crop conditions, and delivering timely market information (Serbulova et al., 2019; Sørensen et al., 2019). Additionally, ICT is crucial to strengthening the connections between farmers, extension services, and research entities, guaranteeing that even the most marginalised farming communities acquire valuable innovations and knowledge (Campo et al., 2017). Furthermore, ICT-enabled value chains enhance input procurement, production efficiency, food traceability, and market access, thereby contributing directly to food security and supply chain resilience (Anam et al., 2025; Wasihun and Maumbe, 2012). In areas constrained by resources and infrastructure, such as Sub-Saharan Africa and certain parts of Asia, the adoption of ICT has shown considerable potential to enhance farmer welfare and foster sustainable development (Maumbe, 2012; Sharma and Bhambri, 2024).

The increasing influence of ICT in transforming agriculture has been significantly propelled by the strategic actions of international organisations, particularly the Food and Agriculture Organisation (FAO) and the World Bank, in the global shift towards digitalisation. These institutions have established digital agriculture, encompassing smart farming, digital extension, and e-agriculture, as a fundamental element of modern rural development strategies (El Bilali et al., 2020; Maumbe, 2012). They have encouraged precision agriculture, remote sensing, big data analytics, and smart greenhouse systems to boost agricultural output and sustainability through comprehensive initiatives and funding (Birner et al., 2021). These programs have expanded market access, reduced intermediary dependency, and strengthened research-extension-farmer links to empower farmers and enhance efficiency. Particularly in developing regions, international agencies have facilitated knowledge transmission and capacity building by collaborating with private sector innovators and local stakeholders to bridge the technological divide. The global attempt to digitally transform agriculture is nevertheless hindered by systemic constraints such as low digital literacy, infrastructure gaps, and expensive technology adoption costs (Finger, 2023).

Although technological advancement presents a great opportunity for enhancing agricultural output, its effectiveness is closely linked to the overarching notion of rural wellbeing, which encompasses more than income generation. Farmers not only react to market incentives but also consistently adjust to social and ecological challenges through diverse livelihood choices, balancing on-farm and off-farm activities based on access to land, education, financial resources, and local opportunities (Caulfield et al., 2021). In several contexts, especially within resource-dependent rural areas, natural resource extraction serves as both a coping mechanism and a livelihood enhancer, mitigating income inequality and contributing to poverty reduction, despite concerns over long-term environmental sustainability (Lopez-Ridaura et al., 2018). In addition to household-level modifications, organised initiatives like social security programs and livelihood diversification have demonstrated the capacity to enhance rural wellbeing comprehensively. Initiatives that facilitate non-agricultural income production have continuously shown substantial effects on poverty reduction and livelihood sustainability, both by increasing incomes and by diminishing households' vulnerability to agricultural disruptions while enhancing food security (Rahut et al., 2018). However, scholars have noted the transient nature of rural livelihoods, where the diversity of income sources fluctuates over time, leading to welfare volatility despite diversification (Dzanku, 2015). The integration of off-farm income into household strategies reshapes farm management practices and livelihood trajectories, further complicating the assessment of welfare beyond income alone (Caulfield et al., 2021). The Sustainable Livelihoods Approach (SLA) offers a pertinent framework, acknowledging welfare as a result of intricate interactions between asset endowments, institutional arrangements, and individual capabilities. It underscores the necessity of tackling vulnerability, resilience, and social equity in rural development (Möllers and Buchenrieder, 2005).

Studies indicate that ICT facilitates farmers' access to timely and pertinent information regarding markets, weather, pest outbreaks, and agronomic practices, thereby enhancing their decision-making and resource management skills (Aldosari et al., 2019; Anand et al., 2022). Rural women and youth, who frequently cannot access traditional extension programs, benefit greatly from mobile-based advisory services and digital platforms (Jennifer and Enwelu, 2023; Rathnachandra and Malkanthi, 2022). The capacity of ICT to enhance information dissemination and technical support via improved extension systems has been shown to promote the adoption of innovative and climate-smart agricultural practices, essential for managing climate variability and market uncertainties (Gangopadhyay et al., 2019; Ma et al., 2020). Furthermore, empirical studies demonstrate that farmers who actively participate in ICT platforms report enhanced adaptive capacity and livelihood resilience, in addition to increased income (Oyelami et al., 2022; Setu et al., 2022), reinforcing the importance of embedding ICT-driven interventions within rural development and welfare programs.

Despite the promising evidence on ICT's contribution to agricultural productivity and income generation, critical evaluations of existing literature reveal that many studies adopt a fragmented approach, often reducing farmer welfare to economic outputs alone. While several works successfully demonstrate the positive correlation between ICT adoption and increased productivity or income (Oyelami et al., 2022), they frequently neglect the broader welfare dimensions such as social inclusion, psychological well-being, and farmers' perceived quality of life. For instance, Wossen et al. (2017) focus on how access to extension services and cooperative membership enhances household welfare primarily through income effects, yet fall short of analyzing how ICT influences social capital, community engagement, or collective empowerment. Similarly, Zulu et al. (2024) emphasize the economic advantages of credit accessibility and ICT adoption without addressing essential welfare components such as education, healthcare access, or gender equity. Moreover, Kalita and Deka (2024) expose persistent gaps in farmers' knowledge and utilization of ICT, suggesting that limited digital literacy may further constrain the potential of ICT to holistically improve rural welfare. This gap is further highlighted by Chen et al. (2023), who argue that farmers' well-being is also shaped by their environmental quality perceptions and participation in sustainable practices, areas that remain underexplored in the majority of ICT-agriculture studies. Collectively, these critiques underscore the necessity of advancing a more comprehensive framework to assess ICT's influence on rural welfare, incorporating economic, social, and psychological dimensions beyond productivity alone.

While numerous studies have documented the positive influence of ICT on agricultural productivity and income (Aker and Ksoll, 2016; Ma et al., 2020; Oyelami et al., 2022), they frequently neglect critical welfare dimensions such as social inclusion, environmental awareness, psychological well-being, and overall life satisfaction. For example, although Rahman and Huq (2023) illustrate how ICT benefits women's livelihoods, they do not sufficiently capture how these benefits integrate into broader welfare improvements such as empowerment, education, or household resilience. Similarly, variations in regional outcomes, as reflected in Van Campenhout et al. (2020) in Uganda versus Oyelami et al. (2022) in sub-Saharan Africa, highlight inconsistencies in methodological approaches, measurement frameworks, and targeted welfare outcomes. This inconsistency limits the formulation of universally applicable policy recommendations. Furthermore, studies by Kalita and Deka (2024) reveal that even where ICT adoption occurs, its influence on environmental quality perceptions, social cohesion, and quality of life remains underexplored. The scattered nature of these findings calls for a systematic review that not only aggregates existing evidence but also critically evaluates how ICT shapes farmer welfare beyond economic returns.

Against this backdrop, this study aims to systematically consolidate and critically analyze the existing body of literature by addressing three core research questions. First, what indicators of farmer welfare have been employed in ICT-related research? Second, what types of ICT interventions have been documented across the existing studies? Third, how does ICT influence farmers' welfare in its multiple dimensions? To answer these questions, this review is designed with five specific objectives. First, it seeks to assess the extent to which the application of ICTs affects farmers' welfare across different contexts. Second, the study aims to identify the most widely adopted welfare indicators used to measure farmer welfare within ICT-related studies. Third, it will explore which dimensions of farmer welfare, economic, social, psychological, and environmental, are most influenced by ICT interventions. Fourth, this review intends to map the various pathways through which ICT adoption contributes to improving farmer welfare, identifying both direct and indirect mechanisms. Lastly, the study aims to uncover the driving and inhibiting factors that shape the adoption and effectiveness of ICTs in enhancing farmer welfare, thus offering valuable insights for policy-makers, development agencies, and future research. This systematic review offers several important contributions to the existing body of knowledge on ICT and farmer welfare. First, it provides a comprehensive synthesis of fragmented and often isolated studies by systematically mapping the diverse indicators, interventions, and pathways through which ICT influences farmer welfare. While prior research has largely focused on productivity and income effects, this review broadens the lens by incorporating a multidimensional welfare perspective, encompassing social, psychological, and environmental aspects that have often been overlooked. Second, by identifying the most frequently used welfare indicators and categorizing ICT interventions documented in the literature, this study establishes a structured foundation for future empirical research and policy development. Third, this review contributes by uncovering the enabling and constraining factors that shape the success or failure of ICT interventions in enhancing farmer welfare, offering insights into the mechanisms that either amplify or limit ICT's potential. Finally, the review generates a conceptual framework that links ICT adoption pathways with farmer welfare outcomes, bridging theoretical gaps and providing actionable insights for development practitioners, policymakers, and scholars aiming to design more effective ICT-based interventions for rural development.

The remainder of this article is organized as follows. The next section presents the methodology employed to conduct the systematic literature review, including the review protocol, search strategy, selection criteria, and analytical approach. This is followed by the results section, which systematically reports the findings related to the types of ICT interventions identified, the various farmer welfare indicators used, and the pathways through which ICT influences welfare outcomes. Subsequently, the discussion section interprets the findings by linking them to existing theories and empirical evidence, highlighting implications for policy, practice, and future research. The article concludes by summarizing the key insights, addressing limitations, and proposing directions for advancing research on the relationship between ICT and farmer welfare.

Materials and methods

This study systematically followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 protocol to ensure transparency, comprehensiveness, and methodological rigor (Page et al., 2021). The protocol provided a structured framework for identifying, screening, and selecting relevant studies while minimizing potential biases throughout the review process. By adhering to the updated guidelines, this study ensured the credibility and replicability of the systematic review, facilitating a robust synthesis of existing evidence on the relationship between ICT adoption and farmer welfare.

Eligibility criteria

In conducting this review, explicit inclusion and exclusion criteria (Table 1) were rigorously established to ensure methodological precision and scholarly relevance. Literature published within the period from 2014 to 2024 was included to maintain contemporary relevance and capture recent advancements in the field. Articles published outside this timeframe were systematically excluded

Inclusion	Exclusion
Published in 2014 to 2024 Written in English Research article The topic is the effect of ICT on farmer welfare Peer-reviewed article Studies in agriculture The samples are farmers	Out of 2014 to 2024 Non-English Book chapter, review article, short communication, proceeding, dissertation or thesis Methodological comparison Topics outside agriculture No ICT intervention or welfare indicator Only discuss the technical aspects of ICT Only use one variable of ICT or farmer welfare The samples are not farmers or farming households

Source: Authors' own elaboration based on the eligibility criteria of this systematic literature review.

Table 1: The inclusion and exclusion criteria.

to limit potential historical bias and outdated information. English was selected as the exclusive language for included articles to facilitate clear analysis and international scholarly communication. Consequently, non-English language publications were excluded from consideration. The review was limited strictly to peer-reviewed research articles to guarantee methodological robustness and credibility, while publications such as book chapters, review articles, short communications, conference proceedings, dissertations, and theses were systematically excluded to maintain scientific rigour. The central thematic criterion for inclusion was the explicit investigation into the effect of ICT on farmer welfare. Therefore, studies outside the agricultural sector or those that solely discussed technical aspects of ICT without linking to farmer welfare were excluded. Additionally, articles that did not explicitly address ICT interventions or failed to provide measurable welfare indicators were excluded to ensure the review's focus remained precise and analytically useful. Included studies were required to have clearly defined samples consisting specifically of farmers or farming households. Articles with samples outside of this demographic were excluded to maintain homogeneity and relevance to the research objectives. Furthermore, studies employing only a single variable related to either ICT or farmer welfare, as well as methodological comparison studies without direct relevance to welfare outcomes, were excluded to ensure a comprehensive analysis of the interrelationship between ICT interventions and farmer welfare.

Source and search strategy

This review utilised a structured search methodology to identify relevant scholarly articles indexed in Scopus and Web of Science (WoS). Those databases were chosen for their extensive inclusion of peer-reviewed academic journals spanning multiple disciplines, ensuring rigorous and high-quality source material. The search strategy incorporated a carefully constructed combination of keywords specifically aimed at encapsulating the central research theme, namely the interplay between ICT and farmer welfare. The primary search string employed was as follows:

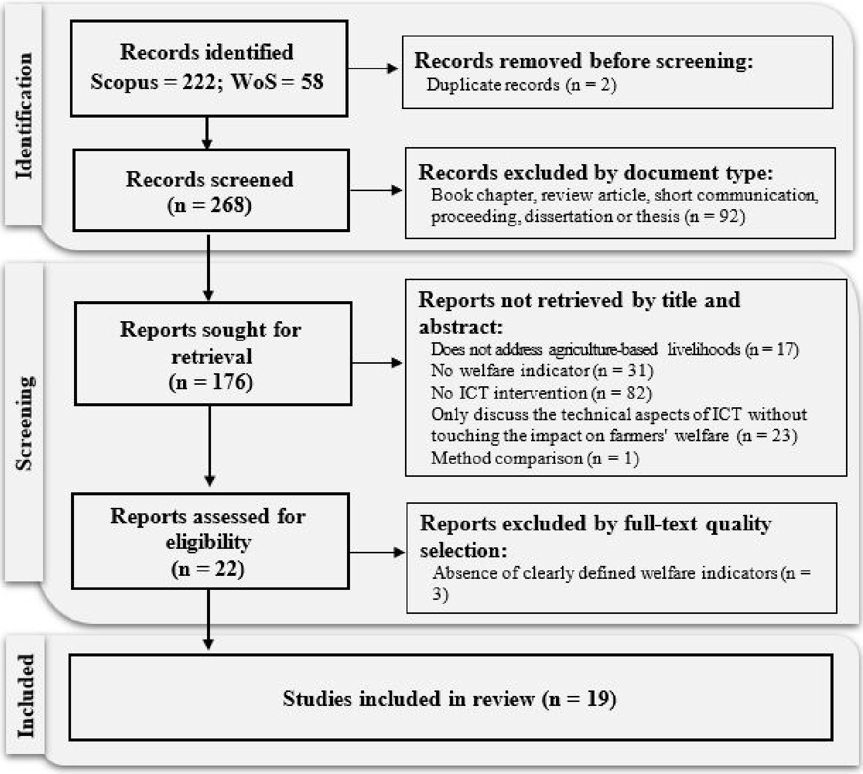
TITLE-ABS-KEY (("ICT" OR "information and communication technology") AND ("farmer" OR "smallholder") AND ("welfare" OR "well-being" OR "livelihood" OR "income" OR "prosperity"))

The abbreviation "ICT" was complemented by its expanded form, "information and communication technology," to ensure comprehensive coverage of the existing literature. Similarly, the keyword "farmer" was augmented with "smallholder" to include literature relevant to small-scale agricultural contexts. Additionally, the concept of welfare was broadly represented through multiple synonymous terms: "welfare," "well-being," "livelihood," "income," and "prosperity," thus capturing diverse terminological variations employed within agricultural economics, rural development, and socioeconomic research.

Selection process

The selection process for identifying eligible studies was conducted systematically and rigorously. Initially, all identified records from the database were imported into bibliographic management software to eliminate duplicate records. Subsequently, the remaining records underwent a two-stage screening process. In the first stage, titles and abstracts were independently screened against the pre-defined inclusion and exclusion criteria. Discrepancies in screening outcomes were resolved through consensus-based discussions, with unresolved cases adjudicated by an additional evaluation. In the second stage, full texts of potentially eligible articles were retrieved for detailed assessment, again employing the established inclusion and exclusion criteria. Each full-text article was independently evaluated to confirm eligibility. Any disagreements were resolved through further discussions to reach consensus or, if necessary, by consulting an additional evaluator. Throughout this systematic selection process, automation tools were not utilized; all screenings were manually performed to ensure methodological precision and consistency in decision-making. Figure 1 illustrates the detailed article selection flow used to finalize studies included in this systematic literature review.

The article selection process commenced with an initial identification of 270 records from the database. Duplicate records (n = 2) were subsequently eliminated, resulting in 268 unique records eligible for screening. During the initial screening phase, records were assessed based on document type. A total of 92 records were excluded as they comprised book chapters, review articles, short communications, conference proceedings, dissertations, or theses, leaving 176 records for further review. In the subsequent retrieval stage, the titles and abstracts of these 176 records were evaluated in detail against specific thematic and methodological criteria. As a result, 17 records were excluded for addressing



Source: Authors' own elaboration based on the PRISMA 2020 protocol and the study selection process.

Figure 1: Article eligibility screening flow diagram (PRISMA protocol).

non-agricultural sectors, 31 lacked explicit welfare indicators, 82 did not include ICT interventions, 23 discussed only technical aspects of ICT without analyzing impacts on farmers' welfare, and one study was excluded for methodological comparison without direct relevance to welfare outcomes. Thus, 22 articles proceeded to full-text evaluation. During the final full-text evaluation, three additional articles were excluded due to the absence of clear welfare indicators. Ultimately, 19 studies met all inclusion criteria and were included in this review.

Data collection process

Data from the included reports were systematically extracted using an artificial intelligence-based tool (GPT-4o). This extraction process leveraged advanced Natural Language Processing (NLP) capabilities, enabling efficient identification and synthesis of relevant information. The tool was prompted to accurately extract specific data points, including year of publication, article title, keywords, country of study, journal name, sample size, respondent type, data type, data source, data analysis technique, welfare indicators, types of ICT interventions, and the reported effects of ICT interventions on farmer welfare. Following the automated extraction, all synthesized data were independently reviewed to ensure accuracy, completeness, and consistency. Any discrepancies or uncertainties identified during the review were carefully re-examined and clarified, thereby reinforcing the reliability and validity of the extracted information.

Data items

Outcomes sought for data extraction included clearly defined welfare indicators (such as income, food security, social capital, livelihood assets, subjective well-being, and bargaining power), with explicit effects of ICT interventions. All compatible results related to these outcomes, including various measures, time points, and analytical methods, were systematically collected to ensure a comprehensive assessment of the impact of ICT on farmer welfare. Moreover, other variables systematically collected included the year of publication, title, keywords, country of study, journal, sample size, respondent characteristics, type of data (primary or secondary), data source (e.g., surveys, randomized controlled trials, panel data), analytical techniques (e.g., econometric analysis, qualitative analysis), and types of ICT interventions used. Assumptions regarding missing or unclear information were minimized through careful re-examination of each included report. When certain information remained unclear or incomplete, assumptions were explicitly documented based on contextual details provided in the studies.

Study risk of bias assessment

Risk of bias assessment for each included study was systematically conducted using a customized quality assessment checklist specifically designed for this systematic literature review. The checklist comprised three criteria: clarity of objectives and research questions, relevance and appropriateness of research methodology, and clarity of data related to the measurement of farmers' welfare. The researcher independently evaluated each study according to these criteria. Areas where information was unclear or incomplete were explicitly documented to transparently communicate potential biases and limitations within the included studies.

Effect measures

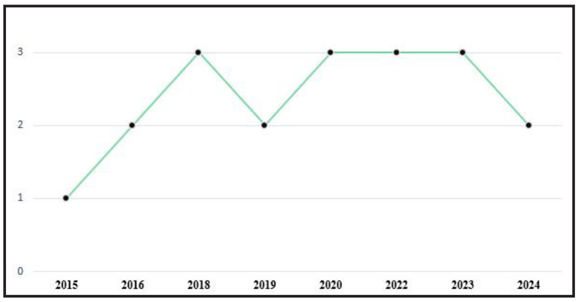
For each welfare outcome, specific effect measures were employed to synthesize and present results. Income-related outcomes used percentage increases, mean differences, and absolute income gains. Food security measures included changes in food availability, dietary diversity scores, and reductions in food insecurity rates. Social capital outcomes involved assessments of changes in network size and qualitative evaluations of community engagement. Livelihood assets outcomes measured both quantitative and qualitative changes in resources such as land, livestock, and savings. Subjective well-being and bargaining power outcomes were primarily assessed through qualitative evaluations or ordinal scales indicating improvement levels.

Synthesis methods

Studies were included in the synthesis based on explicit alignment with the predefined inclusion criteria, particularly relevance to ICT interventions and measurable farmer welfare outcomes. Intervention characteristics were tabulated and systematically compared to ensure accurate grouping and synthesis of results. Data preparation involved converting and harmonizing diverse measurement units through careful estimation when data were unavailable. Results were systematically tabulated to facilitate clear visual presentation through tables, a Sankey diagram, a Venn diagram, a word cloud, and descriptive summaries. A narrative synthesis approach was employed due to methodological diversity and heterogeneity of outcomes among the included studies. This method allowed for comprehensive integration and detailed explanation of findings. Possible causes of heterogeneity among study results were explored through comparative analysis of factors such as regional differences, variations in ICT types, and methodological approaches.

Results and discussion

Following the PRISMA 2020 protocol, this review synthesises 19 carefully selected studies to show how ICT adoption affects farmer welfare. The findings demonstrate both the diversity of ICT interventions employed in various agricultural settings and the numerous ways these technologies influence farmers' welfare. This section systematically reports studies by geography, intervention type, welfare indicators, and analytical methods to provide an integrated understanding of both direct and indirect pathways linking ICT adoption to farmer welfare improvements in economic, social, and psychological areas.

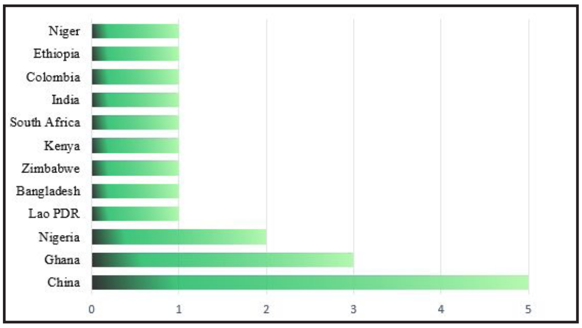


Source: Authors' own elaboration based on the systematic literature review results.

Figure 2: Number of articles evaluating the impact of ICT on farmer welfare by year for 2015 to 2024.

Figure 2 presents the trend in the number of publications discussing the effect of ICT on farmer welfare. Over the ten-year period from 2015 through 2024, the annual number of research article publications exhibited a modest but discernible upward trajectory punctuated by minor fluctuations. Beginning with a single article in 2015, output doubled to two in 2016 and reached a peak of three publications in 2018. A slight dip occurred in 2019 before rebounding to three articles in 2020. Although data for 2017 and 2021 are absent, potentially reflecting gaps in data collection rather than zero output during the period, the number of publications from 2022 to 2023 remained steady at three articles per year. In 2024, there was a marginal decline to two articles, suggesting a possible transient ebb in productivity rather than a definitive downturn.

The distribution of research articles by country reveals a pronounced concentration of scholarly output within a small subset of nations (Figure 3).

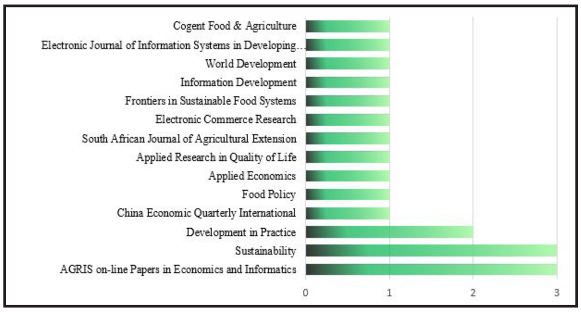


Source: Authors' own elaboration based on the systematic literature review results.

Figure 3: Number of articles evaluating the impact of ICT on farmer welfare by countries for 2015 to 2024.

China emerges as the predominant contributor, accounting for five publications, surpassing Ghana's three articles by 67% and doubling Nigeria's output. In contrast, nine countries (Lao PDR, Bangladesh, Zimbabwe, Kenya, South Africa, India, Colombia, Ethiopia, and Niger) each contributed a single article, collectively representing only 30% of the total corpus. This marked asymmetry indicates a skewed geographic distribution of research activity, suggestive of disparities in research infrastructure, funding allocation, and institutional capacity. Scientifically, such heterogeneity may introduce bias in the global evidence base, potentially limiting the generalizability of findings and underscoring the need for targeted capacity building initiatives in underrepresented regions.

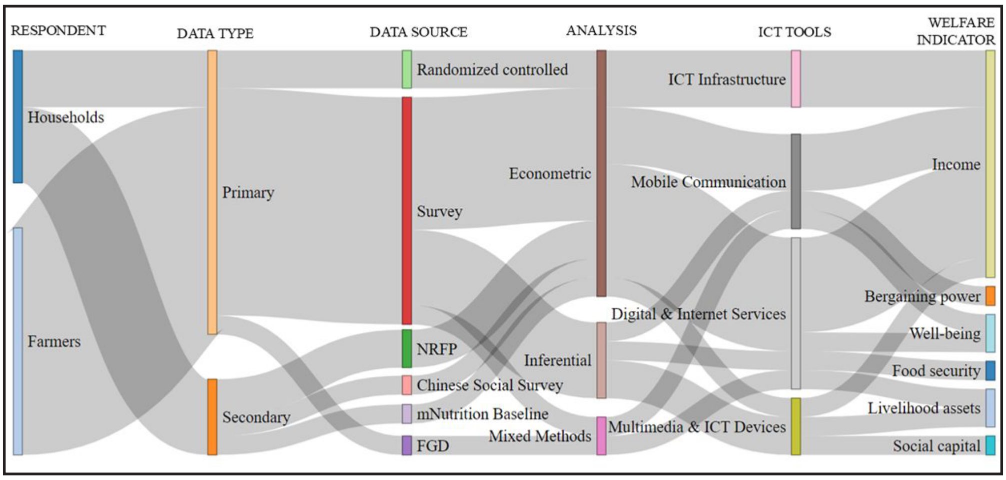
Figure 4 shows the distribution of articles across academic journals. The observed concentration of publications within AGRIS on-line Papers in Economics and Informatics and Sustainability suggests these outlets occupy central roles in disseminating research on the topic, potentially reflecting their editorial focus and perceived relevance to the field. The presence of Development in Practice as a secondary contributor indicates a modest breadth of engagement beyond the primary journals. Meanwhile, the dispersion of single articles across fourteen diverse journals signals an interdisciplinary research landscape, wherein scholarship intersects with domains ranging from agricultural economics and food policy to information systems and sustainable development. Collectively, these patterns indicate both a core set of journals that serve as focal dissemination channels and a wider periphery that accommodates specialized or cross-disciplinary contributions.



Source: Authors' own elaboration based on the systematic literature review results.

Figure 4: Number of articles evaluating the impact of ICT on farmer welfare by journal for 2015 to 2024.

The Sankey diagram and accompanying tabular data together illustrate the pathways through which distinct respondent groups, data types, sources, analytical methods, ICT modalities, and welfare indicators interrelate in the assembled body of research (Figure 5). Specifically, households and

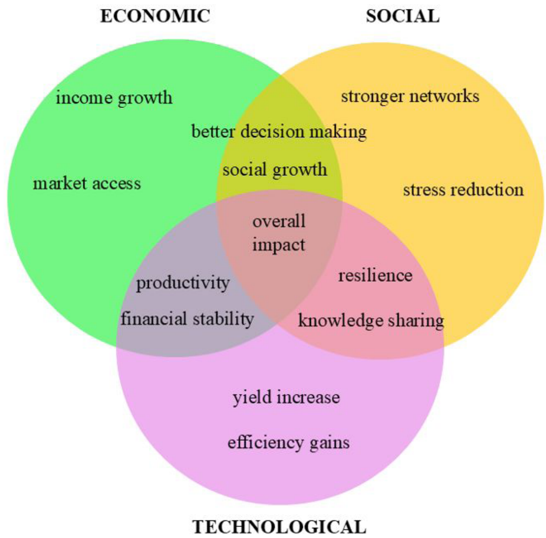


Source: Authors' own elaboration based on the systematic literature review results.

Figure 5: Sankey diagram flow of the sample, data type, data source, and welfare indicators connections.

farmers constitute the two principal respondent cohorts. Moreover, primary data predominate whereas secondary data are drawn from established panel instruments (National Rural Fixed-Point Survey, Chinese Social Survey, and mNutrition baseline), with randomized controlled trial datasets featuring in two instances. Methodologically, causal econometric analysis emerges as the dominant analytic framework, followed by descriptive-inferential procedures and, to a lesser extent, qualitative mixed-methods inquiry. In terms of ICT modalities, digital and Internet services represent the most extensively investigated intervention, channelled from both primary surveys and secondary sources into predominantly econometric analyses that principally quantify effects on household income. Mobile communication constitutes the second most frequently studied technology; causal econometric designs based on randomized trials and survey data link this modality primarily to income enhancement, with secondary associations to subjective well-being and bargaining power. Multimedia and ICT devices are examined exclusively through primary survey and mixed-methods approaches, yielding empirical linkages to social capital accumulation and the augmentation of livelihood assets. ICT infrastructure appears in two secondary-data econometric studies, both of which focus on its impact on income. Collectively, the flows depicted in the diagram underscore the predominance of causal econometric evidence for digital and mobile technologies vis-à-vis income outcomes, whereas non-income welfare dimensions are explored chiefly through descriptive and qualitative methodologies. Furthermore, it is highlighted that the strongest empirical evidence base resides in causal econometric studies of digital/internet services and mobile communication on income outcomes, whereas qualitative and descriptive work informs non-income indicators (social capital, food security, livelihood assets). The diversity of data sources and analytic approaches underscores the multidisciplinary nature of ICT-welfare research and the varying degrees of methodological rigor applied across different ICT modalities and welfare dimensions.

Figure 6 depicts a framework that traces the effects of ICT adoption on various dimensions of farmer welfare. Adopting information and communication technologies generates a cascade of positive effects on farmer welfare by directly enhancing access to critical resources and market opportunities. When farmers invest in ICT infrastructure, they obtain timely access to market information and agronomic knowledge, which boosts productivity and increases income. Furthermore, leveraging digital and internet services enables farmers to exchange data in real time, participate in online markets, and make evidence-based decisions.



Source: Authors' own elaboration based on the systematic literature review results.

Figure 6: The dimension of the effect of ICT adoption on farmers' welfare.

These capabilities not only elevate household income but also improve food security, foster the accumulation of livelihood assets, and strengthen social capital through enhanced information sharing and collaboration. Moreover, mobile communication significantly enhances connectivity among farmers, buyers, and extension agents, thereby improving transaction efficiency and elevating farmers' bargaining power in local and regional markets. In addition, the use of multimedia and ICT devices facilitates skills acquisition and peer-to-peer knowledge transfer, which expands social networks, augments livelihood asset portfolios, and raises subjective well-being. Across all ICT modalities, income enhancement emerges as the most immediate and measurable outcome, while broader non-monetary benefits, such as improved food security, greater social capital, and enhanced livelihood resilience, arise primarily from digital services and multimedia applications.

The reviewed studies demonstrate a consistent positive association between various ICT interventions and improvements in farmer welfare across diverse geographic contexts (Table 2). In China, multiple studies highlight

Author(s)	Country	ICT Intervention	How ICT Affects Farmer Welfare
Zhu et al. (2022)	China	Village-level coverage (2G/3G, internet)	Promotes income growth; initial inequality, reduces disparity long-term.
Aker and Ksoll (2016)	Nigeria	Basic mobile usage	Diversification to cash crops; long-term resilience benefits.
Bounkham et al. (2022)	Laos	Smartphone apps	Higher yield, profit via real-time info and extension services.
Shaibu et al. (2018)	Ghana	Mobile phone, digital TV, PC	Better social ties, efficiency, income via fast communication.
Zhu et al. (2024)	China	Village-level internet, 3G	Raises labor productivity, income; shifts labor off farm.
Zhu et al. (2020)	China	Smartphones, computers, basic internet	Higher income, improved mental well-being.
Oparinde (2023)	Nigeria	Mobile and internet (price/info access)	Increased agroforestry adoption, income, and food security.
Guo et al. (2018)	China	Distance e-learning (web-based)	Raises productivity, input use intensity, income in intensive-use areas.
Rahman and Huq (2023)	Bangladesh	Smartphones, apps, call centers, SMS alerts	Boosts knowledge, resilience; empowers women; reduces crop losses.
Masuka et al. (2016)	Zimbabwe	Mobile phones (calls, SMS, money)	Improved market info, decision-making; reduced costs.
Okello et al. (2020)	Kenya	Mobile-based market information system (MIS)	Enhances market participation, income, input use.
Ma et al. (2020)	China	Smartphones (internet, social, calls)	Higher farm/off-farm income; gender differences noted.
Zulu et al. (2024)	South Africa	Mobile, radio, TV, internet channels	ICT + credit significantly increases income.
Sarkar et al. (2022)	India	Radio, TV, phone, apps, website, IVR	Enhances all livelihood capitals; improves income and resources.
Siaw et al. (2020)	Ghana	Broad internet usage	Internet use boosts farm (20%) household (15%) incomes.
Anadozie et al. (2021)	Nigeria	Mobile phones	Stronger networks, enhanced income levels and resilience.
Camacho and Conover (2019)	Colombia	Mobile SMS	Slightly better info access; potential long-term welfare gains.
Tirkaso and Hess (2015)	Ethiopia	General ICT	Positive income gains linked to ICT spending.
Abubakari et al. (2023)	Ghana	Mobile phones	Mobile phones raise crop income (7%); strengthen market links.

Source: Authors' synthesis based on the reviewed studies

Table 2: ICT Use and Impact on farmer welfare by study.

the transformative effect of village-level coverage, internet services, and smartphone applications in increasing income, productivity, and psychological well-being (Zhu et al., 2022; Zhu et al., 2024; Zhu et al., 2020; Ma et al., 2020; Guo et al., 2018). These interventions have also contributed to structural shifts in labour allocation, moving workers from on-farm to off-farm sectors, while gradually narrowing income disparities among farmers. In Sub-Saharan Africa, particularly in Nigeria and Ghana, basic mobile usage and more advanced tools such as mobile phones, SMS, and internet-based platforms have also shown promising results. In Nigeria, Aker and Ksoll (2016) found that basic mobile access encouraged diversification into marginal cash crops, with potential long-term benefits. Similarly, more complex ICT usage in the form of market information systems and agroforestry applications enhanced income levels and resilience (Oparinde, 2023; Anadozie et al., 2021). In Ghana, ICTs such as mobile phones, digital TV, and internet connectivity supported improved communication, decision-making, and market participation, resulting in higher incomes and social capital (Shaibu et al., 2018; Abubakari et al., 2023; Siaw et al., 2020).

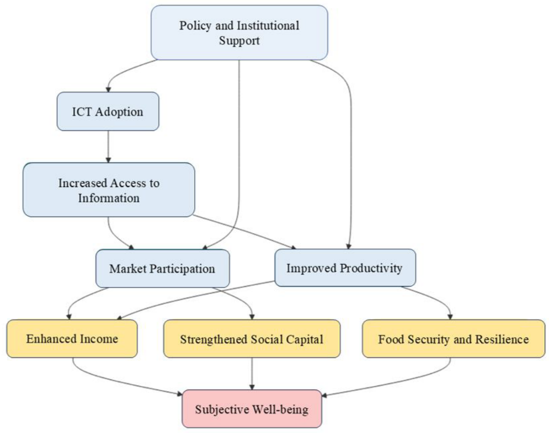
Across South and Southeast Asia, ICT applications also contributed to positive welfare outcomes.

In Bangladesh, the integration of smartphones, apps, call centres, and SMS alerts improved knowledge dissemination, boosted resilience, and empowered women. In India, a comprehensive ICT ecosystem comprising radio, television, mobile apps, and IVR channels contributed to improvements in all five livelihood capitals (Sarkar et al., 2022). Likewise, in Laos, smartphone-based interventions enabled farmers to access real-time information and extension services, which in turn led to increased yields and profits (Bounkham et al., 2022).

In East and Southern Africa, ICTs such as mobile-based market information systems in Kenya and integrated media channels in South Africa were associated with enhanced income and market engagement (Okello et al., 2020; Zulu et al., 2024). In Zimbabwe, mobile phones equipped with financial and informational functions supported decision-making and reduced transaction costs (Masuka et al., 2016). Similarly, in Ethiopia, general ICT investments correlated positively with income gains, especially among wheat producers.

In Latin America, evidence from Colombia indicates that while SMS-based information services improved farmers' engagement with ICTs, short-term welfare outcomes remained limited, with potential for delayed benefits (Camacho and Conover, 2019). This pattern suggests that the effectiveness of ICTs may depend not only on the technology itself but also on user adaptation and the institutional environment. Across these studies, smartphone applications, integrated communication platforms, and internet connectivity appear to yield more substantial impacts on productivity and income compared to basic mobile usage. Moreover, where ICT is combined with institutional support (e.g., credit access or extension services), the synergistic effects tend to be more pronounced, particularly in terms of resilience, social capital, and long-term welfare gains.

The conceptual framework (Figure 7) illustrates the pathways through which ICT adoption influences farmers' welfare. Policy and institutional support serve as a foundational enabler, fostering an environment conducive to ICT adoption through infrastructure development, extension services, and capacity-building initiatives. Once adopted, ICT enhances farmers' access to timely and relevant information, which in turn improves market participation and agricultural productivity. These improvements generate both direct and indirect welfare outcomes. Economically, increased income emerges as the most immediate and measurable benefit. Socially, ICT facilitates the strengthening of social capital by fostering peer-to-peer communication and collective learning, while also improving food security and resilience through better-informed farm management and risk mitigation.

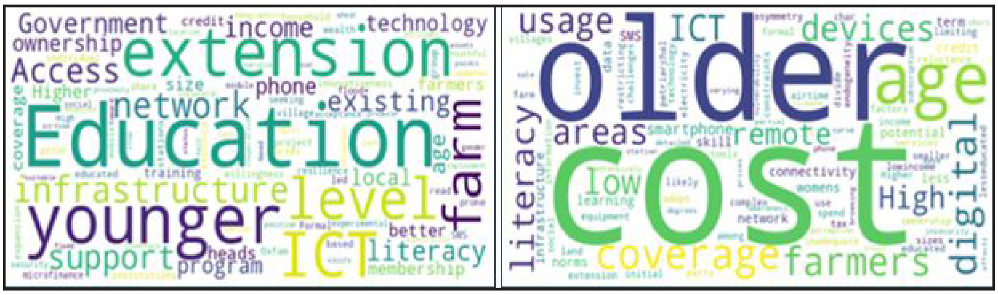


Source: Authors' own elaboration based on the systematic literature review results.

Figure 7: ICT adoption pathways and farmer welfare outcomes.

Ultimately, the combination of economic and social gains leads to enhanced subjective well-being, highlighting that the impacts of ICT extend beyond financial metrics to encompass farmers' overall quality of life. This framework also emphasizes that the effectiveness of ICT adoption is contingent upon the presence of complementary institutional supports, without which welfare outcomes may remain limited or unevenly distributed.

The synthesis of existing literature identifies education and literacy as the most frequently cited driving factors influencing farmers' adoption of ICT , while financial constraints and high technology costs emerge as the main inhibiting factors (Figure 8A and 8B). Studies consistently highlight formal education, digital literacy, and younger age demographics as critical determinants facilitating ICT adoption among farming communities. Additionally, prior exposure to technology and innovativeness significantly contribute to farmers' willingness and capacity to integrate ICT solutions effectively. Moreover, Government initiatives and infrastructure also prominently appear in multiple analyses, particularly emphasizing government-led ICT infrastructure projects, local institutional supports, and comprehensive extension services that collectively enhance ICT adoption rates. Similarly,



Source: Authors' own elaboration based on the systematic literature review results.

Figure 8: Driving (A) and inhibiting (B) factors to ICT adoption.

access to technological resources, including experimental mobile platforms, widespread mobile network coverage, and the provision of specific training programs, emerge as influential in driving technology uptake among farmers. Furthermore, demographic and social factors, notably youthfulness and proximity to ICT service points, are significant predictors of ICT adoption. The younger farming demographic demonstrates greater adaptability and positive attitudes toward new technologies, reflecting an enhanced likelihood of ICT usage. Economic variables, such as income level, cost considerations related to airtime and electricity, and the economic nature of the crops cultivated, have been recognized as vital components influencing farmers' ability to adopt ICT. Finally, financial and institutional supports, including access to credit, cooperative memberships, extension visitation frequency, and the availability of collateral resources, significantly contribute to increased ICT adoption among agricultural communities. Collectively, these factors indicate a multifaceted landscape wherein education, government infrastructure, demographic characteristics, technological accessibility, economic capacity, and institutional support systems interplay critically to shape farmers' decisions regarding ICT adoption.

On the other hand, the reviewed literature highlights financial constraints and the high cost of technology as predominant inhibitors in the adoption of ICT (Figure 8B). Notably, the high initial costs associated with purchasing smartphones, ICT equipment, and ongoing connectivity expenditures significantly deter adoption among low-income and less-educated agricultural communities. Multiple studies underline the pronounced financial barriers, particularly among older farmers and those experiencing income constraints, emphasizing the adverse impact of economic limitations on technology adoption. Moreover, infrastructure and network-related issues are similarly recurrent inhibitors identified across various studies. Limited or inadequate network coverage, especially prevalent in rural and remote regions, restricts farmers' access and reduces the practical applicability of ICT services. Furthermore, persistent infrastructure deficits, including insufficient electricity supply and connectivity challenges, compound the difficulties farmers face when attempting to leverage ICT solutions effectively. Another significant barrier documented is the limited digital literacy and awareness among farming populations, especially older individuals. The literature underscores that older farmers frequently demonstrate lower levels of digital proficiency and awareness, manifesting as reluctance or reduced capability in utilizing digital technologies effectively. Issues such as difficulty navigating digital interfaces, limited trust in digital communication platforms, and insufficient awareness of ICT benefits further obstruct the comprehensive integration of these technologies within agricultural practices.

The results of this review demonstrate that ICT adoption consistently correlates with improved farmer welfare across multiple contexts, reinforcing evidence that digital and mobile technologies yield the strongest gains in income and productivity. Moreover, studies employing causal econometric methods report significant income increases from internet-based services and mobile communication; qualitative and descriptive research highlights non-monetary benefits such as enhanced social capital, food security, and subjective well-being. Although econometric analyses frequently demonstrate that ICT adoption correlates with measurable gains in farm productivity, emerging qualitative evidence underscores equally important non-monetary benefits that vary across agrarian contexts. For example, mobile communication technologies have been shown to streamline agricultural operations and improve efficiency, albeit without directly quantifying income effects (Böttcher et al., 2023). In contrast, digital platforms foster social capital by facilitating peer networks and collective problem-solving, thereby strengthening community resilience (Hoang and Tran, 2023). Moreover, improved access to timely agronomic information via ICT contributes to enhanced food security and risk management, as farmers use weather forecasts and pest alerts to optimise production decisions (Pogonyshev et al., 2022). Beyond tangible outcomes, ICT engagement also promotes subjective well-being by increasing farmers' sense of connectedness and autonomy (Polyakov, 2021). These multifaceted impacts highlight the necessity of integrating both quantitative and qualitative measures when evaluating ICT interventions (Chao and Yu, 2023), especially given that effectiveness depends on local infrastructure, cultural practices, and demographic characteristics (Budiastuti et al., 2023). Finally, persistent digital divides, rooted in socioeconomic disparities and uneven access to technology, continue to shape adoption patterns and determine who benefits from ICT innovations (Abdulai, 2022).

Despite regional and technological differences, integrated ICT platforms, especially those with institutional support such as credit access and extension services, produce more substantial and sustained welfare improvements than basic mobile usage alone. Simultaneously, geographic inequalities in research output, particularly the concentration of studies in China, Ghana, and Nigeria, highlight potential limitations to the generalisability of findings. While primary survey data and causal econometric analyses provide strong evidence for income outcomes, the lack of rigorous evaluations of non-income dimensions highlights the need for diverse methods to fully understand ICT's impact on farmer welfare.

ICT adoption is frequently lauded for its potential to improve agricultural productivity and farmers' welfare. However, contrasting evidence suggests that its benefits are neither uniform nor guaranteed. For instance, Castle et al. (2021) demonstrate that agroforestry interventions enhanced productivity only under specific socio-economic and training conditions, indicating that ICT's effectiveness is contingent on contextual factors such as infrastructure and capacity building. Moreover, Alant and Bakare (2021) identify significant usability challenges among smallholder farmers with limited ICT literacy, which can impede the equitable realization of ICT's benefits. Similarly, Rajkhowa and Qaim (2021) argue that generic digital extension services often fail to address the localized information needs of farmers, thereby limiting improvements in productivity and welfare. Furthermore, Li et al. (2022) warn that over-reliance on digital tools risks marginalizing traditional knowledge systems that contribute to resilience when technological solutions fail. Financial barriers also constrain ICT adoption, as Yusuf et al. (2024) report that the costs associated with new technologies exacerbate disparities among resource-poor farmers.

Digital platforms and mobile communication may yield varying degrees of effectiveness depending on the specific characteristics of local agricultural systems and farmer demographics. For instance, studies in China show that internet-based solutions can facilitate off-farm employment and enhance household income, particularly where robust infrastructure and extension services are in place (Ma et al., 2020; Zhu et al., 2020). By contrast, smallholder farmers in settings with limited bandwidth or inconsistent network coverage, such as certain rural areas of Sub-Saharan Africa, appear to derive more immediate benefits from basic mobile communication tools that support market information systems (Okello et al., 2020; Siaw et al., 2020). Moreover, interventions involving smartphone applications have proven highly effective in regions where younger or more tech-literate farmers predominate (Bounkham et al., 2022). However, many studies reveal contrasting perspectives on ICT's broader societal impact. While ICT tools may provide rapid access to market information and agronomic expertise, they often necessitate stable infrastructure, ample financial resources, and a baseline of digital skills (Rajkhowa and Qaim, 2021). In regions where poverty and illiteracy rates are high, farmers may lack the means to purchase devices or the knowledge to navigate online services, thus reinforcing socio-economic divides instead of bridging them (Mtega, 2021). Similarly, concerns exist that a heightened emphasis on digital platforms could overshadow the value of traditional ecological knowledge, potentially creating reliance on external inputs and eroding local farming adaptations that have proven resilient across generations (Zulu et al., 2024). Critics also argue that fragmented approaches to digital adoption, focused narrowly on short-term productivity, can undermine long-term sustainability by neglecting site-specific soil, water, and cultural practices (Mapiye et al., 2021).

Education and digital literacy are key factors in helping farmers to adopt ICT. They underpin farmers' capacity to adopt ICT by reducing perceived complexity and enhancing self-efficacy, thereby increasing both perceived usefulness and ease of use (Alant and Bakare, 2021). Formal education equips farmers with the cognitive skills needed to navigate digital interfaces and critically appraise online information, which in turn fosters confidence in technology use (Rajkhowa and Qaim, 2021). Likewise, digital literacy training improves practical competencies, such as interpreting market data and weather forecasts, thus directly influencing adoption decisions (Bounkham et al., 2022). Empirical evidence further indicates that farmers with higher literacy levels adopt ICT at significantly higher rates than less-educated peers, whereas low digital skills remain a key barrier, particularly among older cohorts (Camacho and Conover, 2019; Okello et al., 2020). Moreover, enhanced literacy mitigates information asymmetry by enabling farmers to exploit digital extension services more effectively, which supports more informed agronomic and marketing choices (Guo et al., 2018). Despite the recognised importance of formal education in facilitating ICT uptake, substantial disparities in digital knowledge endure among marginalised cohorts, most notably women and farmers with limited schooling (Byamukama et al., 2023). Furthermore, even when training initiatives are available, reluctance to engage with unfamiliar technologies frequently engenders inertia and impedes adoption (Li et al., 2022). Such behavioural resistance, coupled with persistent skill deficits and uneven resource availability, constrains the diffusion of ICT innovations across heterogeneous farming populations. These dynamics underscore the need for phased, context-sensitive implementation strategies that address both cognitive barriers and infrastructural deficits. Accordingly, effective policy design must integrate targeted capacity-building, inclusive pedagogical approaches, and incremental deployment of digital tools to ensure equitable access to ICT benefits irrespective of farmers' educational attainment or locale.

The reviewed studies show a complex interaction of enabling and restricting factors that influence farmers' ICT adoption. The most common drivers are formal education and digital literacy, as higher education equips farmers with cognitive skills to navigate digital interfaces and comprehend agronomic data. ICT use is higher among younger people and people who have used technology before. This is because these groups tend to be more confident in their abilities and more open to new ideas. Institutional supports, such as government-led infrastructure upgrades, extension services, and finance access, reduce transaction costs and enhance network availability, facilitating adoption. This finding is consistent with previous research, which has shown that education improves farmers' technological skills. Alant and Bakare (2021) demonstrate that farmers with higher educational attainment tend to exhibit stronger ICT literacy, enabling them to effectively access and apply information for agricultural decision-making. Next, Abdulai (2022) also shows that farmers with better digital skills more actively engage with digital platforms, improving their participation in agricultural services. Moreover, researchers have highlighted the pivotal role of targeted training programs in complementing formal education. Dhehibi et al. (2023) report that digital skill enhancement through structured interventions equips farmers with not only technical knowledge but also the confidence required for active ICT utilization. This evidence indicates that education and training do not operate independently but mutually reinforce farmers' ability to adopt ICT successfully.

On the other hand, financial constraints serve as a significant barrier: elevated initial expenses for smartphones and data services disproportionately impact low-income farmers, while ongoing deficiencies in network coverage and electricity supply in rural regions restrict effective ICT utilisation. Moreover, the restricted digital competencies of older and less-educated farmers, along with a lack of trust in digital platforms, exacerbate barriers to usage despite the presence of technology. These findings highlight the necessity for comprehensive strategies that target both human capital development and infrastructural deficiencies to facilitate equitable ICT adoption in agricultural communities. This suggests that education and digital literacy alone do not guarantee widespread adoption. Dhungana (2024) identifies socio-economic constraints, including poverty and limited infrastructure, as persistent barriers, even for digitally literate farmers. Sunam et al. (2024) further reveal that older farmers tend to adopt ICT at lower rates due to low digital readiness, despite their educational background. Additionally, Dhehibi et al. (2023) argue that when educational content lacks relevance to the practical realities of rural agriculture, farmers may struggle to translate knowledge into effective ICT use.

The reviewed studies indicate a clear pattern regarding the impact of ICT adoption on enhancing farmers' welfare; however, certain limitations exist that could provide valuable insights for future research. Many studies employed cross-sectional designs, which limit causal inference and understate long-term effects. Some studies relied on region-specific samples, thus reducing generalisability and overlooking variations in infrastructure or social contexts (Bounkham et al., 2022; Zhu et al., 2020). Several studies also lacked standardised measures for welfare indicators and placed greater emphasis on income-based metrics than non-monetary outcomes. Furthermore, some interventions targeted younger or better-educated individuals, leaving older or less-literate farmers underrepresented (Aker and Ksoll, 2016; Guo et al., 2018). In addition, many studies did not control for potential endogeneity or selection bias, so their estimates may not fully capture the effects of ICT adoption in heterogeneous farming populations.

Conclusion

This systematic review confirms that ICT adoption is a transformative force for improving farmers' welfare, particularly through its capacity to enhance income, food security, livelihood assets, and social capital. However, the impacts are neither automatic nor universal. Evidence reveals that digital and mobile technologies yield the most significant welfare gains when integrated with institutional supports such as credit access, extension services, and market linkages. Farmers benefit not only economically but also socially and psychologically, as ICT facilitates better information access, stronger networks, and greater autonomy in decision-making. Yet, the digital divide rooted in infrastructure gaps, affordability constraints, and digital illiteracy continues to marginalize vulnerable groups, particularly the poor, the elderly, and less-educated farmers. Moreover, research remains disproportionately concentrated in a few countries, limiting the generalizability of insights and leaving critical gaps in understanding ICT's role in diverse agroecological and socio-cultural contexts.

Moving forward, future research must go beyond income-centric evaluations to capture the broader and long-term welfare dimensions of ICT adoption. Rigorous longitudinal studies and mixed-method approaches are urgently needed to unpack how ICT interacts with local realities, institutional arrangements, and farmers' lived experiences. It is equally vital to expand research coverage to underrepresented regions, particularly Southeast Asia, Latin America, and marginalized rural communities worldwide. Future interventions should focus on designing context-sensitive ICT solutions that are affordable, literacy-friendly, and compatible with limited infrastructure. Crucially, future studies must assess how bundling ICT with financial inclusion, extension services, and capacity-building programs can deliver not just higher incomes, but resilience, empowerment, and sustainable rural transformation.

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Monetary Policy and Food Inflation in Central Europe: Evidence from the Visegrad Countries

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Abstract

This study examines the relationship between monetary policy and food inflation in the Visegrad Group, using monthly data and applying both OLS and quantile regression methods. Because the model is estimated in first differences and includes a three-month lag of the policy rate, all results reflect short-run month-to-month dynamics of food inflation. The analysis reveals that the monetary policy rate is significantly associated with food inflation across several quantiles, with stronger effects observed during periods of higher inflation. The study also examines the roles of exchange rates, industrial and transport inflation, with a robustness check replacing transport inflation with energy prices. This adjustment confirmed the relevance of energy prices in food inflation dynamics. The results indicate that while monetary policy does affect food prices, its effectiveness depends on the level of inflation and underlying supply-side factors. Quantile regression proves to be a valuable tool in capturing these heterogeneities. These findings can support policymakers in designing more responsive and effective strategies to manage food inflation under varying economic conditions.

Keywords

Visegrad group countries, food inflation, monetary policy, quantile regression, OLS.

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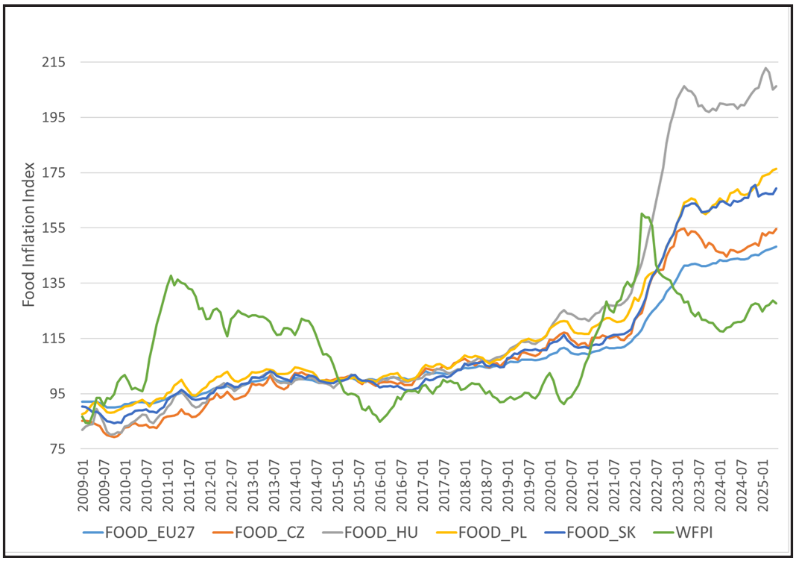
Introduction

Inflation represents one of the most important macroeconomic indicators (Mügge, 2016). Its central role is further reflected in the strategic frameworks of many central banks, which identify price stability as the primary objective of their monetary policy. From a policy perspective, food inflation poses a unique and growing challenge, particularly because of the monetary policy instruments, and especially interest rates, which have shown a measurable effect in influencing food inflation dynamics. For instance, Bhattacharyya and Jain (2020) show that an unexpected monetary tightening tends to have a statistically significant and positive impact on food prices, both in advanced and emerging markets. Also, Kaur (2023) or Sami and Makun (2024) present how monetary policy responses to food inflation vary across countries and reviews growing academic interest in this area. Moreover, De Gregorio (2012) highlights that food inflation, more than energy inflation, tends to exert stronger propagation effects on core inflation, underscoring its importance for price stability. Despite growing research on the relationship, a recent study by Fertő and Bareith (2024) emphasizes that food inflation continues to receive relatively limited attention in the literature.

Why is the issue of food inflation particularly important in the countries of the Visegrad Group (V4)? Despite their geographic and economic proximity, the Visegrad countries operate under different monetary policy frameworks. From the monetary policy standpoint, Slovakia has been regulated by the European Central Bank since 2009, whereas Czechia, Hungary, and Poland retain independent central banks with their own inflation targeting strategies. Regardless of those differences, the Visegrad countries recently exhibit a similar trend: persistently elevated food inflation. What is particularly striking is that food inflation in all four countries has exceeded both the average for the European Union and, according to the Food and Agriculture Organization (FAO, 2025) data, the global food price benchmark.

Figure 1 shows this trend using monthly data from January 2009 to May 2025, capturing the post-Euro adoption period for Slovakia and allowing for a comparative analysis of monetary policy divergence within the V4 region. As illustrated, while food inflation remained relatively stable and close to the European Union average (FOOD_



Note: FOOD denotes the Food Price Index published by Eurostat. WFPI refers to the World Food Price Index published by the FAO. Food inflation index for HICP indices are expressed with base year 2015 = 100; WFPI is expressed with base period 2014–2016 = 100

Source: Prepared by author

Figure 1: Evolution of the food inflation in the Visegrad Group and other regions.

EU27) until 2020, the post-pandemic period shows a sharp divergence. The most significant increase was recorded in Hungary, reaching levels significantly above both the EU and global averages (WFPI). By mid-2023, WFPI began to decline, yet V4 countries continued to face elevated food inflation. These differences raise a crucial question: can monetary policy and other related macroeconomic indicators be held responsible for the observed differences in food price inflation across these countries?

Understanding food inflation has become increasingly important in the post-pandemic period, when price pressures intensified globally and exposed vulnerabilities in food supply chains. The Visegrad region is a particularly relevant case because it combines structural similarities (geography, economic openness, integration into EU markets) with substantial differences in monetary policy frameworks. These differences create a unique natural setting for examining how food prices respond to monetary tightening under distinct institutional regimes. Moreover, food inflation carries strong social and political implications in the V4 countries, where household expenditure shares on food remain above the EU average, making price volatility more damaging to welfare and consumption stability. Despite the relevance of the topic, systematic evidence for the Visegrad countries is surprisingly limited. Existing research has largely focused on developing regions or larger emerging economies, while central Europe has received significantly less attention (Fertő and Bareith, 2024), even though the region has experienced some of the sharpest food price increases in the EU. Therefore, expanding empirical research in this area is essential for understanding both country-specific inflation patterns and broader regional trends.

While conventional OLS regression provides insights into the average relationship between monetary policy and food inflation, such an approach may overlook important distributional patterns. According to several authors (e.g., Iddrisu and Alagidede, 2021; Ali et al., 2022), quantile regression offers a clear advantage: it allows the analysis to capture heterogeneous effects along the entire distribution of food inflation, distinguishing periods of low, moderate, and high inflation. This study addresses the following research question: How does monetary policy affect food inflation in the Visegrad countries across different inflation regimes? This method has been increasingly used in mentioned empirical studies and provides additional insights beyond OLS by revealing whether monetary policy has stronger effects in the upper tail of inflation, where pressures tend to be most persistent. Given the substantial variability and cross-country differences in food inflation within the Visegrad Group, quantile regression is particularly well suited to uncover the asymmetric nature of monetary transmission in this region.

Literature review

Understanding the relationship between monetary policy and food inflation has its relevance stems not only from growing inflationary pressures in the examined region (e.g., Fertő and Bareith, 2024), but also other studies underscore its significance worldwide. For example, Kargbo (2000, 2005), Asfaha and Jooste (2007) or Iddrisu and Alagidede (2020) have examined this relationship in several African economies, or have been focused on Asian countries (Ali et al., 2025), particularly India (e.g., Anand et al., 2014; Samal et al., 2022), Iran (Hatami et al., 2022), Pakistan (e.g., Ali et al. 2022) and in the United States (Frankel, 2006 or Alam and Gilbert, 2017). A more recent contribution by Sami and Makun (2024) examines how monetary policy can help stabilize food inflation across five major emerging economies (Brazil, China, India, Russia, and South Africa, also known as BRICS). These studies converge on the central theme of understanding how food inflation reacts to monetary and macroeconomic conditions, especially in developing or transforming economies. Despite this, there is a noticeable lack of empirical research examining the nexus between monetary policy and food inflation in European contexts. Notably, Bhattacharya and Jain (2020) have already confirmed that food inflation serves as a leading indicator for the policy rate in Hungary. Given the heterogeneity in monetary frameworks and economic structures across the Visegrad Group countries, this finding motivates a closer examination of the relationship between monetary policy and food inflation in the region.

Many of the mentioned studies (e.g., Iddrisu and Alagidede, 2021; Ali et al., 2022 or Sami and Makun, 2024) employ quantile regression to uncover asymmetric effects across different levels of food inflation, emphasizing the importance of context-specific and distribution-sensitive policy responses. Applying quantile regression to the Visegrad countries allows us to uncover whether the effects of monetary policy on food inflation vary across the distribution of food price changes, and whether monetary policy has a stronger effect during periods of low or high food inflation. While the core aim of the research is to examine the relationship between monetary policy and food inflation, the analysis also considers other key macroeconomic variables, such as exchange rates, global food prices, industry, transport and energy prices that can be identified in the literature as relevant determinants of food price movements.

Building on the growing body of literature, this study employs the ordinary least squares (OLS) and quantile regression (QR) to examine the relationship between monetary policy and food inflation in the Visegrad Group countries. Ali et al. (2022) argue that conventional econometric methods such as VAR and ARDL fail to capture the tail behaviour of food inflation, which is critical in countries like Pakistan, where food inflation disproportionately affects vulnerable households. Their findings indicate that contractionary monetary policy and rising transportation costs significantly raise food inflation across all quantiles. Similarly, Iddrisu and Alagidede (2021) provide empirical evidence from Ghana showing that tight monetary policy destabilizes food prices especially in the lower to middle parts of the food inflation distribution, suggesting asymmetric effects not visible in average-based models. Sami and Makun (2024) extend this perspective to a panel of BRICS countries and confirm a causal link between monetary policy and food inflation. Their analysis highlights the heterogeneous effects of external shocks, such as energy prices and exchange rates, on domestic food prices, while also noting that contractionary monetary policy tends to reduce food inflation when macroeconomic coordination is effective. These findings support the use of econometric methods, such as OLS and especially quantile regression, which enable a more nuanced understanding of how monetary policy interacts with food inflation across different inflationary environments.

Materials and methods

The empirical strategy of this study is designed to systematically examine how monetary policy influences food inflation in the Visegrad countries. The research design follows a structured sequence: (i) identifying the relevant macroeconomic channels through which food prices adjust, (ii) constructing country-specific datasets that reflect the institutional differences in monetary policy frameworks, and (iii) estimating econometric models capable of capturing both average and distributional effects.

The analysis is conducted separately for each Visegrad country, rather than as a pooled panel, because the monetary policy frameworks differ fundamentally across the region. Czechia, Hungary, and Poland operate independent inflation-targeting regimes, where domestic central banks adjust policy rates in response to local economic conditions. In contrast, Slovakia has been part of the euro area since 2009, meaning its monetary stance is determined at the supranational level by the European Central Bank. The data employed in this study consists of monthly observations from January 2009 to May 2025 and the choice of variables is grounded in previous studies. The variables used in this analysis include food inflation (FOOD), monetary policy rate (MPR),world food price index (WFPI), exchange rate (ER), production development (INDUSTRY), harmonised index of consumer prices for transport (TRANSPORT) and energy (ENERGY) as a variable for the robustness checks. The selection of these variables is as follows:

- FOOD serves as the dependent variable in all estimated models. It is measured using the Harmonised Index of Consumer Prices (HICP) for food, sourced from Eurostat. As the HICP follows a unified and internationally comparable methodology across EU member states, it enables consistent cross-country comparison of food price developments within the Visegrad Group. The use of this indicator as the main measure of food inflation is in line with recent empirical studies on food price behaviour (e.g., Ali et al., 2022).
- MPR represents the key interest rate set by each country's central bank and is one of the key explanatory variables in the analysis. The data are sourced from the Bank for International Settlements (BIS). Specifically, for the Czech Republic, it corresponds to the two-week repo rate set by the Czech National Bank. In Slovakia is the rate on the deposit facility of the Eurosystem. For Hungary and Poland, the MPR is represented by the base rate determined by the Magyar Nemzeti Bank and the National Bank of Poland, respectively. To reduce simultaneity bias, the monetary policy rate enters the model with a three-month lag (MPR_{t-3}), reflecting the short-run transmission window documented by Fertő and Bareith (2024).
- WFPI refers to the World Food Price Index by the Food and Agriculture Organization of the United Nations on a monthly basis. Although Ali et al. (2022) analyse this relationship in Pakistan and Samal et al. (2022) in India, both studies highlight a general mechanism that is relevant for any open economy: domestic food prices tend to co-move with global commodity prices due to import dependence, integrated supply chains and exposure to global shocks.
- ER is expressed as the number of units of local currency per one euro based on monthly data. It captures the exchange rate between the euro and the local currency of each Visegrad country. For Slovakia, this variable was excluded from the analysis, as Slovakia has used the euro as its official currency throughout the examined period. As emphasised by Fertő and Bareith (2024), in small open economies, the strength of the national currency plays a crucial role in shaping inflation outcomes, given their high exposure to international markets and imported price pressures.
- INDUSTRY captures domestic production dynamics and is measured using the industrial production index, reflecting changes in output over the previous three months, sourced from Eurostat. Ali et al. (2022) employ a similar indicator, changes in large-scale manufacturing output, to show that fluctuations in domestic production capacity can exert meaningful effects on food inflation, particularly in emerging economies.
- TRANSPORT is derived from the HICP sub-index for transport from Eurostat. Ali et al. (2022) demonstrate that rising transport costs exert a significant upward pressure on food inflation across multiple quantiles.
- ENERGY also based on Eurostat HICP sub-indices, is used as a control variable in robustness checks. Energy prices can significantly affect both production and transportation costs, potentially making this variable even more influential than transport inflation in certain contexts.

The expected effects of the selected explanatory variables on food inflation are guided by previous empirical work, particularly the methodologies and findings of the mentioned studies. Based on their findings, we anticipate that an increase in the MPR will be associated with rising food inflation, as consistently observed in both studies. The impact of the WFPI and ER is assumed to be variable and possibly inconsistent across quantiles, given the mixed results reported in both studies. In terms of INDUSTRY, we expect a negative relationship with food inflation, while a positive relationship is expected for TRANSPORT, as highlighted by Ali et al. (2022). The data is collected from Eurostat

(2025), while the MPR is collected from BIS Data Portal (2025) and the WFPI data is collected from the FAO (2025).

A key methodological concern in estimating the relationship between monetary policy and food inflation is the potential endogeneity of the policy rate. Because central banks adjust interest rates in response to inflation developments, contemporaneous regressions may suffer from reverse causality. To ensure that non-stationarity does not bias the results, all variables are tested for unit roots using the Phillips–Perron test. Variables that are non-stationary in levels are transformed into first differences.

As a baseline approach, the study estimates a standard linear regression model (OLS) by using 1st differences (Δ):

$$\Delta FOOD_t = \beta_0 + \beta_1 MPR_{t-3} + \beta_2 \Delta WFPI + \beta_3 \Delta ER + \\ + \beta_4 \Delta INDUSTRY + \beta_5 \Delta TRANSPORT + \varepsilon_t \quad (1)$$

The dependent variable $\Delta FOOD_t$ therefore reflects the monthly change in food inflation, while the explanatory variables capture monthly changes in global food prices, exchange rates, industrial production, and transport inflation. The monetary policy rate is included in its lagged form (MPR_{t-3}) to account for the delayed transmission of monetary policy. Because all macroeconomic variables enter the model in first differences and the monetary policy rate is included with a three-month lag, the estimated coefficients should be interpreted as short-run effects. They capture how changes in the policy rate three months earlier and contemporaneous changes in the control variables are associated with the current month-to-month change in food inflation, rather than long-run equilibrium relationships. In the robustness section, the ΔTRANSPORT variable in equation (1) is substituted with ΔENERGY, following evidence that energy price inflation can significantly affect food price developments. This adjustment has been economically justified according to Moessner (2025) who states that energy inflation has a significantly positive effect on food inflation, considering a panel of 36 OECD countries. Energy costs influence both agricultural production and food distribution, and may therefore capture broader input-cost pressures than transport inflation alone. This alternative specification allows us to evaluate whether the impact of monetary policy remains stable when the model incorporates a more comprehensive cost-side indicator.

Then, we apply quantile regression to examine how monetary policy and selected control variables affect various quantiles of food inflation in the Visegrad group countries.This method allows us to examine the relationships between the dependent and independent variables across different points of the conditional distribution, specifically the 20th, 40th, 60th, and 80th quantiles. Such an approach enables the analysis of distributional heterogeneity that cannot be captured through mean-based regression techniques. We consider quantile regression framework originally developed by Koenker and Bassett (1978), leading by the following equations:

$$f_t = x'_t \beta + \mu_t \quad (2)$$

$$E\,(f_t \mid x_t) = x'_t \beta \quad (3)$$

$$Q_{ft}(\tau \mid x_t) = x'_t \beta_\tau \quad (4)$$

$$\beta_\tau = \beta + \vartheta F^{-1}(\tau) \quad (5)$$

In this context, it is assumed that the error terms μ_t are independently and identically distributed. The variable F denotes the cumulative distribution function of the error term μ_t, while ϑ represents a constant. The number of quantiles is represented by τ, while $Q_{ft}(\tau|x_t)$) refers to the conditional quantile function of food inflation given the covariates x_t. We use a dataset with 197 observations, dividing the dependent variable into quantiles (20th, 40th, 60th, 80th) to ensure that each quantile contains a sufficient number of observations (Ali et al., 2022), thus avoiding issues related to degrees of freedom and estimation accuracy. β_τ reflects the effect of the explanatory variables at a specific quantile of the distribution, capturing the marginal impact of the regressors.

The estimation of the quantile coefficients (parameters in equations 1 to 4) involves minimizing the following loss function:

$$\max_{\beta_\tau \in \Re p} \sum_{t=1}^{T} \rho_\tau \,(f_t - x'_t \beta), \quad (6)$$

$$\rho_\tau(\mu) = \mu(\tau - I(\mu < 0)) \quad (7)$$

where an indicator functionI that equals 1 when $\mu < 0_\mu < 0$, and 0 otherwise. In contrast to mean regression techniques, quantile regression minimizes the sum of the absolute residuals, making it more robust to outliers and non-normal error distributions (Iddrisu and Alagidede, 2020 and Ali et al., 2022).

Results and discussion

Firstly, to better understand the variable behaviour across the Visegrad countries, we begin by providing a summary of the descriptive statistics for the key indicators included in our analysis. Table 1 presents the descriptive statistics of the variables used in the analysis for the Visegrad Group countries: Czechia, Hungary, Poland, and Slovakia.

In Table 1, FOOD shows notable variation across the countries. The highest mean value is observed in Hungary (120.82), followed by Poland (115.35), Slovakia (112.41), and Czechia (109.28). The volatility, as captured by the standard deviation, is also greatest in Hungary (38.93), reflecting stronger fluctuations in food prices over time. The maximum food inflation index reaches 212.78 in Hungary, significantly higher than in the other countries. MPR also varies considerably among the countries, reflecting differences in policy frameworks and responses to inflation. Hungary again shows the highest average rate (4.37%)

Statistics		Czechia	Hungary	Poland	Slovakia
FOOD	Min:	79.3	80.17	87.6	84.22
	Median:	103.8	102.37	104.6	101.59
	Mean:	109.28	120.82	115.35	112.41
	Max:	154.8	212.78	176.4	170.48
	STD:	21.27	38.93	24.59	24.65
MPR	Min:	0.05	0.6	0.1	0
	Median:	0.75	3.2	2.5	0.25
	Mean:	1.72	4.37	3.02	0.9
	Max:	7	13	6.75	4.5
	STD:	2.24	3.72	1.94	1.31
WFPI	Min:	84.3			
	Median:	114.1			
	Mean:	111.5			
	Max:	160.2			
	STD:	17.13			
ER	Min:	23.44	265.29	3.88	x
	Median:	25.65	311.96	4.29	x
	Mean:	25.78	325.97	4.3	x
	Max:	28.46	418.31	4.8	x
	STD:	1.06	41.19	0.2	x
INDUSTRY	Min:	-62.9	-59.1	-53.3	-76.3
	Median:	5.1	0.8	-0.4	7.6
	Mean:	2.04	-5.18	-2.3	6.41
	Max:	26.1	24.7	16.1	56.3
	STD:	13.73	18.47	10.25	20.71
TRANSPORT	Min:	92.6	78.24	87	94.7
	Median:	104.1	105.82	104.6	106.4
	Mean:	109.63	111.67	109.52	109.09
	Max:	141.6	158.75	141.1	138.39
	STD:	13.93	20.38	13.69	12.49
ENERGY	Min:	86.8	87.09	81.7	90.68
	Median:	103.7	108.36	103.7	101.12
	Mean:	114.72	115.97	113.55	105.07
	Max:	185.5	173.43	173.1	130.43
	STD:	28.61	21.62	25.63	11.62

Source: Prepared by author

Table 1: Descriptive statistics.

and maximum value (13.00%), suggesting a more aggressive monetary stance compared to its regional peers. In contrast, Slovakia, which is part of the euro area, records the lowest average policy rate (0.90%), aligned with the historically low policy rates set by the European Central Bank. Czechia and Poland fall in between, with average rates of 1.72% and 3.02%, respectively. Regarding INDUSTRY, Slovakia exhibits the highest mean growth (6.41) and a maximum value of 56.30, while Hungary and Poland show negative average values, indicating structural weaknesses or downturns during parts of the sample period. ENERGY and TRANSPORT indices show relatively higher variability in Hungary, reflecting volatility in these sectors. This descriptive statistics reveal strong heterogeneity in food inflation, reflected in wide min–max ranges, high volatility, and cross-country differences. This indicates that food inflation behaves differently across various inflation regimes, which motivates the use of quantile regression to capture these heterogeneous effects.

Then, to assess the stationarity of the data, we applied the Phillips and Perron (1988) test similarly as Ali et al. (2022), Samal et al. (2022) or Fertő and Bareith (2024). The results in Table 2 indicate that most variables are non-stationary in levels but become stationary after first differencing.

To address concerns regarding endogeneity and reverse causality, we perform Granger causality tests separately for each Visegrad country and show those results in Table 3. The tests are estimated on country-specific series, as monetary policy rates differ fundamentally across countries and cannot be meaningfully pooled into a panel structure. For each country, we evaluate whether the policy rate Granger-causes food inflation and whether food inflation Granger-causes the policy rate. This approach allows us to assess the direction of causality within each monetary regime.

The Granger causality tests reveal a clear and consistent pattern across the three countries with independent monetary policy (Czechia, Hungary, and Poland). In all three cases, changes in the monetary policy rate Granger-cause changes in food inflation. This indicates that monetary policy contains predictive information for subsequent food price dynamics. In contrast, food inflation does not Granger-cause the policy rate in any of these countries, suggesting the absence of reverse causality and mitigating concerns about endogeneity. For Slovakia, although the underlying data on food inflation and the ECB policy rate are complete, the policy rate exhibits very limited month-to-month variation over most of the sample. As a result, the first-differenced policy rate contains insufficient variation for estimating a VAR model

Variable	Czechia		Hungary		Poland		Slovakia	
	Level	1st diff	Level	1st diff	Level	1st diff	Level	1st diff
FOOD	-4.73	-166.74***	-1.79	-74.60***	-0.3	-101.82***	-1.35	-128.90***
MPR	-5.92	-149.8***	-4.39	-54.94***	-3.24	-54.941***	-4.37	-172.31***
WFPI	-6.26	-119***	-6.26	-119***	-6.26	-119***	-6.26	-119***
ER	-8.99	-172.88***	-17.51	-167.68***	-19.24*	-157.65***	x	x
INDUSTRY	-30.57***	x	-13.1	-217.45***	-24.95**	-137.48***	-71.10***	x
TRANSPORT	-3.75	-117.13***	-3.03	-110.72***	-4.13	-176.68***	-4.59	-144.89***
ENERGY	-3.92	-204.46***	-3.91	-129.77***	-1.33	-212.34***	-2.71	-191.76***

Source: Prepared by author

Table 2: Stationary test.

Country	Direction of Causality	F-Statistic	p-value	Interpretation
Czechia (CZ)	ΔMPR → ΔFOOD	3.3756	0.0030	Significant causality
	ΔFOOD →Δ MPR	1.2692	0.2708	No causality
Hungary (HU)	ΔMPR → ΔFOOD	5.9981	<0.001	Significant causality
	ΔFOOD →Δ MPR	1.5216	0.1700	No causality
Poland (PL)	ΔMPR → ΔFOOD	4.6948	<0.001	Significant causality
	ΔFOOD → ΔMPR	1.3225	0.2461	No causality
Slovakia (SK)	ΔMPR →ΔFOOD	—	—	Not estimable
	ΔFOOD → ΔMPR	—	—	Not estimable

Source: Prepared by author

Table 3: Granger causality test results for country-specific models.

or conducting Granger causality tests. This is consistent with Slovakia's membership in the euro area, where monetary policy is not determined at the national level. While causality cannot be assessed, quantile regression could evaluate how the common monetary stance of the euro area and other macroeconomic factors are associated with different parts of the distribution of Slovak food inflation.

While Granger causality tests do not identify structural causal effects, they help to mitigate endogeneity concerns by clarifying the temporal ordering between monetary policy and food prices. The finding that changes in the policy rate Granger-cause food inflation, but not vice versa, supports the use of lagged policy rates in the subsequent regressions and reduces the risk that our estimated coefficients merely capture the reaction of central banks to inflation. The choice of a three-month lag for the policy rate (MPR_{t-3}) is motivated by the literature on food price dynamics (e.g., Fertő and Bareith, 2024), which documents that short-run adjustments occur mainly within one to three months after a monetary shock.

Table 4 presents the OLS and quantile regression estimates for food inflation in Czechia across the 20th, 40th, 60th, and 80th quantiles. The results for Czechia reveal that the determinants of food inflation operate asymmetrically across the distribution, underscoring the relevance of quantile regression for capturing heterogeneous price dynamics. The monetary policy rate shows a positive and statistically significant effect only in the upper tail (80th quantile), suggesting that interest rate changes matter primarily during high-inflation period. Once ENERGY is included (Table 8 in Appendix A), the policy rate becomes insignificant across all quantiles, suggesting that short-run monetary transmission is weak in an environment where energy and production costs dominate price formation. This aligns with recent evidence for small open European economies, where energy price shocks have been shown to transmit rapidly into food prices, often overshadowing the direct impact of monetary policy.

The results for Hungary (Table 5) reveal a clear and economically meaningful pattern. The monetary policy rate shows a stronger and more systematic relationship with food inflation than in any other Visegrad country. In the baseline specification, MPR_{t-3} is statistically significant in the 20th and 80th quantiles, with a negative effect at the lower tail and a positive effect in periods of elevated food inflation. Tighter monetary policy dampens food prices when inflation is low but amplifies them in high-inflation regimes. The negative effect in the lower tail suggests that when food inflation is low, tighter monetary policy helps reduce price pressures through weaker demand. In contrast, the positive and significant effect at the 80th quantile indicates that during high-inflation periods, interest rate increases can push food prices up. This finding is consistent with the evidence reported by Ali et al. (2022). INDUSTRY is negative and consistently significant in the OLS, 60th, and 80th quantiles, suggesting that stronger industrial output helps ease food price pressures, particularly

Variable	OLS		20th Quantile		40th Quantile		60th Quantile		80th Quantile	
Intercept	0.22323	**	-0.62957	***	0.04998		0.41500	***	1.04032	***
	(0.12672)		(0.13088)		(0.13762)		(0.09827)		(0.21782)	
MPR_{t-3}	0.07034		-0.04918		-0.04493		0.07242		0.23976	**
	(0.04478)		(0.05908)		(0.00412)		(0.06568)		(0.12048)	
ΔWFPI	-0.04104		0.03831		0.04952		-0.02785		-0.13674	*
	(0.03759)		(0.05444)		(0.53763)		(0.03940)		(0.07216)	
ΔER	-0.00467		0.69187		0.44112		0.41163		0.25720	
	(0.35007)		(0.54236)		(0.42513)		(0.26384)		(0.50820)	
ΔINDUSTRY	-0.02166		-0.02613		-0.02064		-0.01096		-0.01652	
	(0.01435)		(0.01727)		(0.01591)		(0.01528)		(0.02074)	
ΔTRANSPORT	0.15399	**	-0.03515		-0.12642		0.05442		0.38146	**
	(0.08602)		(0.12328)		(0.10297)		(0.10597)		(0.15998)	
R-squared	0.0417									
F-statistic	1.636									
Observations	194		194		194		194		194	

Note: *, **, *** represents significant at 10%, 5% and 1%; value in parenthesis () represents the standard error
Source: Prepared by author

Table 4: Quantile regression estimates for Czechia.

Variable	OLS		20th Quantile		40th Quantile		60th Quantile		80th Quantile	
Intercept	0.50813	**	-0.11267		0.21703	*	0.48900	***	0.95108	***
	(0.20682)		(0.16434)		(0.12643)		(0.18695)		(0.23572)	
MPR_{t-3}	0.02246		-0.11990	**	-0.00754		0.06489		0.12039	***
	(0.03607)		(0.05585)		(0.03583)		(0.04790)		(0.05567)	
ΔWFPI	-0.03750		0.00919		0.03971		0.09556		0.02826	
	(0.04582)		(0.06889)		(0.05816)		(0.05902)		(0.09013)	
ΔER	-0.01626		-0.00252		-0.03530		-0.04254		-0.00863	
	(0.02540)		(0.04278)		(0.02836)		(0.02985)		(0.03434)	
ΔINDUSTRY	-0.04547	**	-0.01488		-0.03076		-0.04303	**	-0.05807	**
	(0.02101)		(0.02194)		(0.02137)		(0.02069)		(0.02593)	
ΔTRANSPORT	0.13054	**	0.02491		0.09389		0.09893		0.12442	
	(0.06231)		(0.08786)		(0.06878)		(0.07614)		(0.09171)	
R-squared	0.0493									
F-statistic	1.95	*								
Observations	194		194		194		194		194	

Note: *, **, *** represents significant at 10%, 5% and 1%; value in parenthesis () represents the standard error
Source: Prepared by author

Table 5: Quantile regression estimates for Hungary.

in the middle and upper parts of the distribution. Other variables, such as WFPI, ER, and TRANSPORT, are generally insignificant, which implies that short-run domestic food price changes in Hungary are driven more by local cost and supply conditions than by immediate global or exchange-rate shocks. The robustness check (Table 9 in Appendix A), strengthens this interpretation. Taken together, the results highlight that Hungary's food inflation is heavily shaped by domestic production and cost factors, while monetary tightening tends to raise food prices during periods of high inflation rather than dampen them.

The results for Poland (Table 6) indicate a strong and fairly consistent role of monetary policy across the higher parts of the food inflation distribution. This pattern suggests that tighter monetary policy is associated with higher monthly food inflation particularly during moderate-to-high inflation regimes. Industrial production (ΔINDUSTRY) shows a negative and significant effect in the OLS, 20th, and 40th quantiles, implying that stronger domestic production capacity helps dampen food price pressures, but primarily in lower-inflation environments. Other variables, including global food prices (ΔWFPI) and the exchange rate (ΔER) remain statistically insignificant across quantiles. This suggests that external price pressures may transmit to Polish food inflation more gradually, beyond the monthly horizon examined here. When ENERGY is introduced in the robustness specification (Table 10 in Appendix A), the results for Poland become even more consistent. The monetary policy coefficient remains positive and significant in the higher quantiles, while ENERGY emerges as a strong and statistically significant driver of food inflation across almost the entire distribution.

Slovakia (Table 7) shows no measurable impact of monetary policy on food inflation across any part of the distribution, reflecting the fact that the country does not set its own policy rate within the euro area. Most macroeconomic controls also remain insignificant in the baseline model, indicating limited short-term pass-through of external and structural shocks. By contrast, ENERGY (Table 11 in Appendix A) becomes strongly significant across nearly all quantiles in the robustness test, suggesting that cost-push factors—rather than monetary policy—drive monthly food price fluctuations in Slovakia.

The quantile regression results across Czechia, Hungary, Poland, and Slovakia show that the transmission of monetary policy to food inflation is heterogeneous and concentrated mainly in higher-inflation regimes. In Poland, and to a lesser extent in Hungary, the three-month lagged policy rate is positively and significantly associated with food inflation in the middle and upper quantiles, indicating that monetary tightening amplifies food price pressures when inflation is already high. In Czechia, the effect appears only in the upper tail of the distribution, and in Slovakia the policy rate is insignificant at all quantiles, consistent with the absence of a national monetary policy under the euro area framework.

Variable	OLS		20th Quantile		40th Quantile		60th Quantile		80th Quantile	
Intercept	0.10274		-0.47450	**	-0.17857		0.12748		0.80110	***
	(0.16586)		(0.19826)		(0.16959)		(0.16502)		(0.23843)	
MPR_{t-3}	0.11028	**	0.01881		0.11078	**	0.17030	**	0.14490	*
	(0.04670)		(0.08531)		(0.05265)		(0.05444)		(0.08663)	
ΔWFPI	-0.00370		-0.01562		0.03446		0.01850		0.00695	
	(0.03261)		(0.05859)		(0.04252)		(0.03113)		(0.05426)	
ΔER	-0.48457		1.47467		-0.32335		-0.10649		0.39600	
	(1.38370)		(2.01541)		(1.61178)		(1.39118)		(2.08754)	
ΔINDUSTRY	-0.04344	**	-0.04375	*	-0.03944	**	-0.02774		0.00307	
	(0.02047)		(0.02634)		(0.01802)		(0.01935)		(0.03268)	
ΔTRANSPORT	0.09685	*	0.07658		0.07488		0.13766	*	0.10392	
	(0.05369)		(0.11760)		(0.08046)		(0.07060)		(0.07924)	
R-squared	0.0609									
F-statistic	2.439	**								
Observations	194		194		194		194		194	

Note: *, **, *** represents significant at 10%, 5% and 1%; value in parenthesis () represents the standard error
Source: Prepared by author

Table 6: Quantile regression estimates for Poland.

Variable	OLS		20th Quantile		40th Quantile		60th Quantile		80th Quantile	
Intercept	0.42151	***	-0.50605	***	0.04375		0.42084	***	1.15785	***
	(0.10621)		(0.10652)		(0.08724)		(0.11392)		(0.18079)	
MPR_{t-3}	-0.02426		-0.05371		-0.00571		0.00536		0.03874	
	(0.06735)		(0.09782)		(0.05869)		(0.08423)		(0.15322)	
ΔWFPI	-0.01117		0.01494		-0.00830		-0.03728		-0.04978	
	(0.03099)		(0.04947)		(0.03647)		(0.03792)		(0.05692)	
ΔINDUSTRY	-0.00281		-0.00734		-0.00520		-0.00125		-0.00864	
	(0.00485)		(0.00532)		(0.00499)		(0.00738)		(0.00730)	
ΔTRANSPORT	0.07749		-0.03408		0.06025		0.07469		0.26621	*
	(0.05438)		(0.09506)		(0.04760)		(0.08958)		(0.15133)	
R-squared	0.01277									
F-statistic	0.6112									
Observations	194		194		194		194		194	

Note: *, **, *** represents significant at 10%, 5% and 1%; value in parenthesis () represents the standard error
Source: Prepared by author

Table 7: Quantile regression estimates for Slovakia.

Across countries, the significance of WFPI and ER is generally weak or inconsistent, implying that global food price shocks and exchange rate movements exert only limited short-run effects on monthly food inflation—a finding consistent with earlier evidence that their pass-through operates with longer lags (e.g., Iddrisu and Alagidede, 2020; Ali et al., 2022). The INDUSTRY variable shows a predominantly negative association with food inflation, particularly in Poland and Hungary, although statistical significance is confined to the lower and middle quantiles, where domestic production dynamics appear more stabilising. TRANSPORT inflation provides only weak and irregular explanatory power, with coefficients often insignificant across quantiles. In contrast, the robustness check (Appendix A) replacing TRANSPORT with ENERGY reveals a clearer and more stable positive effect of energy price inflation, especially in Poland and Slovakia. This pattern underscores the importance of cost-push channels, most notably energy-intensive inputs, in shaping food price dynamics in the region and confirms that supply-side factors can overshadow the direct effects of monetary policy in certain inflation environments.

Regarding to the Visegrad region, the results suggest that domestic monetary conditions matter primarily in countries with independent monetary policy and mainly during high-inflation episodes. The repeated insignificance of global food prices and exchange rates implies that their short-run pass-through is limited in monthly data, while cost-side pressures, particularly energy, play a more prominent role. The findings also show that in Slovakia, unlike the other V4 countries, energy inflation systematically shapes food price changes, whereas the interest rate channel is largely absent.

From a policy perspective, the results suggest that the short-run impact of monetary policy on food inflation in the Visegrad countries operates over a horizon of three months, with the strongest effects observed in higher-inflation regimes and in countries with independent monetary policy, most notably Hungary and Poland. This implies that central banks in these economies should take into account the delayed and asymmetric response of food prices when calibrating interest-rate decisions, particularly during periods of elevated inflation when monetary tightening appears to exert upward cost-push pressure rather than dampening food price dynamics. For Czechia, the monetary policy effect is confined to the upper quantile and disappears once energy inflation is included, suggesting that domestic food prices respond more strongly to cost-side shocks than to the policy rate itself. In Slovakia, where monetary policy is determined at the euro area level, national food inflation is largely unresponsive to the policy rate. Instead, the results indicate that domestic food prices are primarily driven by fundamental cost factors such as energy inflation, which remains consistently significant across quantiles. This highlights that, in the absence of national monetary tools, external price pressures and energy-related input costs dominate short-run food price developments.

Conclusion

The interaction between food price inflation and monetary policy is a complex and increasingly relevant issue and recently it has been highlighted by several authors such as Sami and Makun (2024), Fertő and Bareith (2024) or Ali et al. (2025).The main objective of this study was to examine how monetary policy affects food inflation, while simultaneously assessing the role of key fundamental determinants such as global food prices, exchange rates, industrial production, transport costs, and energy inflation, in the Visegrad Four countries – Czechia, Hungary, Poland, and Slovakia. To capture the heterogeneous effects of monetary and other economic variables across different levels of food price inflation, both OLS and quantile regression methods were applied. This dual approach allowed for a better understanding of the determinants of food inflation beyond average effects and revealed how relationships differ across the inflation distribution.

The OLS results provided an initial overview, indicating that monetary policy rates are positively associated with food inflation in several V4 countries. However, the quantile regressions revealed a more nuanced picture: the effect of monetary policy is asymmetric and becomes statistically significant primarily in the upper quantiles of the inflation distribution. The model is estimated in first differences, and the policy rate enters with a three-month lag, therefore these results reflect only short-run, month-to-month dynamics. Within this short-run horizon, monetary transmission to food prices is most evident during periods of heightened inflation and in countries with independent monetary policy frameworks. This pattern is especially pronounced in Hungary and Poland, where MPR_{t-3} exhibits strong positive effects during periods of elevated food inflation. In Czechia, the effect is visible only at the upper tail, and in Slovakia, where monetary policy is determined at the euro area level, the policy rate is largely insignificant.

From an economic and policy perspective, the results highlight important limitations in the ability of monetary policy to stabilise food inflation. Although interest rate adjustments influence price dynamics at the margin, food inflation in the V4 countries is strongly shaped by supply-side and cost-push factors. This is underscored by the robustness checks, where the inclusion of energy inflation substantially improves model fit and reveals a consistently significant positive relationship with food prices across countries, most notably in Slovakia. Energy costs, global commodity price movements, and exchange rate fluctuations appear to exert larger and more persistent effects than short-term monetary policy measures. These insights point to the need for a multidimensional policy framework. While monetary policy can help anchor inflation expectations and dampen demand-driven pressures, it is insufficient to address structural and external drivers of food inflation.

In conclusion, the study provides empirical evidence that the impact of monetary policy on food inflation in the V4 countries is real but conditional: it is visible primarily in high-inflation regimes and interacts strongly with underlying structural and external factors. Quantile regression proves particularly valuable in uncovering these heterogeneous effects, offering a richer and more policy-relevant understanding of food price dynamics than traditional OLS estimates. The robustness results reinforce the central role of energy costs, indicating that future food inflation dynamics in the region will depend not only on monetary tightening cycles but also on global cost conditions and domestic structural adjustment.

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Landlocked: A Boon or Bane for EU Member States' Agricultural Trade Competitiveness?

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Abstract

Some European countries have no sea and are close to other countries' mainlands. Trading agricultural products from different places may be difficult because of this circumstance. This study assesses EU Member States' agricultural trade competitiveness and the impact of landlocked conditions on that competitiveness. This study analysed 27 EU countries between 2000 and 2022 using the Revealed Comparative Advantage, the Error Correction Model, and Propensity Score Matching. Landlocked conditions reduced the EU Member States' agricultural competitiveness. These findings support Diamond Porter's theory, which holds that any country must have factor conditions to generate advantages. Similarly, the New Trade theory promotes economic scale for all countries, even landlocked ones. Other factors in this study have varying impacts on the agricultural competitiveness of EU Member States.

Keywords

Production, value added, capital, temperature, unemployment, politics.

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Introduction

Landlocked countries do not always face difficulties because they can become transit countries and create economic opportunities. The key is the development of modern service infrastructure for cost efficiency and the formation of a new logistics industry (Sharapiyeva et al., 2019). In addition, countries without seaports can build infrastructure to facilitate the transportation of goods to and from neighboring countries (Adhikari and Ma, 2022). However, having access to the sea is a blessing for many countries. Countries with seaports have greater access to global markets than those without, as maritime routes are the most economical and effective means of cargo transport (Adhikari and Ma, 2022). If every country has access to seaports, the cost of shipping goods worldwide will decrease, raising competitiveness and lowering prices (Lane and Pretes, 2020).

In Europe, landlocked countries are supported by various regional trade agreements, such as the European Union (EU). The landlocked countries of Austria, the Czech Republic, Hungary, Luxembourg and Slovakia have excellent locations for trade in goods and services, particularly for Western European target consumers. The countries' locations also influence investment and decision-making. Numerous countries have achieved significant progress in enacting institutional and economic reforms and attracting trade and investment (Sharapiyeva et al., 2019). The EU's landlocked countries will make significant financial investments to update their infrastructure and capabilities, thereby strengthening their institutional frameworks, customs authority structures and transportation laws (Sharapiyeva et al., 2019).

Meanwhile, several researchers have conducted studies on the impact of landlocked countries on economic growth (Chaudhary and Paudel, 2024) and agricultural exports (Abdullahi et al., 2021). However, both studies have not examined the impact of landlocked areas on agricultural competitiveness or without regional agreements. In contrast, the object of this study is the EU, which has regional trade agreements that support trade among member states. Effective EU regional collaboration can support economic progress and strategic infrastructure investments for landlocked countries in the region (Chaudhary and Paudel, 2024). In this way, this regional policy can potentially change landlockedness to land-linkedness. Hence, landlocked European countries have a much lower share of maritime transport, as substantial trade flows convey commodities over very short distances via road, rail, and inland waterways (Verschuur et al., 2022). The question naturally arises: is it true that agricultural competitiveness in EU landlocked countries is not affected by geographical disadvantages?

Theoretically, this study contributes to the Diamond Porter's and the New Trade Theories. Diamond Porter's theory shows that the competitiveness of a product can be created by considering several aspects, namely factor conditions, demand conditions, related and supporting industries, and firm strategy, structure and rivalry (Porter, 1990). However, international trade is complex, so production factors and efficiency do not always determine a commodity's competitiveness. According to the New Trade Theory, economies of scale are crucial because, even without a production factor advantage, a country's ability to produce on a large scale is necessary for its commodities to dominate the market (Krugman and Obstfeld, 2003). According to both theories, landlocked areas may present challenges or growth opportunities. Being landlocked poses challenges, as it forces a country to depend on other countries for economic activity, particularly in logistics and distribution. However, when a country can optimise its economic size through numerous technologies, landlocked countries also have a lot of promising thing. This theoretical gap serves as a foundation for the study, which aims to demonstrate the effects of a landlocked position on a country and solutions to address this detrimental circumstance.

Material and methods

Data source

This study used panel data that combines cross-sectional and time-series data. These data were obtained from the FAO, the Federal Reserve, the World Bank, the ILO, the OECD, and CEPII. Cross-sectional data from 27 EU Member States were used in this study, and the time-series data covered the years 2000–2022. Fourteen variables were analysed in this study (Table 1).

The selection of explanatory variables in Table 1 was based on the findings of other researchers. Agricultural competitiveness in a country is influenced by production (Rumankova et al., 2022), value added (Jung and Park, 2014), capital (Kozelský et al., 2024), exchange rate (Kozelský et al., 2024), education (Nugroho et al., 2023), labor (Rumankova et al., 2022), policies or political conditions (Rumankova et al., 2022), temperature change (Nugroho et al., 2023), bioenergy (Waldenström et al., 2016), research and development (Jung and Park, 2014) and geographical position/landlocked (Sharma, 2020).

Variable	**Symbol**	**Source**	**Expected sign.**
Agricultural Trade Comparative Advantage	TCA	Calculated by authors from FAO data	
Gross Production Index	GPI	FAO	+
Agricultural Value Added (million USD)	AVA	FAO	+
Agricultural Gross Fixed Capital Formation (million USD)	CAP	FAO	+
Real Effective Exchange Rates: CPI Based (%)	RER	Federal Reserve Economic	+
School Enrollment, Secondary (% gross)	SCH	World Bank	+
Employment in Agriculture, Female (% of female employment)	FEMA	ILO	+
Employment in Agriculture, Male (% of male employment)	MALE	ILO	+
Youth Unemployment Rate (%)	YOU	OECD	-
Political Instability	POL	World Bank	-
Temperature Change (0C)	TEMP	FAO	-
Total Bioenergy Consumption (TJ)	BIO	World Bank	-
Research and Development Expenditure (% of GDP)	RES	World Bank	+
Landlocked Country0 = no landlocked1 = landlocked	LOCK	CEPII	-

Source: Authors

Table 1: Variable in this study.

Data analysis

The Revealed Comparative Advantage (RCA) index can be used to quantify TCA. This method computes comparative advantage by analysing a country's export trade flow for specific products in specific markets. RCA measures the agricultural export performance of 27 EU Member States (Balassa, 1965):

$$RCA_{ij}=\left(\frac{X_{ij}}{X_{it}}\right) / \left(\frac{X_{ej}}{X_{et}}\right) \quad (1)$$

where: X_{ij} = the current year's total value of agricultural exports of a country (US dollars), X_{it} = the current year's total value of exports of a country (US dollars), X_{ej} = the current year's total value of EU agricultural exports (US Dollars) and X_{et} = the current year's total value of EU exports (US dollars). The formula produces the following results: 1) a country has a comparative advantage if the index generated by the RCA calculation is greater than 1 and 2) a country has a comparative disadvantage if the RCA value is less than 1.

The empirical analysis begins with the Levin-Lin-Chu (LLC) unit root test before the estimation (Levin et al., 2002). The unit root test reveals that TCA, AVA, CAP, RER, SCH, FEMA, MALE, YOU, and POL are stationary at the level, but the other variables are not stationary at the level (Table 2). GPI, TEMP, BIO and RES are stationary at the first-difference level. The analysis's findings also indicate that TCA is a significant dependent variable at this level, suggesting that the Error Correction Model (ECM) is the model that best fits this study. This is because most dynamic models require the dependent variable to be significant at the first difference. Meanwhile, static analysis could not be used because some variables in this study are significant at the first difference (Wooldridge, 2016).

Variable	Level	Sign.
TCA	At level	-3.779***
GPI	1st difference	-11.629***
AVA	At level	-4.388***
CAP	At level	-4.110***
RER	At level	-2.345***
SCH	At level	-2.693***
FEMA	At level	-8.636***
MALE	At level	-4.460***
YOU	At level	-3.691***
POL	At level	-7.126***
TEMP	1st difference	-11.229***
BIO	1st difference	-3.876***
RES	1st difference	-6.246***

Note: ***: sig 0.01
Source: Own elaboration (2025)

Table 2: LLC unit root test.

The results of the cointegration test indicate that the variables in the models have a long-term relationship (Wooldridge, 2016). The TCA, GPI, AVA, CAP, RER, SCH, FEMA, MALE, YOU, POL, TEMP, BIO and RES variables are cointegrated (Table 3). The trace statistics value is higher than the critical value at the 1% confidence level, indicating that ECM is the appropriate analysis model for this study.

Hypothesized No. of CE (s)	Trace statistics
None	318.221***
At most 1	236.549***
At most 2	124.146***
At most 3	49.228***

Note: ***: sig 0.01
Source: Own elaboration (2025)

Table 3: Cointegration test.

The dependent and explanatory variables are rarely in equilibrium, so it is necessary to observe the disequilibrium relationship:

$$\begin{aligned}\Delta TCA_{it} = {} & b_0 + b_1\Delta GPI_{it} + (b_1 + b_2)GPI_{it\text{-}1} + \\ & + b_3\Delta AVA_{it} + (b_3 + b_4)AVA_{it\text{-}1} + b_5\Delta CAP_{it} + \\ & + (b_5 + b_6)CAP_{it\text{-}1} + b_7\Delta RER_{it} + (b_7 + b_8)RER_{it\text{-}1} + \\ & + b_9\Delta SCH_{it} + (b_9 + b_{10})SCH_{it\text{-}1} + b_{11}\Delta FEMA_{it} + \\ & + (b_{11}+ b_{12})FEMA_{it\text{-}1} + b_{13}\Delta MALE_{it} + \\ & + (b_{13} + b_{14})MALE_{it\text{-}1} + b_{15}\Delta YOU_{it} + \\ & + (b_{15} + b_{16})YOU_{it\text{-}1} + b_{17}\Delta POL_{it} + \\ & + (b_{17} + b_{18})POL_{it\text{-}1} + b_{19}\Delta TEMP_{it} + \\ & + (b_{19} + b_{20})TEMP_{it\text{-}1} + b_{21}\Delta BIO_{it} + \\ & + (b_{21} + b_{22})BIO_{it\text{-}1} + b_{23}\Delta RES_{it} + \\ & + (b_{23} + b_{24})RES_{it\text{-}1}+ D_{LOCK} - \omega TCA_{it\text{-}1} + \varepsilon_i \end{aligned} \quad (2)$$

Δ = first difference and $\lambda = 1 - \Phi$.

Propensity Score Matching (PSM) is an additional instrument used in this study to investigate how the landlocked dummy (LOCK) affects trade comparative advantage. PSM can be carried out using several stages of analysis. First, determine the control and treatment groups. Second, an effect evaluation study should identify which outcomes can be measured. Third, carry out a characteristic matching process between the treatment group (a landlocked country) and the control group (a non-landlocked country) to determine the effect of the treatment on the predefined outcomes (Kuss et al., 2016):

$$ATT = E(R_1 \,|I = 1) - E(R_0 \,|I = 0) \quad (3)$$

$$ATT = E\{R_1 \,|\, I = 1, p(Z)\} - E\{R_0 \,|I = 0, p(Z)\} \quad (4)$$

Where *ATT* (Average Treatment effect of the Treated group) is the value of the impact of treatment on outcomes based on all the data used, I denotes the treatment indicator used in the study (I = 0 for the control group's outcome, I = 1 for the treatment group), R_0 for the control group's value, R_1 for the treatment group's value, and $p(Z)$ denotes the propensity score obtained from the PSM analysis. p(Z) is calculated using the LOCK dummy variable's probit estimate results. Two assumptions must be met for the PSM's findings to be valid: conditional independence and overlapping.

Results and discussion

Most EU Member States are included in the agricultural competitiveness category since their value is more than 1 (Table 4a-4c). Austria, Portugal and Romania have become highly competitive in the agricultural sector compared to 2 decades ago. Czech, Finland, Germany, Malta, Slovakia, Slovenia and Sweden are among the countries that fall into the category of not having competitiveness because their competitiveness value has been less than 1 for the previous 20 years. EU Member States' agricultural competitiveness fluctuates over time and between countries. Austria, Croatia, Finland, France, Germany, Italy, Lithuania, Malta, Slovakia, Slovenia, Spain and Sweden are among the countries that have seen a marginal gain in agricultural competitiveness.

In the meantime, countries such as Bulgaria, Latvia, Luxembourg, Poland, Portugal and Romania have seen a notable rise in competitiveness. However, certain countries—such as Belgium, Hungary, Ireland and the Netherlands—have seen a decline in competitiveness. Greece, Denmark and Cyprus saw a sharp drop in competitiveness. Estonia is the only EU Member States whose agricultural competitiveness has stagnated over the last twenty years.

The probability of ECT is less than 0.01, indicating that the model is valid (Table 5). According to the ECT, the error term from the prior year was adjusted at a convergence speed of 0.099 during the current year. The first explanatory factor that has a significant impact on agricultural trade competitiveness (TCA) is gross production (GPI). GPI raises TCA by 0.00003 in the short term and 0.00008 in the long term. The increasingly high and stable GPI value can be interpreted as evidence that the agricultural production process in the EU Member States is efficient and conducted on a large scale. Production cost efficiency drives cheaper products, creating a comparative advantage (Kuzmenko et al., 2022). The high GPI of the European Union is supported by implementing policies to increase agricultural production. These policies include subsidies and production incentives through the Common Agricultural Policy (CAP) scheme (Garrone et al., 2019) and precision

Year	Austria	Belgium	Bulgaria	Croatia	Cyprus	Czech	Denmark	Estonia	Finland	France	Germany	Greece
2000	0.79	1.42	1.53	1.32	6.81	0.67	2.57	1.05	0.27	1.58	0.68	3.40
2001	0.80	1.34	1.68	1.29	6.13	0.58	2.55	1.11	0.28	1.45	0.64	3.47
2002	0.78	1.26	1.86	1.48	4.24	0.52	2.39	1.33	0.29	1.55	0.62	3.50
2003	0.84	1.27	1.52	1.56	4.05	0.51	2.36	1.50	0.28	1.56	0.63	3.15
2004	0.96	1.29	1.61	1.22	3.57	0.56	2.45	1.00	0.29	1.57	0.65	3.01
2005	1.11	1.30	1.71	1.52	2.45	0.67	2.41	1.00	0.29	1.63	0.70	3.35
2006	1.21	1.33	1.65	1.68	2.79	0.62	2.51	0.99	0.30	1.72	0.71	3.31
2007	1.05	1.30	1.41	1.52	3.00	0.63	2.47	1.31	0.30	1.73	0.70	3.00
2008	1.05	1.32	1.91	1.37	2.64	0.65	2.31	1.28	0.30	1.69	0.75	2.95
2009	1.04	1.29	2.20	1.53	2.66	0.62	2.21	1.18	0.32	1.58	0.75	3.15
2010	1.04	1.28	2.40	1.47	2.65	0.58	2.30	1.17	0.34	1.68	0.75	3.34
2011	1.02	1.26	2.17	1.46	2.37	0.58	2.21	1.05	0.37	1.74	0.76	2.23
2012	1.04	1.30	2.17	1.62	2.30	0.66	2.25	1.13	0.37	1.72	0.78	2.31
2013	1.03	1.28	2.42	1.56	2.40	0.67	2.22	1.11	0.38	1.77	0.79	2.36
2014	1.00	1.26	2.18	1.56	1.46	0.64	2.25	1.09	0.47	1.64	0.76	2.23
2015	0.98	1.28	2.05	1.63	1.17	0.66	2.17	1.00	0.49	1.59	0.71	2.56
2016	0.97	1.26	2.01	1.71	1.46	0.62	2.02	0.93	0.40	1.49	0.69	2.66
2017	0.97	1.27	1.77	1.64	1.50	0.56	2.08	0.96	0.39	1.50	0.69	2.35
2018	1.01	1.29	1.93	1.82	1.23	0.55	2.08	0.89	0.35	1.57	0.69	2.31
2019	1.01	1.28	1.98	1.75	1.73	0.55	1.95	1.01	0.36	1.52	0.68	2.25
2020	1.02	1.26	1.92	1.76	1.90	0.55	1.81	0.96	0.34	1.59	0.68	2.45
2021	1.02	1.20	2.12	1.73	1.70	0.56	1.82	0.85	0.36	1.67	0.68	2.37
2022	1.04	1.13	2.13	1.78	1.52	0.61	1.81	1.04	0.36	1.75	0.72	2.07

Source: Own elaboration (2025)

Table 4: Agricultural trade competitiveness of EU member states. (to be continued).

Year	Hungary	Ireland	Italy	Latvia	Lithuania	Luxembourg	Malta	Netherland	Poland	Portugal	Romania
2000	1.22	1.40	1.02	1.12	1.85	0.88	0.37	1.88	1.17	0.91	0.54
2001	1.18	1.05	0.96	1.33	1.73	0.79	0.53	1.80	1.14	0.90	0.57
2002	1.13	1.02	1.00	1.67	1.46	0.81	0.65	1.96	1.06	0.94	0.48
2003	1.09	1.17	0.99	1.67	1.57	0.77	0.65	2.04	1.10	0.94	0.49
2004	0.97	1.34	1.04	1.14	1.62	0.68	0.47	2.02	1.34	1.02	0.49
2005	1.02	1.46	1.08	1.47	1.84	0.69	0.49	2.00	1.52	1.12	0.50
2006	0.97	1.72	1.13	1.65	2.03	0.62	0.48	2.00	1.54	1.18	0.63
2007	1.02	1.53	1.03	1.89	2.37	0.68	0.34	1.97	1.47	1.25	0.62
2008	1.07	1.41	1.04	2.14	2.23	0.68	0.48	1.88	1.38	1.28	0.98
2009	1.01	1.11	1.09	2.08	2.28	0.69	0.38	1.98	1.44	1.32	1.00
2010	1.10	1.24	1.14	2.21	2.25	1.00	0.35	1.91	1.45	1.40	1.17
2011	1.15	1.32	1.09	1.89	2.06	1.09	0.35	1.87	1.44	1.31	1.22
2012	1.29	1.37	1.11	2.52	2.33	0.89	0.45	1.83	1.63	1.37	1.22
2013	1.23	1.52	1.14	2.44	2.31	1.09	0.54	1.83	1.67	1.38	1.42
2014	1.15	1.49	1.12	2.31	2.27	1.16	0.66	1.69	1.63	1.43	1.38
2015	1.07	1.26	1.13	2.18	2.20	1.08	0.66	1.67	1.61	1.40	1.37
2016	0.99	1.18	1.11	2.17	2.05	1.00	0.45	1.72	1.51	1.36	1.29
2017	1.02	1.28	1.12	2.40	1.95	1.12	0.57	1.85	1.57	1.33	1.25
2018	0.99	1.17	1.19	2.34	1.97	1.26	0.52	1.85	1.64	1.39	1.29
2019	0.99	1.11	1.18	2.62	2.03	1.10	0.49	1.80	1.59	1.35	1.35
2020	0.97	0.94	1.22	2.48	2.17	1.22	0.48	1.76	1.54	1.43	1.32
2021	1.01	1.06	1.24	2.17	1.91	1.20	0.43	1.74	1.53	1.46	1.63
2022	1.07	1.06	1.21	2.50	2.01	1.22	0.49	1.62	1.67	1.47	1.57

Source: Own elaboration (2025)

Table 4: Agricultural trade competitiveness of EU member states (Continuation + to be continued).

Year	Slovakia	Slovenia	Spain	Sweden
2000	0.50	0.57	1.91	0.32
2001	0.48	0.59	1.85	0.38
2002	0.52	0.55	1.91	0.39
2003	0.45	0.52	1.97	0.38
2004	0.54	0.49	2.00	0.39
2005	0.66	0.54	2.18	0.45
2006	0.66	0.68	2.16	0.44
2007	0.57	0.67	1.96	0.44
2008	0.54	0.71	1.96	0.46
2009	0.61	0.75	1.89	0.46
2010	0.62	0.83	1.95	0.44
2011	0.66	0.75	1.85	0.41
2012	0.79	0.89	1.99	0.46
2013	0.67	0.78	1.95	0.50
2014	0.55	0.70	1.97	0.51
2015	0.51	0.71	1.98	0.49
2016	0.50	0.69	1.95	0.46
2017	0.47	0.67	1.94	0.46
2018	0.46	0.72	2.00	0.46
2019	0.46	0.68	2.04	0.46
2020	0.48	0.64	2.16	0.47
2021	0.51	0.69	2.11	0.48
2022	0.61	0.65	2.01	0.49

Source: Own elaboration (2025)

Table 4: Agricultural trade competitiveness of EU member states (Continuation - the end).

agricultural technology (Barnes et al., 2019).

The following explanatory variable with a significant detrimental effect is Agricultural Value Added (AVA). In the long term, a 1% increase in AVA will result in a 0.00001 drop in TCA. Short-term changes in AVA do not affect TCA. Generally, countries with greater agricultural value added have greater comparative advantages (Török and Jámbor, 2013). EU agricultural products will compete with similar products from other countries with greater AVAs but at lower prices. This makes EU products less competitive by discouraging consumers from choosing them.

In the long term, a 1 million USD increase in agricultural gross fixed capital formation (CAP) results in a 0.0001 increase in TCA. In the short term, CAP has no impact on TCA. CAP increases productivity, efficiency and competitiveness. Increasing food crop yields is currently focused on efficiency, with output increasing with the same production factors (Iglesias et al., 2012). This way, food crop prices can be lowered and produce competitive advantages in the global agricultural market.

Youth Unemployment Rate (YOU) significantly impacts TCA. In the long term, a 1% drop in YOU causes TCA to drop by -0.007. YOU have no significant impact on TCA in the short term. Many countries' economic success is at risk due to YOU. The agricultural sectors of European economies saw significant structural labour reforms in the years following World War II. On the one hand, economic growth and rising agricultural productivity have led to a continuous net labour outflow from agriculture. On the other hand, specialisation and changes in the demand structure and the scale of production have led to structural quantity and skills shifts in the demand for agricultural labour (Dries et al., 2012).

Long-term political instability (POL) will cause TCA to fall by 0.835. Like YOU, though, the POL variable does not affect TCA in the short term. One of the biggest obstacles to the development of European agriculture is POL. Low productivity and farmer income, inefficient farming businesses and firms, deteriorating environmental conditions and risks to the competitiveness and sustainability of European agriculture are all results of geopolitical problems and inaccurate political policymaking (Kravčáková Vozárová and Kotulič, 2025).

The following explanatory factors have a long-term impact on TCA: temperature change (TEMP) and bioenergy usage (BIO). TCA will decrease by -0.121 for every 1 0C TEMP increase and -0.000003 for every 1 TJ increase in BIO. The rise in TEMP will exacerbate the imbalance in water availability for crop production, intensify pest and plant disease attacks and accelerate agricultural land degradation (Yuan et al., 2024). Soil respiration increases with temperature and reducing ecosystems' carbon uptake. All of this leads to a sharp decline in agricultural competitiveness and productivity. Meanwhile, BIO will increase its price relative to conventional energy, thereby reducing production efficiency in the agricultural sector (Estevez et al., 2022).

Variable	Short run		Long run	
	Coeff.	Std. error	Coeff.	Std. error
GPI	0.00003*** -3.433	0.00001	0.00008*** -3.715	0.00002
AVA	-0.000001 (-0.231)	0.000004	-0.00001* (-1.704)	0.000007
CAP	0.00001 -1.2	0.00001	0.0001*** -4.268	0.00002
RER	-0.00001 (-0.735)	0.00002	0.00003 -0.763	0.00004
SCH	0.00001 -0.525	0.00002	0.00002 -0.749	0.00002
FEMA	-0.016 (-1.228)	0.013	-0.012 (-1.520)	0.008
MALE	0.005 -0.328	0.014	0.0005 -0.056	0.008
YOU	0.0007 -0.364	0.002	-0.007** (-2.377)	0.003
POL	-0.004 (-0.086)	0.044	-0.835*** (-10.342)	0.081
TEMP	0.003 -0.336	0.01	-0.121** (-2.999)	0.04
BIO	0.00000008 -0.216	0.0000004	-0.000003*** (-7.740)	0.0000007
RES	-0.03 (-0.457)	0.066	-0.072 (-1.622)	0.045
LOCK	0.015 -0.88	0.017	-0.468*** (-6.272)	0.074
C	-0.01 (-1.234)	0.008	1.469** -2.727	0.539
ECT(-1)	-0.099*** (-8.720)	0.011	-	-
Adj R^2	0.117		0.397	
F-stat	6.589***		32.381***	

Note: *** sig 0.01, ** sig 0.05 and * sig 0.1
Source: Own elaboration (2025)

Table 5: Determinant factors of EU member states' agricultural trade comparative advantage.

The primary variable in this study, landlocked (LOCK), significantly impacts TCA. The analysis's findings demonstrate that countries with seas are more competitive in the agricultural sector than landlocked countries. Next, a Propensity Score Matching (PSM) analysis was conducted to determine the differences of TCA value between landlocked and non-landlocked countries.

PSM requires a balancing test to ensure the model is consistent and does not introduce bias into the analysis results (Sseguya et al., 2021). The balancing test shows that the matching process has reduced bias by 86.41% (Table 6). Another indicator, pseudo R^2 after matching, is better than the pseudo R^2 value before the matching process.

Parameters	Value of Parameter
Pseudo R^2 Before Matching	0.14
Pseudo R^2 After Matching	0.47
Prob. LR chi^2 Before matching	0.00
Prob. LR chi^2 After matching	0.00
Mean Standardised Bias Before Matching	57.40
Mean Standardised Bias After Matching	7.80
Total % |Bias|Reduction	86.41

Source: Own elaboration (2025)

Table 6: Balancing test for matching based on the propensity score.

Impact evaluation analysis shows that LOCK harms agricultural trade competitiveness (Table 7). The landlocked decreased TCA value of 0.53. This is consistent with the ECM analysis, which indicates that LOCK reduces TCA.

Parameters	Value of Parameter
Treated	0.85
Control	1.38
Difference	-0.53
t-statistics	-3.19 ***

Note: *** Significant at 1% alpha (t-table = 2.33)
Source: Own elaboration (2025)

Table 7: Impact evaluation results.

The EU countries rely on cross-border maritime infrastructure to import and export commodities through ports in neighboring countries or to use transshipment services to send goods from the origin to the destination. Several European ports, such as Algeciras, Valencia and Marsaxlokk, have a high share of foreign throughout. In addition, the ports of Le Havre, Antwerp, Rotterdam, and Bremen handle the largest volumes of imports and exports, as they compete for trade to and from the Central European hinterland (Verschuur et al., 2022).

This study shows landlocked countries experience a decrease in competitiveness. Landlocked countries experience limited autonomy in their trade policies and are heavily influenced by neighboring countries with port access policies (Sharma, 2020). Meanwhile, countries with seaports tend to have lower trading costs. Trade costs have been shown to affect a country's export competitiveness and composition (Abdullahi et al., 2021). Landlocked countries face trade restrictions at their borders and must pay higher costs for loading, unloading, transportation, and other logistical costs (Chaudhary and Paudel, 2024). Landlocked countries have reported that uncertainty reduces agricultural competitiveness by forcing exporting firms to use more dependable but more costly forms of transportation, such as flights (Sharapiyeva et al., 2019). Consumers of imported goods must also pay higher prices due to higher land transportation costs from entering through alternative ports (Lane and Pretes, 2020). The higher trade costs reduce trade volumes and overall competitiveness, posing challenges to maintaining strong economic growth (Chaudhary and Paudel, 2024).

Additionally, all trade in goods will pass through customs at the border. When border customs are backed up due to increased product volume, this can lead to transport delays. These processes make the situation less predictable and delay the delivery of goods (Sharapiyeva et al., 2019). This will be a problem for perishable agricultural products, thereby reducing their competitiveness.

There is also evidence of the detrimental impact of permanent shocks on landlocked countries, including a decline in goods production by -2% annually, consumption and social welfare, and aggregate investment by -7% (Rivero et al., 2020). This situation can worsen when a landlocked country conflicts with a neighboring country. For instance, Nepal is a landlocked country that depends heavily on India for imports and exports because it can access only the seaport of Kolkata. Political concerns prevented Nepal from accessing ports in 1969, 1989, and 2015 due to India's monopoly over Nepal's maritime access (Adhikari and Ma, 2022).

The landlocked position is also a barrier to economic integration and FDI entry. A study by Kasimov et al. (2024) shows that landlocked countries in the Commonwealth of Independent States have difficulty attracting FDI. These countries have a smaller FDI proportion of 56.8% than coastal countries in the same area. One obstacle to economic activity, including agriculture, is the difficulty of attracting FDI, which results in suboptimal production and low competitiveness. The study from Liu et al. (2023) suggests otherwise, China is more eager to deploy FDI to landlocked countries with underdeveloped infrastructure and logistics capabilities because these countries frequently face greater uncertainty. However, this context is not ideal in the EU, which is generally wealthy despite having little access to the sea.

The EU region can overcome the detrimental effects of landlocked conditions due to its strong institutional economics. Institutional economics focuses on how governance frameworks and institutional quality influence the economic results of landlocked countries (Chaudhary and Paudel, 2024). Institutional economics is the most effective means of mitigating various shocks in landlocked countries, reducing them by up to 68% and improving their economic performance (Rivero et al., 2020). Furthermore, strong institutional economics will promote trade relationships for landlocked countries. Initiatives to lower trade and market access restrictions are part of the deal, which will increase supply chains and competitiveness (Chaudhary and Paudel, 2024).

From the study findings, five explanatory variables—the real effective exchange rate (RER), school enrollment (SCH), female employment in agriculture (FEMA), male employment in agriculture (MALE) and research and development expenditure (RES)—do not significantly affect TCA in the short or long term.

Conclusion

Landlocked countries in the EU, such as Austria, the Czech Republic, Hungary, Luxembourg, and Slovakia, are less competitive than non-landlocked countries. This study's findings align with Porter's Diamond Theory, which holds that factor conditions influence competitiveness. Landlocked countries face unfavorable geographic conditions because their agricultural products must transit through other countries. This results in higher transportation costs and product prices. Meanwhile, this study shows the importance of more efficient economies of scale in landlocked countries to increase competitiveness, as the New Trade Theory expresses.

Landlocked conditions pose challenges for EU Member States and require tailored strategies. One of the main strategies is improving the supply chain. Based on Institutional Economics Theory, this strategy will be easy to implement in the EU, considering integration between member states already exists. The mobility of agricultural products should make it easier to enter and exit neighboring countries with seas. However, the EU must map the distribution flow of agricultural product supply chains between countries. This mapping needs to be complemented by additional intervention steps, such as identifying raw materials and consumer demand sources, distribution networks and logistics infrastructure.

Several factors in this study indicate the potential to increase agricultural competitiveness by boosting capital and production. However, this study also indicates that the EU Member States' agricultural competitiveness will be reduced due to temperature change, political instability and rising youth unemployment.

In general, EU Member States must also take several steps to improve agricultural competitiveness, including 1) increasing agricultural production through agricultural intensification and adoption of modern technology (precision farming, IoT and big data); 2) increasing agricultural investment by ensuring that the Common Agricultural Policy provides subsidies for innovation, farmer empowerment and research collaboration; 3) massive climate change mitigation and adaptation through the development of climate-resistant crop varieties, sustainable agricultural practices and optimisation of water use; 4) selection of bioenergy from non-agricultural raw materials, such as solar/wind-powered farms, which use clean energy for agricultural operations and reduce dependence on fossil fuels; 5) creating political stability within the EU Member States by strengthening EU cooperation, democracy and the rule of law and 6) increasing youth participation in agriculture through agricultural education and training in schools, access to land and capital and pro-young farmer EU policies.

Although this study can holistically capture several phenomena that affect agricultural competitiveness, it must be improved to capture current phenomena. This study did not examine differences across countries, so future studies can use FMOLS or DOLS to assess the influence of domestic factors on agricultural competitiveness. Further studies also need to address the development of information technology to improve agricultural competitiveness. The role of this technology is to facilitate coordination between actors engaged in farm businesses, thereby increasing their competitiveness. Another condition that other researchers should consider is the logistics infrastructure indicator, given its vital role in improving competitiveness. Further studies should expand their scope to include regions such as Africa, Asia, and the Americas to comprehensively examine the impact of landlockedness on agricultural competitiveness.

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European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI): Systematic Literature Review and Future Research Agenda

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Abstract

This systematic literature review synthesizes current knowledge on the European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI) by analyzing 31 peer-reviewed studies published between 2013 and 2025. The review identifies three interconnected research directions: implementation mechanisms and governance structures, multi-actor collaboration and knowledge co-creation processes, and impact assessment. Findings reveal substantial heterogeneity in national and regional governance approaches, with critical structural barriers including horizontal and vertical fragmentation, inadequate funding, and compartmentalized implementation. The research highlights the importance of boundary-spanning actors, trust-building mechanisms, and structured facilitation in enabling effective multi-actor collaboration. Evidence suggests that EIP-AGRI contributes to sustainable agricultural innovation through enhanced knowledge exchange and network formation; however, impact assessment remains challenging due to methodological limitations and temporal constraints. The review establishes a future research agenda that emphasizes longitudinal evaluation, cross-country comparative analysis, and the potential for systemic transformation.

Keywords

EIP-AGRI, agricultural innovation systems, multi-actor collaboration, operational groups, interactive innovation.

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Introduction

The European Innovation Partnership for Agricultural Productivity and Sustainability (EIP-AGRI), established in 2012 as part of the Europe 2020 Flagship Initiative "Innovation Union," represents a paradigm shift in European agricultural innovation policy (Cioloş and Geoghegan-Quinn 2013). This initiative aims to bridge the gap between agricultural research and practice through an interactive innovation approach, fundamentally challenging the traditional linear model of knowledge transfer. The EIP-AGRI framework operates through Operational Groups (OGs), which bring together farmers, researchers, advisors, businesses, and other stakeholders to co-create innovative solutions addressing real-world agricultural challenges (Arzeni et al., 2023; Fieldsend et al., 2021).

Since its inception, EIP-AGRI has generated substantial scholarly attention, with researchers examining various dimensions of its implementation, effectiveness, and transformative potential. This review synthesizes findings from 31 peer-reviewed studies published between 2013 and 2025, revealing three distinct yet interconnected research directions that have emerged in the literature: (1) implementation mechanisms and governance structures, (2) multi-actor collaboration and knowledge co-creation processes, and (3) impact assessment and effectiveness evaluation. Each direction addresses critical questions about how this innovation framework operates in practice, its capacity to facilitate genuine collaboration, and its contribution to agricultural sustainability and competitiveness.

Within the EIP-AGRI literature, the concept of 'innovation' carries varied meanings, reflecting both the breadth of the initiative and divergent theoretical framings. At the most general level, the European Commission defines innovation in EIP-AGRI as the introduction of new or significantly improved products, processes, or organisational methods in agricultural practice or along agri-food value chains. However, the reviewed studies employ a spectrum ranging from narrow technical innovation (e.g., fertiliser management optimisation, new crop varieties) to broader process innovations (co-creation mechanisms, brokerage practices, governance models) and systemic innovations (transformative changes to Agricultural Knowledge and Innovation Systems). For the purposes of this review, we adopt an inclusive understanding of innovation that encompasses all three levels, while distinguishing between them when interpreting findings, particularly in relation to impact assessment, where the type of innovation strongly conditions the measurability and timeframe of outcomes.

This review aims to synthesize the current state of knowledge on EIP-AGRI by systematically analyzing peer-reviewed literature to identify key research directions, evaluate the effectiveness of implementation mechanisms across different European contexts, and establish a research agenda for strengthening multi-actor collaboration and innovation outcomes in agricultural systems

Material and methods

This review article employed a systematic literature search to identify and analyze relevant publications addressing the EIP-AGRI. The search strategy was designed to capture peer-reviewed articles that discuss the implementation, outcomes, and impacts of EIP-AGRI initiatives across European Union member states.

The literature search was conducted in two major citation databases: Web of Knowledge and Scopus. These databases were selected due to their comprehensive coverage of academic literature in the fields of agricultural sciences, innovation studies, and rural development. The search query utilized the Boolean operator "AND" to combine the keywords "EIP" and "AGRI", ensuring that retrieved publications addressed both the innovation partnership framework and its agricultural focus. The search was restricted to the document type "article" to maintain focus on peer-reviewed research contributions. The keyword search was applied across three bibliographic fields: article titles, author-assigned keywords, and abstracts, thereby capturing publications where EIP-AGRI featured as either a central focus or a significant component of the research.

The initial search yielded 30 articles from the Web of Knowledge database and 34 articles from the Scopus database. Following the identification of potentially relevant publications, all retrieved articles underwent a detailed assessment of their relevance. This screening process evaluated whether each publication substantively addressed EIP-AGRI themes, implementation experiences, or related policy mechanisms. Articles that mentioned the keywords only peripherally or in unrelated contexts were excluded from further analysis. Table 1 demonstrates the selection process.

PRISMA Stage	Action	Records
Identification	Records identified in Web of Knowledge (search: EIP AND AGRI, article type)	30
Identification	Records identified in Scopus (search: EIP AND AGRI, article type)	34
Identification	Total records before deduplication	64
Screening	Duplicates removed	17
Screening	Records after deduplication	47
Screening	Records excluded after title/abstract screening (peripheral mention)	16
Eligibility	Full-text articles assessed for eligibility	31
Eligibility	Articles excluded after full-text review	0
Included	Final corpus for in-depth content analysis	31

Source: authors

Table 1: PRISMA-style study selection flow.

After completing the relevance screening and removing duplicate entries appearing in both databases, a final corpus of 31 articles was compiled for in-depth content analysis. Authors applied explicit inclusion/exclusion criteria:

Inclusion criteria:

- Published in peer-reviewed journals or conference proceedings indexed in Web of Knowledge or Scopus.
- Document type: article (no editorials, book chapters, grey literature, or policy reports).
- Keyword 'EIP' AND 'AGRI' present in title, abstract, or author keywords.
- Substantive empirical or conceptual treatment of EIP-AGRI - not merely peripheral mention.

- No temporal restriction (to capture full trajectory since 2010 inception).
- No ranking restriction to Q1/Q2 journals.

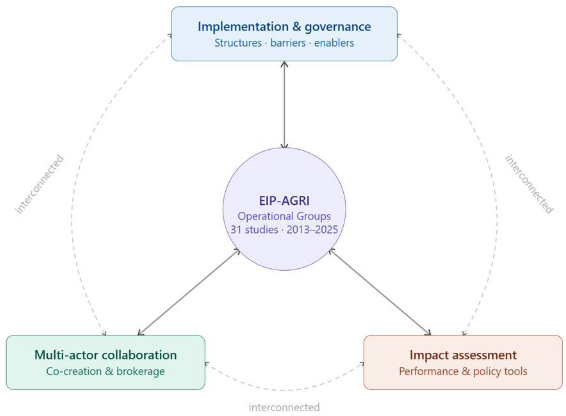
Exclusion criteria:

- Articles in which EIP-AGRI appears only in references or as a passing footnote.
- Duplicate entries across the two databases (removed after deduplication).
- Non-English articles without available English abstract sufficient for assessment.

The selected 31 articles were subjected to qualitative content analysis using an inductive thematic coding approach. Each article was read in full and coded along the following dimensions: (1) primary research topic and stated objectives, (2) conceptualisation of EIP-AGRI and of innovation, (3) governance structures and actor roles described, (4) key empirical findings, (5) identified barriers and enabling factors, and (6) policy recommendations. Initial codes were generated openly and subsequently grouped into broader themes using constant comparison. Three iterative rounds of coding were conducted to ensure consistency and to resolve ambiguities. The resulting themes were compared across studies to identify convergences, divergences, and research gaps, providing the basis for the three research directions reported under Results and Discussion and for the future research agenda articulated in the Conclusions section.

Results and discussion

Figure 1 presents a hub-and-spokes conceptual framework illustrating the three interconnected research directions identified in this systematic review. EIP-AGRI and its Operational Groups occupy the central position, reflecting their role as the primary unit of analysis across all 31 reviewed studies published between 2013 and 2025. Three research directions radiate outward from this hub: implementation mechanisms and governance structures (top), multi-actor collaboration and knowledge co-creation (bottom left), and impact assessment and effectiveness evaluation (bottom right). The solid bidirectional spokes connecting the hub to each direction indicate that EIP-AGRI both operates through and is continuously shaped by each of these research domains - governance arrangements condition what kinds of collaboration are possible, collaboration processes in turn influence how implementation is adapted at the local level, and the outcomes captured through impact assessment feed back into both governance redesign and collaborative practice. The dashed bidirectional arcs linking the three directions to one another reflect a second layer of interdependence: the quality of multi-actor collaboration directly affects the measurability and magnitude of impacts, while evaluation findings inform the institutional conditions under which governance structures are reformed. Equally, governance fragmentation - one of the most consistently documented structural barriers in the reviewed literature - constrains both the depth of co-creation processes and the capacity to conduct robust longitudinal impact assessments. The framework is therefore not hierarchical but cyclical, suggesting that advances in understanding EIP-AGRI require simultaneous attention to all three directions rather than isolated investigation of any single one.



Source: authors

Figure 1: Research directions.

Research direction: implementation mechanisms and governance structures

The first major research direction addresses how EIP-AGRI has been translated from EU policy into national and regional implementation frameworks. This stream of literature reveals substantial variation in governance approaches and highlights critical structural factors that enable or constrain the interactive innovation model.

National and Regional Governance Approaches

The implementation of EIP-AGRI across European member states demonstrates considerable heterogeneity in governance structures and regulatory frameworks. Giarè and Vagnozzi (2021) conducted a comparative analysis of four Italian regions (Veneto, Emilia-Romagna, Umbria, and Basilicata), revealing that regional governance significantly affects crucial dimensions of the EIP-AGRI approach, including co-creation between research and practice, centrality of farm needs, promotion of networks, and interactive action among innovation actors. Their findings indicate that while all examined regions demonstrated substantial consistency with the interactive approach emerging from international literature, they employed different methods and degrees of consistency, with some factors clearly implemented through adequate rules and criteria, while others lacked appropriate implementation mechanisms.

Similar governance challenges emerge in other national contexts. Eckerberg et al. (2023) critically examined Sweden's implementation of EIP-AGRI, finding that despite expectations for cross-sectoral collaboration, implementation rests on compartmentalized networking within the agricultural sector, prioritizing increased competitiveness over environmental development, and interpreting innovation mainly in technical rather than systemic terms. This Swedish case illustrates how state steering capacity faces obstacles when overall policy goals from the top are both too numerous and too vague, leaving administration to interpret which features should be prioritized from below. Contrary to previous research suggesting that European agricultural policymaking has recently become more integrated, the Swedish case demonstrates that steering relies mostly on internal agricultural expertise.

System failures and structural barriers

Beyond governance design, research has identified fundamental system failures that impede effective EIP-AGRI implementation. Stoeva and Pickard (2020) applied system innovation theory to examine the capacity of Bulgarian agricultural policy to implement the interactive innovation approach, revealing a low potential to address limited cooperation and knowledge transfer among science, farms, and other institutions. Their analysis, viewed through the lens of the system failures concept, exposed misalignments between top-down programming and bottom-up understandings of interactive innovation among Agricultural Knowledge and Innovation System (AKIS) actors.

Hermans et al. (2015) adapted the Innovation System Failure Matrix to investigate structural conditions across eight European countries (England, France, Germany, Hungary, Italy, Latvia, the Netherlands, and Switzerland), identifying lack of funds combined with horizontal and vertical fragmentation as among the most important threats to effective collaboration in innovation networks. Their study emphasized that the lack of proper evaluation criteria for collaborative innovation networks represents a significant structural barrier. The research demonstrates that each national Agricultural Innovation System (AIS) possesses unique features, necessitating that implementation of policies promoting collaboration and social learning depend on critical reflection of existing structural elements and whether certain innovations for collective goods should be promoted.

Prerequisites and enabling conditions

Research has also identified positive conditions that facilitate successful implementation. Kruzmetra et al. (2021) identified eight prerequisites for promoting the development of innovation projects in agriculture, based on an analysis of the views of European Innovation Partnership project managers in Latvia. Their findings emphasize the importance of institutional support, adequate funding mechanisms, and capacity building among innovation actors. Similarly, Maziliauskas et al. (2018) employed force field analysis to examine external and internal factors influencing EIP effectiveness in Lithuania, revealing that negative factors outnumbered positive factors. However, they also identified factors that enable the timely identification of potential negative consequences and opportunities to predict project effectiveness.

The German experience, documented by Göbel et al. (2022), provides insights into how comprehensive support structures can enhance implementation. Their analysis of over 320 EIP projects implemented since 2014 demonstrates how continuous exchange between science and practice, supported by innovation service providers, can accelerate knowledge transfer and establish new innovation culture for the agricultural sector. The Portuguese case study by Oliveira et al. (2019) in the Lis Valley Irrigation District further illustrates implementation challenges, particularly highlighting how restrictive concepts of innovation within Rural Development Programs may fail to embrace the full range of activities intended within AKIS frameworks.

Regional variations and context specificity

The literature consistently emphasizes that effective implementation requires attention to regional specificities and local contexts (Table 2).

Agricultural system type	Regional context	Key implementation barriers	Key enabling factors
Intensive arable farming	Emilia-Romagna (IT)	Short timeframes for environmental outcomes, reluctance to adopt soil management changes	Strong governance; propensity score matching evaluation
Mixed/organic farming	Italy (national)	Fragmented topics, underfunding (<0.1% of sector value)	Multi-disciplinary projects; multi-actor approach recognition
Grassland systems	8 EU member states	Cross-border knowledge gaps, language barriers	Thematic network; farmer-to-farmer exchange (Inno4Grass)
Dairy/bioeconomy	Ireland	Farmer passivity in decision-making; segmented actor roles	Social network structure; clear OG coordinators
Protein crops (arable)	EU-wide (11 countries)	Market structure constraints; cultural factors	EIP consultation process with experts
CEE agricultural sectors	Central & Eastern Europe	Structural disadvantage in R&I; productivity gaps vs. EU-15	Greater structural support needed; context-specific approaches
Wine sector	Italian regions	Regional governance heterogeneity; coordination deficits	Mixed-methods facilitation; stakeholder perception mapping

Source: authors

Table 2: Contextual factors and OG success.

Pokrivčák et al. (2019) examined perspectives from Central and Eastern European countries, arguing that despite evident productivity gaps between EU-CEE and EU-15 farms, greater support for research and innovation is not a priority for EU-CEE countries due to structural differences in agricultural sectors and comparative disadvantage in research and innovation relative to more developed EU countries. This finding challenges the assumption of the universal applicability of innovation support mechanisms and highlights the importance of contextualizing EIP-AGRI implementation within broader agricultural and economic development trajectories.

Costantini et al. (2020) further emphasized the necessity of local adaptation strategies for addressing specific agricultural challenges, demonstrating how soil organic carbon management under arable farming requires techniques tailored to local conditions, including combinations of environmental factors (climate and soil characteristics), farming systems (land use type, farm specialization, crop management), and social and cultural contexts (market conditions, subsidies, farmers' education, and propensity for innovation). Their case studies across Europe illustrate how OGs must be designed to facilitate local adaptation rather than imposing standardized solutions.

Table 3 synthesises the contextual factors shaping EIP-AGRI Operational Group implementation across twelve distinct agricultural systems and regional settings documented in the reviewed literature. Reading across the barrier column, several challenges recur irrespective of context: funding constraints, fragmented governance, short project timeframes, and difficulties in measuring outcomes beyond the project period appear in studies from Bulgaria and Sweden as much as from Ireland and Italy, suggesting that these are structural features of the EIP-AGRI framework itself rather than local anomalies. The enabling factors column tells a different story: the conditions that support successful OG implementation - from results-based payment design in Irish high-nature-value areas to thematic network infrastructure for cross-border grassland innovation - tend to be specific to the agricultural system, institutional setting, and local knowledge base in question. This asymmetry has a direct policy implication: while structural barriers may be addressable through common EU-level reforms, enabling conditions cannot be transplanted wholesale from one context to another but must be designed in response to the particular combination of farming system characteristics, regional governance capacity, and actor relationships present in each setting.

Agricultural system type	Country / region	Key study/studies	Key implementation barriers	Key enabling factors
Intensive arable farming	Emilia-Romagna, Italy	Bonfiglio (2023)	• Short project timeframes prevent environmental outcomes from becoming measurable • OG participation does not reduce pesticide use, energy, or water consumption • Difficulty distinguishing genuine innovation from conventional farm practices	• Propensity score matching provides a replicable counterfactual evaluation design • Performance-based conditionality (ex-ante plans, ex-post reporting) recommended as systemic fix • OG participation positively associated with fertiliser efficiency and farm profitability
Mixed and organic farming systems	Italy (national level)	Canali et al. (2020); Arzeni et al. (2023)	• Research and innovation funding scattered across topics, disciplines, and supply chains • Funding extremely limited (<0.1% of sector value for R&I; <10% of available RDP funds for OGs) • Low internal and external communication reduces OG effectiveness • Limited dissemination of results to broader farming community	• Relatively high share of multi- and interdisciplinary projects • Multi-actor approach recognised as fundamental step toward co-research and co-innovation • OG implementation helps capture real farmer and rural entrepreneur issues
Diverse farming systems (regional governance focus)	Veneto, Emilia-Romagna, Umbria, Basilicata (Italy)	Giarè and Vagnozzi (2021)	• Significant regional variation in how co-creation, farm-centricity, and networking are operationalised • Some governance factors implemented through adequate rules; others lack appropriate mechanisms • No standardised quality criteria for OG governance across regions	• All four regions demonstrate substantial consistency with interactive innovation principles • Regional governance can be designed to reinforce co-creation between research and practice • Comparative regional analysis reveals which governance dimensions are most transferable
Productionist/ commercial agriculture (competitiveness-oriented)	Sweden (national level)	Eckerberg et al. (2023)	• Implementation compartmentalised within agricultural sector; cross-sectoral collaboration absent • Innovation interpreted primarily in technical terms; systemic and environmental innovation sidelined • Policy goals from EU level too numerous and vague; national administration forced to prioritise selectively • Governance relies on internal agricultural expertise rather than broader AKIS integration	• Explicit mission-oriented framing could redirect implementation toward sustainability transitions • Documented as a cautionary case highlighting risks of narrowing innovation scope in national programming
Post-socialist/ transitional agricultural systems	Bulgaria (national level)	Stoeva and Pickard (2020)	• Low institutional capacity to implement interactive innovation approach • Limited cooperation and knowledge transfer among science, farms, and other AKIS actors • Misalignment between top-down EU programming and bottom-up understanding of interactive innovation • System failures across multiple dimensions: infrastructure, institutions, interactions, capabilities	• System innovation theory (Innovation System Failure Matrix) provides a structured diagnostic tool • Identifying specific system failures enables targeted rather than generic policy responses
Diverse national Agricultural Innovation Systems	England, France, Germany, Hungary, Italy, Latvia, Netherlands, Switzerland	Hermans et al. (2015)	• Lack of funds combined with horizontal and vertical fragmentation: most frequently cited threats • Absence of proper evaluation criteria for collaborative innovation networks • Each national AIS has unique features that prevent uniform policy transfer	• Innovation System Failure Matrix adapted as a cross-country analytical tool • Critical reflection on existing structural elements before introducing collaboration policies • Differentiated support for collective goods innovation vs. private innovation activities

Note: Barriers and enablers are drawn directly from the findings reported in the cited studies. Where a study addresses multiple themes, only those findings pertaining to contextual factors and OG implementation are included. Studies reporting primarily on methodological contributions (e.g. Baranauskienė et al. 2021; Maziliauskas et al. 2018) are not included in this table as they do not report context-specific implementation findings.

Source: authors

Table 3: Agricultural system type, regional context, and key contextual factors shaping EIP-AGRI Operational Group implementation. (to be continued).

Agricultural system type	Country / region	Key study/studies	Key implementation barriers	Key enabling factors
Permanent grassland and forage systems	8 EU member states (Inno4Grass network)	Krause et al. (2021)	• Cross-border knowledge gaps and language differences complicate multi-country exchange • Grassland-related knowledge often not tailored to local conditions • Extension services, education, and research historically work in silos	• Thematic network model creates collaborative spaces across national boundaries • Farmer-led idea collection stimulates bottom-up innovation agenda • Farmland-specific information management systems support local knowledge adaptation
Dairy farming and bioeconomy value chains	Ireland	Harrahill et al. (2022); McCarthy et al. (2021)	• Farmers highly connected but exert limited influence in decision-making in certain OG areas • Segmented actor roles: farmers contribute as input suppliers while scientists handle technical aspects • Depth and quality of knowledge integration remains questionable despite multi-actor structure	• Social network analysis reveals actor connectedness and relative influence - actionable diagnostic • Assemblage-based framing captures how actor motivations emerge from relational context • Diverse actor motivations can be mobilised if OG design allows anticipation of future scenarios
Viticulture and wine value chains	Italian regions (multiple)	Mignani et al. (2025)	• Regional governance heterogeneity creates uneven OG quality across wine-producing areas • Coordination and facilitation deficits limit knowledge network density • Perceived barriers to innovation identified through stakeholder perception surveys	• Mixed-methods approach (quantitative + qualitative) provides richer picture of OG performance • Sector-specific OG design allows addressing viticulture-specific challenges • Best practices identified for enhancing EIP-AGRI policies at regional, national, and EU levels
Structurally disadvantaged agricultural sectors	Central and Eastern European countries (EU-CEE)	Pokrivčák et al. (2019)	• Persistent productivity gap between EU-CEE and EU-15 farms not easily addressed by innovation support • Greater R&I support not a declared priority in CEE due to structural disadvantage • Comparative disadvantage in research and innovation capacity relative to more developed EU countries	• Recognition that universal innovation support mechanisms are not appropriate for all contexts • Contextualising EIP-AGRI within broader agricultural and economic development trajectories is essential
Arable farming systems (soil management focus)	Multiple European case study sites	Costantini et al. (2020)	• Soil organic carbon management requires combinations of climate, soil, and social factors - standardised solutions fail • Local adaptation constrained by land use type, farm specialisation, market conditions, and farmer education • Cultural factors and propensity for innovation vary considerably across sites	• OG design that facilitates local adaptation rather than imposing standardised solutions • Integration of environmental, farming system, and social/cultural contextual variables into OG scoping • Cross-European case studies reveal which adaptation strategies are transferable and which are context-bound
Extensive/high-nature-value farming in designated areas	Aran Islands, Hen Harrier areas, Pearl Mussel catchments (Ireland)	McLoughlin et al. (2020)	• Conventional output-based payments fail to incentivise habitat quality maintenance • Biogeographical specificity makes generalisation of payment schemes difficult • Environmental outcomes require longer timeframes than standard project cycles	• Results-based payment approach rewards habitat quality as surrogate for ecosystem services • Adaptive management tailored to specific biogeographical areas • Wide range of ecosystem services (biodiversity, carbon, water, flood resilience) deliverable simultaneously

Note: Barriers and enablers are drawn directly from the findings reported in the cited studies. Where a study addresses multiple themes, only those findings pertaining to contextual factors and OG implementation are included. Studies reporting primarily on methodological contributions (e.g. Baranauskienė et al. 2021; Maziliauskas et al. 2018) are not included in this table as they do not report context-specific implementation findings.

Source: authors

Table 3: Agricultural system type, regional context, and key contextual factors shaping EIP-AGRI Operational Group implementation. (Continuation).

Figure 2 distils the same contextual variation into a two-dimensional framework, contrasting governance capacity with innovation ambition level to reveal four distinct national implementation patterns.

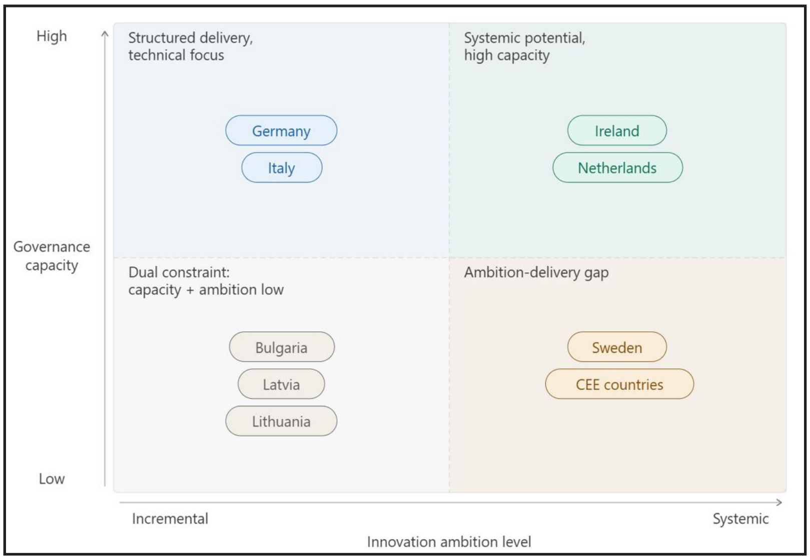


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Figure 2: National EIP-AGRI implementation patterns by governance capacity and innovation ambition level.

The matrix positions eight country cases across the four quadrants, and each pill is clickable for deeper discussion. The quadrant logic follows directly from the reviewed literature:

Top-left (high governance, incremental) - Germany and Italy represent contexts with well-developed institutional support structures and strong OG governance, but where innovation is pursued in technical and productivity terms rather than as systemic change. Germany's 320+ EIP projects operate within a dense advisory infrastructure; Italy's Emilia-Romagna case shows measurable farm-level improvements yet limited environmental transformation.

Top-right (high governance, systemic) - Ireland and the Netherlands anchor the "ideal" quadrant. Ireland's results-based payment schemes and bioeconomy-oriented OGs reflect genuine systemic ambition backed by institutional capacity; Hermans et al. (2015) identify the Netherlands as among the higher-capacity national AIS in their eight-country comparison.

Bottom-left (dual constraint) - Bulgaria, Latvia, and Lithuania face low governance capacity and limited innovation ambition simultaneously, with Stoeva and Pickard (2020) diagnosing systemic failures across multiple AIS dimensions in Bulgaria, while Kruzmetra et al. and Maziliauskas et al. document that enabling prerequisites are largely absent in the Baltic states.

Bottom-right (ambition-delivery gap) - the most theoretically instructive quadrant. Sweden enters with explicitly systemic, green-transition policy goals but delivers compartmentalised, technically narrow implementation (Eckerberg et al. 2023). CEE countries as a group show the reverse problem: structural disadvantage suppresses both governance capacity and the political appetite for systemic innovation ambition (Pokrivčák et al. 2019).

Research direction: multi-actor collaboration and knowledge co-creation

The second major research direction examines the collaborative dynamics within EIP-AGRI initiatives, focusing on how diverse actors interact, share knowledge, and co-create innovations. This body of literature interrogates the fundamental premise of the multi-actor approach and assesses whether it achieves its intended goal of bridging the gap between research and practice.

Theoretical foundations and implementation of the multi-actor approach

The multi-actor approach represents a core principle of EIP-AGRI, premised on the assumption that heterogeneous groups of actors with complementary expertise can effectively co-create and share knowledge (Arzeni et al. 2023). Feo et al. (2022) examined how Horizon 2020 Thematic Networks operationalize this approach, revealing that not all types of actors are equally involved in consortium and participatory activities. This suggests that networks may not be sufficiently demand-driven, and the uptake of results may be suboptimal. Their analysis of multiple thematic networks demonstrated that facilitators play key roles in contributing to relationships and mutual understanding among different actors, while user-friendly digital knowledge platforms linked to demonstration activities and peer-to-peer exchange can enhance knowledge sharing and improve long-term impact.

Fieldsend et al. (2021) provided a comprehensive assessment of user involvement across 200 diverse European Union-funded and non-EU multi-actor partnerships, revealing that all reviewed policy instruments, not just those funded within EIP-AGRI, can be used to involve users in co-innovation in agriculture, forestry, and related value chains. Their research demonstrated that EIP-AGRI constitutes just one part of a complex matrix of multi-actor co-innovation activities involving farmers and foresters in Europe, with many effective methods of supporting co-innovation "sharing the space" within AKIS. The diversity of collaborative structures extends beyond traditional business-to-business models to include business-to-consumer, consumer-to-business, and hybrid relationships, facilitating mutual learning, innovation, and value co-creation that is crucial for the resilience and adaptability of local food systems.

Hauggaard-Nielsen et al. (2021) documented a practical workshop approach for translating the multi-actor approach into research practice, involving 63 participants from an EU H2020 project on species mixtures. Their methodology involved researchers who were mostly unfamiliar with participatory approaches, engaging them in direct interaction with eight actor positions within an agri-food cooperative value chain. The workshop format proved effective in gaining a common understanding of pertinent issues, though expressions of frustration served both as motivation for group members to become more aware of colleagues' scientific concerns and as recognition that some researchers possess better skills in integrating qualitative approaches than others. This study emphasized that working with actor networks was identified as an essential means to overcome existing barriers between academia and practice.

Knowledge integration and co-creation processes

The effectiveness of multi-actor collaboration depends substantially on mechanisms for integrating different forms of knowledge. Müller and Riekötter (2025) examined knowledge integration within EIP-AGRI Operational Groups in Rhineland-Palatinate, Germany, employing communities of practice theory to analyze broker practices, knowledge integration mechanisms, and enabling conditions for co-creation. Their findings revealed that innovation brokers function as knowledge orchestrators, facilitating integration through adaptive facilitation, multi-modal translation, and network cultivation. Successful OGs demonstrated characteristics of communities of practice, including mutual engagement, joint enterprise, and shared repertoire. Key enabling conditions included trust-building, process transparency, and field-based co-learning, while challenges encompassed administrative delays, institutional silos, and rigid regulations.

The co-creation process requires not merely bringing actors together but establishing genuine conditions for collaborative knowledge production. Mosquera-Losada et al. (2025) analyzed 28 Horizon 2020 thematic networks to understand how the deployment of innovation is associated with EU land uses, implementation areas, and farming types. Their results indicated that thematic networks primarily focus on arable lands across all farming types, with most concentrating on rural areas and addressing bioeconomy topics by linking rural, peri-urban, and urban areas. The analysis demonstrated how a multi-actor approach to projects can provide insights into expanding agricultural innovation by identifying underrepresented areas of study and practice, thereby promoting them in future initiatives.

Krause et al. (2021) described a novel approach for creating collaborative spaces for grassland innovations through the Inno4Grass thematic network across eight European member states. Their methodology serves to collect farmers' innovative ideas and stimulate collaboration among various stakeholders, including farmers' groups, extension services, education, and research, even across borders. This interactive innovation model promotes knowledge exchange and establishes farmland-specific information management systems, aiming to stimulate a renewed collaborative innovation culture for EU grasslands, where grassland-related knowledge is tailored to local conditions.

Power dynamics and actor participation

A critical examination of multi-actor collaboration reveals significant power asymmetries and differential participation among the actors. Harrahill et al. (2022) analyzed Irish dairy farmers' participation in a bioeconomy-focused EIP-AGRI Operational Group, employing power theory to explore how farmers' knowledge shaped OG development and innovation. Their social network analysis illustrated diverse actors involved, their relative degrees of connectedness, and differing levels of influence. While farmers were highly connected with other members and viewed their involvement positively, their influence in decision-making processes in certain OG areas was relatively limited. Different member types tended to work in relatively segmented ways, with farmers contributing as input suppliers at the farm level while scientists worked on more technical aspects. This segmentation raises questions about the depth and quality of knowledge integration achieved through the multi-actor approach.

McCarthy et al. (2021) explored the motivations of actors who established and coordinated a collaborative group within an Irish EIP-AGRI initiative, including three farmers, an agri-environmental policy advocate, and a research scientist. Drawing on assemblage literature, they illustrated how each actor's motivations emerged based on specific relationships in which they operated and on their imagining of potential future scenarios they sought to actualize through EIP-AGRI. This qualitative account illustrates how motivations emerge as different actors creatively navigate complex sets of relationships, revealing that the capacity of collaborative approaches to appeal to actors from diverse backgrounds relies heavily on actors' ability to envision and anticipate new possibilities.

The role of intermediaries and innovation brokers

Research increasingly recognizes the crucial role of intermediaries and innovation brokers in facilitating effective multi-actor collaboration. Piñeiro et al. (2021) identified innovation intermediary functions of Spanish Operational Groups through exploratory factor analysis of member survey responses, revealing that Spanish OGs perform three main functions: innovation process management, demand articulation, and institutional support and innovation brokering. These findings suggest that OGs serve not merely as vehicles for project implementation, but also as innovation intermediaries, performing complex facilitation and coordination roles.

The importance of skilled facilitation emerged across multiple studies. Mignani et al. (2025) examined the role of EIP-AGRI Operational Groups as drivers of innovation in the wine sector across Italian regions, employing a mixed-methods approach to analyze stakeholders' perceptions. Their research addressed the extent to which OGs serve as drivers of innovation, provide networks fostering knowledge exchange, and identified perceived barriers to innovation. The study offers valuable insights and best practices for enhancing EIP-AGRI policies at regional, national, and European levels, highlighting the crucial role of effective coordination and facilitation in achieving innovative outcomes.

Challenges in achieving genuine collaboration

Despite the theoretical appeal of multi-actor collaboration, research documents significant challenges in achieving genuine co-creation. Arzeni et al. (2023) found that while the implementation of OGs in Italy helped capture real issues faced by farmers and rural entrepreneurs, it also supported the creation and strengthening of relationships between partners. However, low levels of internal and external communication, as well as a lack of efforts to disseminate results, reduced group effectiveness. Their analysis revealed the complexity of describing processes triggered by the interactive approach, which is influenced by the relationship types existing between partners and external factors. They recommended that the implementation of the next generation of OGs could be strengthened by improving the capacity to address issues of large groups of farmers, promoting the presence of intermediaries to facilitate dialogue between partners, and facilitating the active participation of advisors.

Stoeva et al. (2024) analyzed 14 short food supply chain initiatives across Europe to understand the dynamics of collaboration, identifying seven key interaction mechanisms: information sharing, decision synchronization, goal congruence, incentive alignment, resource sharing, joint knowledge creation, and collaborative communication. Their findings demonstrated that collaborations operate as dynamic ecosystems characterized by complex interdependencies among diverse actors, with the presence of robust interaction mechanisms essential for fostering effective partnerships and generating relational benefits. However, not all mechanisms were consistently present in every type of collaborative relationship, suggesting variability in the quality and depth of collaboration across different initiatives.

Research direction: impact assessment and effectiveness evaluation

The third major research direction addresses fundamental questions about EIP-AGRI's effectiveness and impact. This stream of literature employs diverse methodological approaches to assess whether the initiative achieves its stated objectives of enhancing agricultural productivity, sustainability, and competitiveness. Research in this area reveals both promising outcomes and significant challenges in measuring and attributing impacts.

Economic and environmental performance assessment

Rigorous impact assessment requires comparing the performance of participating farms with appropriate counterfactuals. Bonfiglio (2023) conducted one of the most methodologically sophisticated analyses, applying propensity score matching techniques to Italian farm accountancy data network samples, comparing 45 OG participants with 225 non-participants in Emilia-Romagna from 2017 to 2020. Results indicated that the analyzed OGs might have contributed to improving fertilizer management and profitability levels in participating farms, but failed to preserve biodiversity and reduce consumption of pesticides and other inputs such as water, energy, and fuels. This mixed picture suggests that while economic improvements may be achievable, environmental sustainability goals prove more challenging to realize. Bonfiglio recommended that to increase OG effectiveness, policymakers should condition projects on actual experimentation and implementation of agricultural innovations and apply performance-based indicator systems for ex-ante and ex-post impact assessment.

The challenge of achieving environmental outcomes appears across multiple contexts. McLoughlin et al. (2020) examined three Irish EIP initiatives - Caomhnú Árann, the Hen Harrier Project, and the Pearl Mussel Project - that employ results-based payment approaches, where farmers are rewarded for the habitat quality they maintain on their farms, in addition to the food products they produce. These initiatives enable adaptive approaches tailored to the specific needs and challenges of specific biogeographical areas, allowing for the delivery of vital ecosystem services, including biodiversity conservation, carbon sequestration and storage, improved water quality, agricultural biodiversity, flood resilience, and fire resilience. The results-based approach, which uses habitat quality as a surrogate for ecosystem services linked to payment levels, provides a model demonstrating how a wide range of ecosystem services can be delivered while farmers are rewarded for doing so.

The difficulty of achieving environmental objectives within EIP-AGRI is not attributable to any single cause but reflects the convergence of methodological, organisational, and structural barriers that operate at different levels and on different timescales, and which therefore require differentiated responses.

At the methodological level, the fundamental problem is one of temporal mismatch. Meaningful environmental outcomes - changes in biodiversity, soil health, water quality, or carbon sequestration - typically require years or decades to become measurable, while EIP-AGRI project cycles operate on timeframes of two to five years. Bonfiglio (2023) captures this directly: even in a methodologically sophisticated quasi-experimental evaluation using propensity score matching, no significant effect on pesticide use, energy consumption, or biodiversity could be detected within the observation window, despite positive findings on fertiliser management and profitability. The absence of standardised environmental indicators applicable across different OG types and national contexts compounds this further, as Baranauskienė et al. (2021) demonstrate in their work on evaluation methodology: without agreed metrics established at project inception, ex-post environmental assessment becomes largely impressionistic. The implication is not that environmental impacts are absent but that current evaluation designs are structurally incapable of detecting them.

At the organisational level, the barrier is one of dissemination and follow-through. Arzeni et al. (2023) found that Italian OGs frequently succeeded in capturing real farm-level issues and building inter-partner relationships, yet their environmental effectiveness was curtailed by low levels of internal communication and limited efforts to disseminate results beyond the immediate project consortium. Canali et al. (2020) document a related fragmentation in the organic farming research and innovation landscape, where funded interventions are scattered across topics, disciplines, and supply chain types in ways that prevent the accumulation of knowledge and the scaling of environmentally beneficial practices. Both studies point to the same organisational deficit: the multi-actor structure creates the conditions for knowledge co-creation but does not automatically generate the dissemination and uptake pathways through which environmental benefits are realised at scale.

At the structural level, the barrier is political and programmatic. Eckerberg et al. (2023) show that in Sweden, national programming systematically prioritised agricultural competitiveness over environmental development, interpreting innovation in technical rather than systemic terms and leaving sustainability transition goals effectively unoperationalised. This is not a Swedish peculiarity but an expression of a broader tension within the EIP-AGRI framework itself, which formally endorses both productivity and sustainability objectives while leaving member states discretion over how to balance them in practice. Where administrative traditions and agricultural sector interests favour productivist framings, environmental objectives are routinely subordinated. Borgia et al. (2025) add a further structural dimension: the respondents in their survey of 90 project coordinators identified the need for reinforced public policies to improve the environmental dimension of sustainability as one of the most pressing gaps in the current instrument mix, suggesting that practitioners themselves recognise the structural underfunding of environmental ambition within the existing policy architecture.

Addressing environmental objectives in EIP-AGRI therefore requires simultaneous action at all three levels: longitudinal monitoring plans and standardised environmental indicators embedded at project design stage, stronger organisational requirements for dissemination and knowledge transfer beyond the project consortium, and an explicit rebalancing of national programming priorities toward sustainability outcomes rather than leaving that balance to administrative discretion.

Evaluation methodologies and frameworks

The diversity of EIP-AGRI objectives and implementation contexts necessitates development of robust evaluation frameworks. Baranauskienė et al. (2021) developed an evaluation methodology for assessing the effectiveness of innovation partnerships in agriculture, detailing selected evaluation indicators, establishing their significance, and providing guidelines for interpreting effectiveness evaluation results. Their methodology was tested using data from Lithuanian EIP groups, providing both scientific and practical relevance. This work addresses the fundamental problem of evaluating the effectiveness of innovation partnership projects in agriculture and identifying the indicators that should define and measure it, recognizing that without appropriate evaluation methodologies, the true contribution of these initiatives remains unclear.

Maziliauskas et al. (2018) employed force field analysis to determine external and internal factors influencing EIP effectiveness, involving experts with scientific and practical experience, including scientists, policymakers, and innovators. Their analysis revealed that the number of negative factors exceeds the number of positive factors; however, the factors analyzed enable the timely identification of potential negative consequences and provide opportunities to predict the effectiveness of EIP-based projects. This diagnostic approach offers valuable insights for anticipating and mitigating implementation challenges before they undermine project outcomes.

Sector-specific impact analysis

Research examining specific agricultural sectors offers insights into how the effectiveness of EIP-AGRI varies across different production systems and value chains. Canali et al. (2020) analyzed the dynamics of organic food and farming research and innovation in Italy, examining 70 research projects funded with 21.081 million euros (less than 0.1% of sector value) launched 2009-2018, and 53 regional innovation projects with 14.299 million euros (less than 10% of available funding) activated 2007-2019. Their analysis revealed that the implementation of interventions in research and innovation areas was often scattered in terms of topics, disciplines, and types of supply chains or networks addressed. However, the relatively high share of multi- and interdisciplinary projects and acknowledgement of the multi-actor approach as a fundamental step toward co-research and co-innovation emerged as positive developments. The study's outcomes can inform competent national and regional authorities in designing future research and innovation policies and interventions.

De Visser et al. (2014) examined Europe's dependency on soya bean imports for the animal feed industry through an EIP-AGRI consultation process involving 20 experts from 11 EU countries. The process assessed present-day yield gaps of protein crops using an approach based on market values of protein, starch, and plant oil components, finding that oil-based protein crops seemed overall better positioned than starch-based protein crops because oil price levels are higher than starch prices. The study identified opportunities and constraints to be encountered by the innovation process, combining knowledge and physical infrastructure, market structure, cooperation and interaction, and the influence of culturally determined values and beliefs. This case demonstrates how EIP-AGRI consultation processes can identify strategic innovation priorities with significant implications for European agricultural self-sufficiency and sustainability.

Social and non-economic outcomes

Beyond economic and environmental metrics, research increasingly recognizes the importance of social dimensions and well-being outcomes. Conway et al. (2022) addressed the mental health and well-being of older farmers in the context of generational renewal policies, arguing that policies aimed at stimulating generational renewal pay meager regard to older farmers' mental health and well-being, overlooking their identity and social circles, which are inextricably intertwined with their occupation and farm. The paper proposes "farmer-sensitive" actions at both policy and societal levels to alleviate the fear and anxiety associated with stepping aside and retirement from farming, with a particular focus on the social and emotional well-being benefits of membership in social groups that reflect farmer-relevant values and aspirations in later life. The potential of the multi-actor EIP-AGRI initiative and the established livestock mart sector in facilitating the successful rollout of social organizations designed to fit the specific needs and interests of older farming community generations was outlined, beginning a broad international conversation on transforming farming into an age-friendly sector aligned with the World Health Organization's age-friendly environments concept.

This social dimension extends to how innovation partnerships themselves create or strengthen social capital and networks. Arzeni et al. (2023) found that while Italian OG implementation helped capture the real issues faced by farmers and rural entrepreneurs, and supported the creation and strengthening of relationships between partners, its effectiveness was reduced by low levels of communication and limited dissemination efforts. This suggests that social and relational outcomes, while potentially significant, are not automatically achieved through multi-actor structures; rather, they require deliberate attention to communication and knowledge-sharing processes.

Policy effectiveness and instrument design

Evaluation research is increasingly examining which policy instruments prove most effective in stimulating innovation (Table 4).

Instrument type	Study	Finding on effectiveness
Financial (subsidies, grants)	Borgia et al. (2025)	Perceived as most important by 90 project coordinators
Advisory & extension services	Borgia et al. (2025)	Most in need of stronger public support (paradox)
Results-based payments	McLoughlin et al. (2020)	Effective for ecosystem service delivery in Irish EIP
Peer-to-peer & knowledge platforms	Feo et al. (2022)	Enhance uptake; under-utilised relative to potential
Institutional/capacity support	Kruzmetra et al. (2021)	One of 8 prerequisites for innovation project success in Latvia
Performance-based conditionality	Bonfiglio (2023)	Recommended to ensure genuine innovation activity

Source: authors

Table 4: Policy instrument effectiveness.

Borgia et al. (2025) examined the significance of various policy instruments in promoting sustainable innovation in fruit and vegetable value chains, drawing on the perceptions of 90 project coordinators from the EIP-AGRI platform. The study showed that most respondents, although belonging to different kinds of organizations in terms of typology, provenance, and area of work, converged in recognizing financial instruments as the most important ones. Conversely, educational and informational instruments, such as advisory and extension services, as well as peer-to-peer initiatives, were largely seen as most in need of stronger public support. Most respondents also demanded reinforced public policies to improve the environmental dimension of sustainability and boost technological innovations along agri-food value chains.

The evidence across the reviewed studies points to a structured hierarchy of policy instrument effectiveness, though one that carries an internal tension requiring explicit policy attention. Financial instruments - grants, project subsidies, and results-based payments - are consistently identified as the most important by practitioners.

Borgia et al. (2025), drawing on the perceptions of 90 project coordinators from diverse organisational backgrounds across Europe, found near-universal convergence on this point regardless of country of origin or type of organisation. Yet the same study reveals a paradox: advisory and extension services, while rated as least adequately funded, are simultaneously seen as most in need of stronger public support. This gap between perceived importance and actual investment levels suggests that current policy mixes are structurally skewed toward visible, project-based expenditure at the expense of the relational and capacity-building infrastructure on which OG functioning ultimately depends.

Translating this into concrete recommendations, the reviewed literature collectively supports four actionable directions. First, financial support should be conditioned on genuine innovation activity rather than procedural compliance, with ex-ante innovation plans and ex-post performance reporting required as conditions of project approval - a reform Bonfiglio (2023) identifies as essential to ensuring that funded OGs involve actual experimentation rather than repackaging of conventional practices. Second, public investment in advisory and extension services requires stabilisation and expansion, as the current underfunding documented by Borgia et al. (2025) undermines precisely the facilitation capacity that multiple studies identify as a prerequisite for effective multi-actor collaboration. Third, peer-to-peer knowledge exchange platforms should be embedded as a structural component of OG support architecture rather than treated as an optional supplement, given the evidence from Feo et al. (2022) that user-friendly digital platforms linked to demonstration activities measurably improve knowledge uptake and long-term impact. Fourth, and most specifically for environmental objectives, results-based payment schemes of the kind documented by McLoughlin et al. (2020) in Ireland - where farmers are rewarded for demonstrable habitat quality rather than for following prescribed management actions - offer a model that combines financial incentive with outcome accountability and warrants broader replication across member states. Taken together, these recommendations suggest that instrument effectiveness in EIP-AGRI is not simply a question of funding volume but of the design logic governing how instruments are combined, conditioned, and sequenced across the project lifecycle.

Limitations and measurement challenges

The literature reveals significant challenges in measuring the impacts of EIP-AGRI robustly. Temporal dimensions pose particular difficulties, as innovation processes often require extended periods before outcomes become apparent, while evaluation frameworks typically operate on shorter project timeframes. Attribution challenges arise from the complexity of factors influencing farm performance and the difficulty of establishing clear causal links between participation in OGs and observed outcomes. Additionally, the diversity of OG objectives, from technical innovation to social learning to market development, complicates the development of standardized evaluation metrics applicable across different contexts.

Bonfiglio (2023) noted that actual experimentation and implementation of agricultural innovations should be conditions for project approval, suggesting that many funded projects may not involve genuine innovation activities. This observation raises fundamental questions about what constitutes innovation within the EIP-AGRI framework and whether current selection and monitoring mechanisms adequately distinguish between innovative and conventional activities. The challenge of measuring systemic and transformative impacts, as opposed to incremental improvements, remains largely unaddressed in the existing literature, highlighting significant gaps in current evaluation approaches.

Conclusion

Summary of findings and methodological limitations

The present review yields three clusters of findings that differ substantially in the robustness of their evidentiary base, and it is important to distinguish between them before turning to the future research agenda.

Several findings can be considered robust in the sense that they are supported by multiple studies using methodologically diverse approaches across different national contexts. The substantial heterogeneity in national and regional EIP-AGRI governance is the most consistently documented result in the corpus: comparative analyses covering Italy, Sweden, Bulgaria, Germany, Latvia, Lithuania, Portugal, and eight European countries collectively confirm that administrative traditions, funding architectures, and interpretations of the interactive innovation model diverge markedly across member states, producing very different conditions for OG operation even within the same EU regulatory framework (Giarè and Vagnozzi 2021; Eckerberg et al. 2023; Stoeva and Pickard 2020; Hermans et al. 2015). Equally well-supported is the pivotal role of boundary-spanning actors and innovation brokers: this finding emerges from social network analysis, communities of practice theory, and exploratory factor analysis applied in Ireland, Germany, Spain, and EU-wide thematic networks, lending it considerable cross-methodological credibility (Müller and Riekötter 2025; Piñeiro et al. 2021; Feo et al. 2022). The perceived primacy of financial instruments over advisory and extension services is also backed by a relatively large perception survey of 90 project coordinators drawn from diverse organisational backgrounds across Europe (Borgia et al. 2025).

Other findings, while plausible and theoretically coherent, rest on a narrower evidentiary base and should be treated as tentative. The contribution of OGs to environmental outcomes is genuinely uncertain: the only quasi-experimental study in the corpus - Bonfiglio (2023), comparing 45 OG-participating farms with 225 controls in Emilia-Romagna - found improvements in fertiliser management and profitability but no significant effect on pesticide use, biodiversity, or energy consumption. No comparable counterfactual study exists for other regions or production systems, making generalisation premature. The claim that EIP-AGRI has the potential to catalyse systemic or transformative change in agricultural innovation systems likewise remains largely aspirational: it is grounded in qualitative policy analysis from Sweden (Eckerberg et al. 2023) and in normative argumentation rather than in observed outcomes. Similarly, the finding that farmers frequently occupy passive roles in OG decision-making, while theoretically important, is documented primarily through two Irish case studies (Harrahill et al. 2022; McCarthy et al. 2021) and may reflect features specific to the Irish agricultural context rather than a universal pattern.

The review itself is subject to several methodological limitations that readers should bear in mind when interpreting these findings. The keyword search strategy - combining "EIP" and "AGRI" across titles, abstracts, and author keywords in Web of Knowledge and Scopus - was intentionally broad, but it may have missed relevant articles that discuss the initiative under alternative terminology such as "Operational Groups", "interactive innovation approach", or "AKIS reform". The resulting corpus is heavily weighted towards qualitative and interpretive case studies; only one study employs a quasi-experimental design capable of supporting causal inference, which means that conclusions about what EIP-AGRI actually produces, as opposed to what participants perceive or what documents prescribe, must be drawn with caution. Geographic coverage skews notably towards Ireland, Italy, Germany, and Sweden, while Central and Eastern European countries - which account for a substantial share of EU OG activity and face distinct structural challenges - are underrepresented. The coding and thematic analysis were conducted by the two authors without a formal inter-rater reliability procedure, introducing a potential source of interpretive bias. Finally, the review does not encompass grey literature such as EIP-AGRI network publications, national Rural Development Programme evaluations, or European Commission monitoring reports, all of which contain implementation data that peer-reviewed studies frequently cite but do not themselves constitute.

Directions for future research

Drawing on a comprehensive analysis of 31 studies and integrating insights from recent research conducted between 2023 and 2025, we identify seven critical directions for future research that can advance the understanding of agricultural innovation partnerships and strengthen their contribution to sustainable agricultural transformation.

Developing robust performance-based evaluation frameworks

Future research must address the fundamental challenge of measuring EIP-AGRI impacts beyond project-period assessments. Recent evidence suggests that many funded projects primarily involve feasibility studies rather than actual experimentation and innovation implementation (Bonfiglio 2023). Research should develop methodologies distinguishing genuine innovation activities from conventional practices, establishing clear indicators for ex-ante project selection and ex-post impact assessment.

Evaluation research should employ longitudinal approaches tracking OGs from inception through multiple years post-completion to reveal delayed effects and systemic transformations. Particular attention should be paid to developing metrics for non-economic outcomes, including social capital formation, learning outcomes, network development, and ecosystem service delivery (McLoughlin et al. 2020). The challenge of attribution in complex multi-actor contexts requires sophisticated methodological approaches such as contribution analysis, realist evaluation, synthetic control methods, and carefully constructed matched comparison groups.

Understanding and strengthening innovation brokerage

The critical role of innovation brokers has been consistently identified, yet significant gaps remain regarding optimal brokerage practices and support structures. Müller and Riekötter (2025) identified adaptive facilitation, multimodal translation, and network cultivation as key practices; however, questions remain about how these competencies can be systematically developed.

Future research should examine different brokerage models, comparing the effectiveness of dedicated broker organizations versus rotating roles, external versus embedded brokers, and professional versus peer brokers. Investigating the specific competencies required across various agricultural contexts can inform training curricula and professional development pathways. The role of digital platforms in supporting brokerage represents an emerging frontier, with potential to expand reach while maintaining relational quality. Research should also address political dimensions of brokerage, examining how brokers navigate power asymmetries, mediate conflicts between competing goals, and maintain legitimacy across diverse stakeholder groups.

Addressing power dynamics and enhancing farmer agency

Research consistently reveals that farmers often occupy passive roles, despite nominal participation (Arzeni et al., 2023; Harrahill et al., 2022). Future research must move beyond measuring participation rates to analyzing the quality and depth of farmer engagement in decision-making processes. Power-sensitive methodologies, including network analysis that examines centrality and influence, as well as participatory action research approaches, can reveal how governance structures affect farmer influence in agenda-setting, resource allocation, and knowledge validation.

Particular attention should be paid to farmers in marginal positions, including smallholders, women farmers, and farmers in less-favored areas. Research should examine the barriers these groups face and develop targeted strategies for inclusive participation. Investigation of "innovation sovereignty" – farmers' capacity to determine innovation agendas, control processes, and retain ownership of innovations – represents an important dimension, particularly in relation to intellectual property arrangements and data governance in precision agriculture contexts.

Power-sensitive methodologies that future research should employ include: (a) social network analysis (SNA) to quantify actor centrality, brokerage positions, and information flow asymmetries - as demonstrated by Harrahill et al. (2022) - with particular attention to 'betweenness centrality' as a proxy for influence in OG decision-making; (b) participatory mapping techniques such as stakeholder influence/interest matrices, power cubes, or power mapping exercises conducted with OG members at different project stages, allowing farmers themselves to visualise and articulate perceived power gaps; (c) discourse analysis applied to OG meeting minutes and project documentation to detect whose framings and priorities dominate the agenda; and (d) longitudinal participant observation to track shifts in farmer agency as trust and collaborative norms develop over time. In terms of OG design improvements, research should examine whether structural changes - such as farmer-led OG governance, farmer-controlled data ownership agreements, and rotating facilitation roles - measurably shift decision-making influence toward primary producers.

Advancing understanding of knowledge co-creation processes

While knowledge co-creation is central to EIP-AGRI, substantial gaps remain in understanding how different knowledge forms are integrated and transformed. Müller and Riekötter (2025) demonstrated that successful OGs function as communities of practice, yet questions remain about conditions fostering such communities within institutionalized frameworks.

Future research should examine microlevel processes of knowledge interaction through ethnographic approaches, investigating how farmers, researchers, and advisors communicate and develop shared understandings. The role of boundary objects, shared experiments, and demonstration activities in facilitating knowledge integration deserves attention. Temporal dimensions of knowledge co-creation require investigation, tracking how understanding evolves through iterative cycles of experimentation and adaptation. Digital technologies create new possibilities and challenges; research should examine how online platforms, decision support systems, and data analytics transform knowledge production while potentially creating new exclusions and dependencies.

Exploring sector-specific and context-dependent innovation pathways

The reviewed literature demonstrates substantial variation in EIP-AGRI effectiveness across different agricultural sectors and territorial contexts (Canali et al., 2020; Mosquera-Losada et al., 2025). Future research should develop a nuanced understanding of how innovation pathways differ across production systems, value chains, and territorial characteristics.

Comparative research can identify sector-specific innovation challenges, appropriate knowledge sources, and effective support mechanisms. Innovation dynamics differ substantially between annual crops, perennial systems, livestock, and mixed farming, requiring tailored approaches. Territorial dimensions deserve greater attention, particularly in innovation pathways for marginal agricultural areas, less-favored regions, and territories that provide ecosystem services where conventional productivity-focused models may be inappropriate. Research on bioeconomy and circular economy should examine governance arrangements that enable farmers to capture appropriate value while contributing to sustainability goals, addressing the questions of equity raised by Harrahill et al. (2022).

Strengthening integration between research, advisory, and extension systems

Difficulties in research-practice collaboration, documented across multiple studies (Arzeni et al., 2023; Hermans et al., 2015), point to fundamental challenges in Agricultural Knowledge and Innovation Systems that require systemic research attention. Future research should examine how different AKIS configurations affect innovation outcomes, comparing the effectiveness of public extension services, privatized advisory systems, farmer-to-farmer networks, and hybrid models.

The changing role of agricultural advisors warrants investigation, examining how advisors mediate between research and practice while respecting the autonomy of farmers. Borgia et al. (2025) found a paradox: while financial instruments are perceived as most important, advisory and extension services are seen as most in need of stronger support. Research should examine barriers to investment in advisory systems and the relationship between EIP-AGRI and other innovation mechanisms. Fieldsend et al. (2021) demonstrated that EIP-AGRI constitutes just one part of a complex matrix of activities; research should develop systemic perspectives identifying strategies for enhancing coherence across multiple innovation support mechanisms.

Investigating transformative innovation and sustainability transitions

The most significant research frontier concerns EIP-AGRI's potential contribution to transformative change rather than incremental improvements. Eckerberg et al. (2023) demonstrated that technical innovations and competitiveness objectives dominate over sustainability transition goals in Swedish implementation. This raises fundamental questions about whether current mechanisms can catalyze the structural changes required for agricultural sustainability.

Future research should examine the conditions that enable transformative rather than incremental change, investigating how sustainability visions are articulated and operationalized within contexts where competing values coexist. The concept of mission-oriented innovation policy offers promising frameworks for orienting efforts toward specific societal challenges. Research should examine how mission-oriented approaches can be implemented, developing methodologies for portfolio management balancing diverse projects while maintaining strategic coherence around priority missions. Critical perspectives interrogating whose interests are served by particular innovation trajectories and how marginalized alternatives might be supported offer important contributions. Ultimately, research should examine agricultural innovation within broader sustainability transitions that encompass food systems, rural development, and the bioeconomy, generating insights relevant to policy integration across multiple domains.

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