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Agri-food 4.0: Drivers and links to innovation and eco-innovation

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ABSTRACT

Digital transformation affects all stages of the agri-food value chain. Digitalisation is being combined with innovations and eco-innovations to gain a competitive advantage and ensure greater sustained competitiveness. However, not all technologies have been implemented in the same way and at the same pace by the different companies in the agri-food sector. The aim of this research is to identify the internal and external drivers of digitalisation in agri-food companies and to develop a synthetic index to rank companies based on those drivers, before examining the relationship between the position in the ranking and innovation. The results reveal that the decisive drivers are management support and competitive pressure rather than external support from government policies or suppliers. Higher ranking companies in terms of the digitalisation process are more proactive in introducing product and radical innovations and are the most eco-innovative and thus sustainability-oriented. Finally, results show that the digitalisation of the sector is marked by the depth of technology implementation, specifically IoT, big data and artificial intelligence. Blockchain technology does not currently make a difference as it is not widely used.

1. Introduction

Companies need to become smart businesses and inevitably require some use of digital technologies (DTs) to strengthen their competitiveness (Verhoef et al., 2021). The implementation and application of DTs in the agri-food sector requires the engagement of the different actors in the sector that will be involved in the digital transformation process: farmers, producers, the food industry, the supply chain, and the market (Ancín et al., 2022). DT developments have been referred to using different names, such as Agriculture 4.0, Smart Agriculture 4.0, Smart Farming 4.0 (da Silveira et al., 2021; Rose and Chilvers, 2018), Smart Farming (Wolfert et al., 2017) and Digital Agriculture (Shepherd et al., 2020), among others. If it includes the whole agri-food production chain from agricultural production to food consumption, the term used is agri-food 4.0.

The impact of disruptive events such as climate change, Brexit and the global pandemic has highlighted the role played by innovation capabilities in building resilience, visibility, redundancy, speed, and flexibility into the food supply chain (Oltra-Mestre et al., 2021). Several studies have explored the effects of specific DTs on business performance and innovation, with the focus ranging from the most basic technologies of internet access and use, e-commerce and business management systems, to advanced disruptive approaches aimed at efficiency (cloud computing), connectivity (internet of things, IoT), disintermediation of trust (blockchain) and automation (big data and artificial intelligence) (Brenner and Hartl, 2021). However, there has been less analysis of the effect of DT adoption on a broader set of specific DTs (i.e. the DT portfolio) in the agri-food sector (Blichfeldt and Faullant, 2021).

The effects of this new way of doing business are yet to be defined (Galanakis et al., 2021) and the impacts of DTs remain unknown (Lopez-Ridaura et al., 2021). The literature shows the lack of a global implementation of DTs in the entire agri-food sector, mainly due to the typical profile of companies in the sector: predominantly small and medium-sized enterprises (SMEs) with limited budgets and little access to financial resources (Ahikiriza et al., 2022; Haberli et al., 2017; Makinde et al., 2022). Moreover, they show low levels of generational renewal and underdeveloped information and communications technology skills (Marshall et al., 2020). Top management support is another challenge to the modernisation of the sector (Pu et al., 2019).

In this context, where digitalisation (encompassing the use of the entire DT portfolio) and innovation meet environmental sustainability, this research has a twofold objective. Firstly, it seeks to provide evidence

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Table 1
Literature review according to the drivers of digitalisation.

Author	DT analysed	Sector	Drivers[1]	Drivers Description
(Chatterjee et al., 2021)	Artificial intelligence	Industrial	1; 2; 3; 4; 5; 6	**Internal- Technological**
(Shang et al., 2021)	Digital farming technologies	Agri-food	1; 2; 3	1. **Relative advantage**: Adopting digital technologies improves business productivity and reduces costs.
(Maroufkhani et al., 2020)	Big data	Industrial	1; 2; 3; 4; 5; 6; 8; 9	2. **Compatibility:** Perception and degree of alignment with the company's culture, values, business practices and available infrastructure.
(Zeng et al., 2021)	Land information systems	Agriculture	7	3. **Complexity**: Level of difficulty and limitations to understanding and use
(Yoon et al., 2020)	Smart farming	Agri-food	1; 2; 3; 6; 9	4. **Capacity of the company**: Accessibility of organisational resources needed to implement, operate and/or manage
(Haberli-Junior et al., 2019)-	Enterprise resource planning (ERP)	Agriculture	1; 2; 3; 4; 5; 6; 8	**Internal- Organisational**
(Barnes et al., 2019)	Precision agricultural technologies	Agriculture	7	5. **Management support**: The commitment of the company's leadership has a significant impact because it guides, adapts the budget, integrates services and processes
(Kamrath et al., 2018)	Technologies to improve the packaging	Agriculture	1; 2; 3; 4; 5; 6; 8; 9	**Internal- Behaviour** **Degree of adoption:** Measure of the adoption of DTs by the company. It ranges from total ignorance to having installed them more than a year ago.
(Haberli et al., 2017)	ERP	Agri-food	1; 2; 3; 4; 5; 6; 8; 9	7. **Perceived net benefit:** Improvements in planning and management, problem identification, decision-making, communication and cooperation with suppliers and customers, product quality and productivity.
(Xu et al., 2017)	ERP	Industrial	1; 2; 3; 4; 5; 8	
(Rajan and Baral, 2015))	ERP	Industrial	1; 2; 3; 4; 5; 8	
(Tey and Brindal, 2012)	Precision agricultural technologies	Agricultural	7	**External**
(Adrian et al., 2005)	Precision agricultural technologies	Agricultural	7	8. **Competitive pressure**: The degree of pressure on the **company** caused by competitors in an industry.
(Premkumar and Roberts, 1999)	Information and communication technologies	Agri-food	1; 2; 3; 5; 6; 8; 9	9. **External support: Administrative and financial** support in the process of introduction and use of DTs, both from public administrations and suppliers.

[1] The number refers to the driver described in the following column.

on the internal and external drivers of the digital development of the sector. Secondly, the aim is to develop a synthetic indicator (SI) that can be used to rank companies based on these drivers, thus making it possible to characterise companies according to their position in the ranking. This research represents a novel contribution to the literature, setting out lines of action that will facilitate the transition towards the modern agri-food sector demanded by the market. The scientific community has developed an extensive literature focused on determining the contribution of internal and external factors to this process. The present paper goes a step further by building a *synthetic index (SI)* based on the technological drivers, allowing us to detect the opportunities and obstacles for companies facing the challenge of digitalisation. In addition, the entire DT portfolio is included in the analysis to determine which technologies are playing the greatest role in promoting the digitalisation of the sector. The results will help to guide decision-makers in the arduous task of implementing innovative policies that foster agri-food companies' use of DTs to boost competitiveness and strengthen their market position. The analysis relies on primary statistical information collected in a 2022 survey administered to Spanish agri-food companies to obtain data on their activity in the period 2017–2021. Specifically, the aim is to answer two research questions:

Q1. Do internal and external drivers of digitalisation affect the implementation of DTs in the agri-food sector uniformly?

The aim is to identify whether there are different patterns of company behaviour around internal (Adoption Degree, Benefits, Relative advantage, Compatibility, Complexity, Management Support and Capacity) and external (Competitive pressure and external support) drivers of DT adoption.

Q2. Is the position of agri-food companies in the ranking produced using the synthetic index (SI) conditioned by their innovation and/or eco-innovation orientation?

The answer to this question will depend on the digitalisation ranking according to the results of the SI, which will allow a characterisation of the top-ranked companies that can serve as a model to help improve the sector's strategy towards DT implementation. In the process of characterising the companies, we examine the relationship between the ranking of companies and the type of innovations developed by the company, including eco-innovations. Furthermore, it will be possible to analyse the ranking obtained in relation to the implementation of each type of technology, both in terms of breadth (number of DTs) and depth (degree of use of DTs), enabling a more precise analysis. The results can be used to define policy and sectoral interventions that foster the progress of the agri-food sector.

The rest of the paper is structured as follows. Section 2 presents a review of the literature on the digital transition of the agri-food sector, to show the progress made and define the objectives of the study. Section 3 describes the methodology and statistical information used in the empirical analysis. Section 4 presents the results, which allow us to answer the research questions posed, and discusses them in relation to the existing literature. Finally, section 5 summarises the conclusions, management implications and prospects for future research.

2. Digital transformation of the agri-food sector: Connections and drivers

Companies' technological capability is a critical element in accelerating their innovation activities and is considered one of the most relevant dynamic capabilities needed to achieve a competitive advantage and sustained competitiveness (Blichfeldt and Faullant, 2021; DeLay et al., 2022). A key question is whether technology adoption can benefit companies in their efforts to become more innovative in all types of innovation (product, process, organisational, and marketing). Another question is whether digitalisation provides greater impetus for incremental or for radical innovations (Acemoglu et al., 2022; Blichfeldt and Faullant, 2021; Linnan et al., 2021). Moreover, the development and implementation of DTs are combined with innovations, both general and specifically sustainability-oriented, such as eco-innovations. Mondejar et at. (2021) analyses the link between the digitalisation of the agri-food sector and the achievement of the Sustainable Development Goals (SDGs).

Several studies have explored the effects of specific DTs on business performance (da Silveira et al., 2021) and innovation, and analyse the internal and external drivers. Table 1 presents a selection of studies that analyse the implementation of specific DTs, from sectors related to this study, and the main drivers from a business management point of view. This classification distinguishes the drivers according to whether they

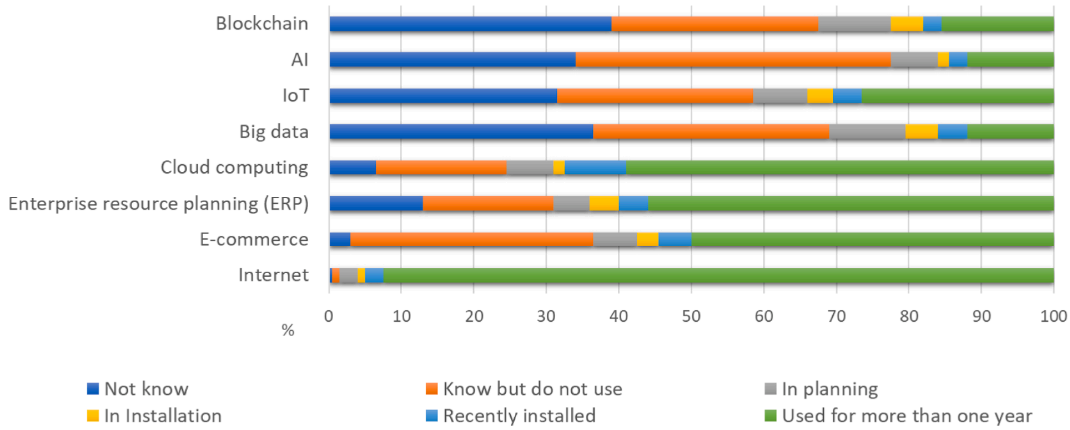

Fig. 1. Degree of adoption of the DTs of the selected portfolio.

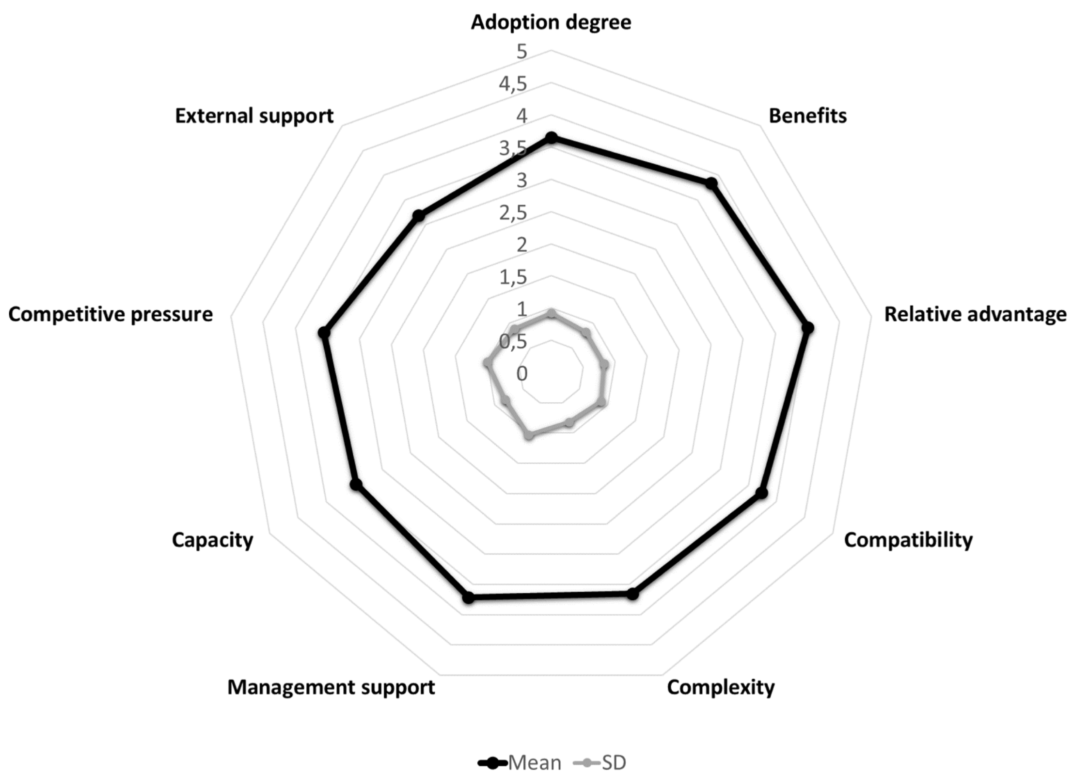

Fig. 2. Mean level of acceptance of the drivers of digitalisation.

are internal or external to the company. Internal drivers include those related to the technology itself (Internal-T), the organisation of the company (Internal-O), the attitude towards the adoption of DTs (Internal-A). External drivers include competitive pressure and the ability to access external support. These drivers will be used to examine the whole DT portfolio and provide a more comprehensive view of the implementation of digitalisation in the sector.

Internal or endogenous drivers that influence the intention to adopt DTs in organisations are analysed by most of the studies. In contrast, external drivers are studied less frequently, with competitive pressure generally being the driver considered and external support being overlooked. However, governments have an impact on the adoption of technologies in SMEs (Yoon et al., 2020). In the European context, initiatives and actions have been developed, such as the Knowledge and Innovation Communities (KIC) of the European Institute of Innovation and Technology (EIT). A specific example of this is EIT Food, which connects partners across the food value chain from universities, research centres, institutes, and companies in European countries. In addition, the creation of the "Smart Specialisation Platform" dedicated to the agri-food sector is enabling collaborative actions between EU regions (Ciampi Stančová and Cavicchi, 2019).

Internal technological drivers are analysed in most of the cited studies, except for capacity. This driver is associated with the skills, knowledge, capabilities, and infrastructure needed to implement and operate DTs, and is thus essential for effective DT performance in a workplace. The internal organisational driver is analysed in the most relevant study related to this one, where top management support is found to be a key determinant of successful innovation adoption. Perception of net benefit is a driver considered in studies analysing precision technologies. These studies highlight the fact that adopters tend to exploit larger areas and point out that this indicates the ability to accommodate some risk when investing in newer and larger technologies (Barnes et al., 2019).

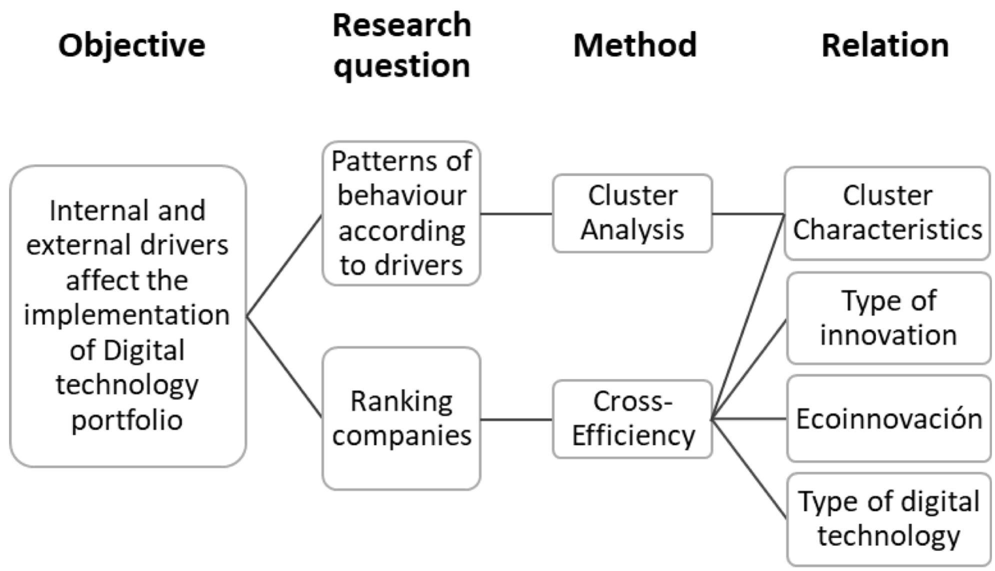

Fig. 3. Research design.

3. Materials and methods

3.1. Materials

The empirical analysis focuses on the Spanish agri-food sector, one of the most important industrial sectors in the country. Moreover, it represents 10.1 % of the total EU agri-food sector, behind only France and Italy (Maudos and Salamanca, 2020).

The sample is composed of companies in both agriculture and the agri-food industry. Statistical data on the agricultural sector in Spain (Gobierno de España, 2022) indicate that it is almost entirely composed of SMEs: only 0.1 % of the companies are large (more than 250 employees). Of the SMEs in the agricultural sector, 62.7 % have no employees, 33.8 % are micro-enterprises (1–9 employees), 3.1 % are small enterprises (10–49 employees) and 0.3 % are medium-sized (50–249 employees). The agri-food industry is the leading manufacturing branch of the industrial sector, with a turnover of 126,354.1 M€, representing 25.4 % of the manufacturing sector, 22.5 % of total employment and 20.6 % of added value. Of these agri-food companies, 96.5 % are small enterprises and 79.5 % are micro-enterprises. The study sample includes companies of all these sizes, reflecting the characteristics of the sector.

The information from Spanish agri-food companies was obtained via telephone during March 2022. A total of 200 surveys were administered to companies selected for having conducted research and development activities in the period 2017–2021, including companies belonging to the different Autonomous Communities and the sector (Agriculture and agri-food industry). The characteristics and the territorial distribution of the sample can be seen in Appendix 1 (Table A1 and Fig. A1 respectively). Of the total sample, 78 % are small companies[1] (<50 workers). Regarding innovation activity, more than two thirds have carried out product and process innovation during the years analysed (78.5 % and 76.5 %, respectively), with more firms carrying out radical innovation than incremental innovation (59 % and 42 %, respectively). In addition, half have demonstrated concern for environmental issues (Eco-innovation, 52.5 %).

The DTs under study range from the simplest (internet, e-commerce, management systems, and cloud computing), to others that are more disruptive, recent, and complex (big data, IoT, artificial intelligence, and blockchain). The degree of adoption of each of these DTs was assessed using a five-point scale, where 1 indicates that the company does not know or has not installed this technology and 5 indicates that it has been installed for more than a year. Fig. 1 shows the mean values obtained for each DT and the percentage of implementation. Thus, the simplest DTs are used by between 70 and 100 % of companies, due to their ease of access and use. Conversely, the more complex ones, such as artificial intelligence, are only used by just over 55 % of companies.

For the remaining drivers, a 5-point Likert scale has been used, where 1 indicates "strongly disagree" and 5 "strongly agree".[2] For most of the drivers, the average degree of acceptance is above 3, which indicates a good degree of acceptance, although with some room for improvement (Fig. 2).

Specifically, internal drivers score higher than external drivers. Relative advantage is the best rated, with a mean score above 4, followed by Benefits (3.83), Compatibility (3.73) and Management support (3.71). This driver has the highest variability (SD = 1.02), i.e. the lowest level of correspondence between companies. Complexity registered a mean score of 3.65, but it is the one with the lowest variability (SD = 0.8). External support (3.18) has the lowest mean value.

4. Methods

Having described the sample, the DTs and the drivers used to provide answers to the two research questions, different methods are applied to the primary information collected from agri-food companies. Fig. 3 shows the main methods used in the empirical analysis.

The application of cluster analysis provides an answer to Q1 by identifying possible patterns of company behaviour around the internal and external drivers that influence DT implementation. This method has previously been used in the digitalisation literature to study the relationship between buyer segments and the use of digital sales channels (Schwering et al., 2022) to compare the degree of penetration in different countries (Popkova and Sergi, 2022) and to analyse user typologies and motivation in relation to farm management information systems (Schulze Schwering et al., 2022).

The clustering process is divided into three stages. First, a hierarchical cluster analysis is performed by means of Ward's method, using the squared Euclidean distance to identify possible clusters. Second, after a systematic comparison of the possible clusters, a dendrogram is constructed to determine the number of clusters suitable for the study

[1] Small companies represent 81% of the agri-food sector in Spain (Ministry of Industry, 2022).

[2] The average values used can be found in Appendix 2.

Table 2
Clusters based on internal and external drivers of DT implementation.

Type.	*Driver*		*Cl 1 Strong adopters.*	*Cl 2 Moderate adopters*	*Cl 3 Emerging adopters*	*Mean Total*	*Kruskal- Wallis H*	*p-value*
Internal-A	Adoption degree		4.11	3.71	3.09	3.65	36.45	0.00
Internal-A	Benefits		4.44	3.96	3.04	3.83	87.30	0.00
Internal-T	Relative advantage		4.69	4.10	3.21	4.01	103.90	0.00
Internal-T	Compatibility		4.57	3.60	3.08	3.74	92.01	0.00
Internal-T	Complexity		4.09	3.77	3.06	3.66	48.32	0.00
Internal-O	Management support		4.64	3.65	2.88	3.71	97.49	0.00
Internal-O	Capacity		3.95	3.47	2.98	3.47	39.26	0.00
External	Competitive pressure		4.32	3.67	2.61	3.55	88.06	0.00
External	External support		3.44	3.59	2.34	3.18	77.01	0.00
Cluster characterisation		**CL1**	**CL2**	**CL3**	**Total**	**Chi-sq**	**Cont. Coeff**	**p-value**
No. of companies (%)		29.5	41.0	29.5				
Sector (%)						4.896	0.155	0.086
Agricultural companies		17.5	20.5	11.5	49.5			
Industrial companies		12.0	20.5	18.0	50.5			
Company size (%)								
Microenterprises (<10 employees)		8.5	7.5	9.5	25.5	8.491	0.202	0.204
Small (10–50 employees)		11.5	22.0	15.5	49.0			
Medium-sized (50–250 employees)		8.0	10.0	4.0	22.0			
Large (greater than250 employees)		1.5	1.5	0.5	3.5			

sample. Finally, the Kruskal-Wallis test is used to test for significant differences between the variables in the established clusters.

Providing an answer to Q2 first requires the construction of an SI based on the technological drivers, with the SI then used to rank the companies. The next step is to examine whether the company's position in the SI is related to the innovative and/or eco-innovative profile of the company, and the breadth and depth of the implementation of the different types of DT. The SI is constructed by means of a variant of Data Envelopment Analysis (DEA) called Cross-Efficiency (CE).

DEA is based on non-parametric linear programming models, where the inputs and outputs that define each observation (decision-making units, DMUs) are combined to construct a production frontier. The aim is either to maximise the outputs with the available resources (output orientation) or to minimise the inputs with the defined outputs (input orientation). The distance of each DMU from the frontier determines the level of efficiency, the value of which is bounded between 0 and 1, with 1 being the observations that reach the maximum degree of efficiency. The original formulation of the DEA is attributed to Charnes et al. (1978), who only considered proportional increases in the variables, i.e. they developed the model under the assumption of constant returns to scale (CRS). Subsequently, to analyse more realistic situations, Banker et al., (1984) reformulated the DEA with variable returns to scale (VRS). This method has been widely used by the scientific community to determine efficiency levels in many different areas of the economy, such as water consumption (García-Mollá et al., 2021), eco-innovation (Kiani Mavi and Kiani Mavi, 2021) and even energy (Wang et al., 2022).

CE is defined under the same premises as DEA, but has a different objective; namely, to establish a ranking of all the observations that make up the sample. This allows researchers to circumvent one of the main limitations of DEA, which is that two different DMUs can obtain the same efficiency score. The original formulation of CE is attributed to Sexton et al., (1986) and was subsequently validated by Doyle and Green (1994). It consists of performing a pairwise evaluation, i.e. determining the efficiency values n times for each of the DMUs, using the optimal weights obtained in the individual evaluation of each one. The CE matrix is constructed from the elements calculated using the following expression:

$$CE_{kj} = \frac{\sum_{r=1}^{s} u_{rk} y_{rj}}{\sum_{i=1}^{m} v_{ik} x_{ij}} \quad j = 1, \cdots, n; \; k = 1, \cdots, n \tag{1}$$

where m and s correspond to the number of inputs and outputs, respectively; y_{rj} the value of output r of the *j-th* DMU; x_{ij} the value of input i of the *j-th* DMU; u_{rk} the weight of output r; v_{ik} the weight of input i; E_{kj} is the efficiency value of DMU j calculated using the optimal weights of DMU k and takes values between 0 and 1. Thus, the CE of each DMU is calculated by averaging the pairwise scores.

$$CE_j = \frac{1}{n} \sum_{k \neq j} E_{kj} \quad j = 1, \cdots, n \tag{2}$$

Like DEA, this method requires the specification of inputs and outputs. For this purpose, a Principal Component Analysis (PCA) was carried out before the CE, to group the variables obtained from the surveys into factors. The varimax rotation method was used for this purpose, using the KMO and Bartlett's test statistics (Schwering et al., 2022).

Given the nature of the data used, it is necessary to convert the inputs into factors to be improved by applying a monotonic decreasing transformation, i.e. by subtracting the maximum value of the variable from the original value (Martí et al., 2017; Puertas Medina et al., 2022). This approach has been widely used in the literature for the construction of SI (de Castro-Pardo et al., 2022; Martí et al., 2022).

The main advantage of CE is that, in addition to providing a unique ranking of DMUs, it eliminates unrealistic weighting schemes without requiring the elicitation of weight restrictions from experts in application (Anderson et al., 2002). The calculations are performed using the statistical package deaR implemented in Rstudio (Coll-Serrano et al., 2018).

Finally, contingency tables are drawn up and the Pearson's chi-squared test is conducted to characterise the clusters established and to identify the association between the position of the companies in the ranking and the innovative and/or eco-innovative profile. To do this, the ranking is divided into quartiles. The first quartile represents the top 50 companies in the ranking, and so on. The connection between the quartiles and companies' innovations is analysed, focusing on the type (product, process, organisational and marketing), speed (incremental or radical), sustainability orientation (whether they have carried out eco-innovation activities). All variables are converted into nominal variables for their analysis using contingency tables. This technique has recently been used to study associations between factors in different fields, such as the energy sector (Martí et al., 2022) food safety (Marti et al., 2021) and education (Aleixo et al., 2020).

5. Results and discussion

5.1. Q1. Do internal and external drivers of digitalisation affect the implementation of DTs in the agri-food sector uniformly?

By applying the cluster analysis, the sample observations have been assigned to three groups according to the internal and external drivers of

Table 3
Rotated component matrix of PCA of digitalisation drivers.

Type	Driver	Factor 1	Factor 2
Internal-O	Capacity	**0.890**	0.097
Internal-T	Complexity	**0.767**	0.204
Internal-T	Compatibility	**0.740**	0.271
Internal-O	Management support	**0.601**	0.471
Internal-A	Adoption degree	**0.541**	0.257
External	Competitive pressure	0.120	**0.835**
Internal-A	Benefits	0.271	**0.808**
Internal-T	Relative advantage	0.379	**0.756**
External	External support	0.166	**0.559**
Test results			
Bartlett, p-value = 0.000 and KMO = 0.848			
Percentage of variance explained 60.96 %.			
Cronbach's Alpha = 0.858			

Table 4
Relationship between the position of the company in the ranking with cluster membership, types of innovation and types of technology.

Variable X-Variable Y	Chi-sq	Contingency coefficient	p-value
Ranking-Cluster membership	**184.733**	**0.693**	**0.000**
Ranking-Type of innovation			
Product	12.887	0.246	0.005
Process	1.418	0.084	0.701
Organisational	1.246	0.079	0.742
Marketing	4.346	0.146	0.226
Incremental	2.791	0.117	0.425
Radical	12.650	0.244	0.005
Eco-innovation	9.845	0.217	0.020
Ranking- Type of technology			
a. Internet access and use	3.125	0.124	0.373
b. E-commerce	8.082	0.197	0.044
c. Enterprise resource planning	11.688	0.235	0.009
d. Cloud computing	18.462	0.291	0.000
e. Big data	19.168	0.296	0.000
f. Internet of Things (IoT)	25.435	0.336	0.000
g. Artificial intelligence	11.097	0.229	0.011
h. Blockchain	5.174	0.159	0.160

digitalisation. The defined clusters reveal different behavioural profiles (Table 2).

Cluster 1 (CL1), *Strong adopters*: This cluster is made up of 59 companies (29.5 % of the sample), most of which are agricultural companies.

CL1 companies register higher values for the drivers than the average for the entire sample. It shows a particularly notable difference from the rest of the clusters in the internal driver related to who should promote and lead the DT adoption (Management support, 4.64), recording a value almost one point higher than the other clusters. This cluster shows high values in the internal technological variables (Relative advantage, 4.69; Compatibility, 4.57; Complexity, 4.09). According to Vecchio et al. (2020), DT implementation is conditional on ease of use and the ability to integrate these technologies into daily routines. The results of the survey by Pathak et al. (2019) confirm that relative advantage and motivation are the factors that most strongly influence DT adoption in agriculture. In addition, external support, both private and public, should be encouraged to achieve a modernisation that helps ease competitive pressure (Competitive pressure, 4.32) and to improve access to financial resources that enable the proper digitalisation of the sector (Capacity, 3.95). At the opposite extreme is External support, which, despite the value registered (3.44), shows little difference with the rest of the clusters, indicating room for improvement. Modernisation makes it easier to increase productivity by adapting to the effects of climate change (Zhai et al., 2020). However, agri-food companies are demanding more flexible access to finance to be able to implement the developments required by the market (Ammann et al., 2022).

Cluster 2 (CL2), Moderate adopters: Includes 82 companies (41 % of the sample), divided evenly between agriculture and industry.

The average scores given by CL2 firms to the drivers of DTs are higher than the sample average, except for the internal organisational variables Management Support (3.65) and Capacity (3.47). The adoption of DTs requires organisational and infrastructural changes that may be difficult to implement for some companies. The results of Vecchio et al. (2020) show that there is "organisational inertia" in the agricultural sector, preventing the implementation of new technologies. There is a certain intolerance towards digitalisation due to its apparent discrepancy with the values, culture, and infrastructure of agricultural enterprises (Compatibility, 3.60). According to Chatterjee et al. (2021), organisational compatibility affects perceived usefulness. The scores for the remaining dimensions are like those described for CL1 companies.

Cluster 3 (CL3), Emerging adopters: This cluster is made up of 59 companies (29.5 % of the sample) and are mostly from the industrial sector.

CL3 companies give below average scores to all drivers. The worst scores are shown in the category of internal organisational drivers (Management Support, 2.88; Capacity, 2.88) and external drivers (Competitive pressure, 2.61; External support, 2.34), key issues to ensure the modernisation of the sector. In this regard, Chatterjee et al. (2021) and Maroufkhani et al. (2020) explain that decisive action and the vision of decision-makers are vital to create a supportive ecosystem

Table 5
Percentage of companies in SI quartiles by cluster, type of innovation, eco-innovation, and type of technology.

SI Digitalisation (Quartiles)		First %	Second %	Third %	Fourth %	Total
Cluster	Strong	19.9	9.5	1.0	0.0	29.5
	Moderate	6.0	15.5	17.0	2.5	41.0
	Emerging	0.0	0.0	7.0	22.5	29.5
Types of innovation						
Product(*)	Yes	22.5	19.5	21.0	15.5	78.5
	No	2.5	5.5	4.0	9.5	21.5
Process	Yes	20.0	20.0	18.0	18.5	76.5
	No	5.0	5.0	7.0	6.5	23.5
Organisational	Yes	15.0	14.0	16.0	16.5	61.5
	No	10.0	11.0	9.0	8.5	38.5
Marketing	Yes	14.0	12.5	17.5	14.5	58.5
	No	11.0	12.5	7.5	10.5	41.5
Incremental	Yes	11.0	11.5	11.5	8.0	42.0
	No	14.0	13.5	13.5	17.0	58.0
Radical(*)	Yes	17.0	17.0	15.5	9.5	59.0
	No	8.0	8.0	9.5	15.5	41.0
Eco-innovation(*)	Yes	14.5	16.5	12.5	9.0	52.5
	No	10.5	8.5	12.5	16.0	47.5
Type of technology						
Internet access-use	Yes	24.0	24.5	24.5	23.0	96.0
	No	1.0	0.5	0.5	2.0	4.0
E-commerce(*)	Yes	17.0	16.0	14.0	10.5	57.5
	No	8.0	9.0	11.0	14.5	42.5
Enterprise resource planning(*)	Yes	18.0	19.0	15.5	11.5	64.0
	No	7.0	6.0	9.5	13.5	36.0
Cloud computing(*)	Yes	20.0	20.0	16.5	12.5	69.0
	No	5.0	5.0	8.5	12.5	31.0
Big data(*)	Yes	9.0	6.0	4.5	1.0	20.5
	No	16.0	19.0	20.5	24.0	79.5
IoT(*)	Yes	14.0	10.0	5.5	4.5	34.0
	No	11.0	15.0	19.5	20.5	66.0
Artificial intelligence(*)	Yes	7.0	5.5	1.5	2.0	16.0
	No	18.0	19.5	23.5	23.0	84.0
Blockchain	Yes	5.0	7.5	6.0	4.0	22.50
	No	20.0	17.5	19.0	21.0	77.50

(*) Significant relationship according to the Chi-square test.

Table A1
Characterisation of the surveyed companies.

	Variable	Percent
Sector	Agriculture	49.5
	Industry	50.5
Size	Microenterprises (<10 employees)	28
	Small (10-50 employees)	50
	Medium-sized (50-250 employees)	19
	Large (> 250 employees)	3
Membership of a business group	Yes, national	28.5
	Yes, multinational	4.0
	No	67.5
Family group participation	Yes	80
	No	20
Sales outside the country	None	40
	From 1-25%	33
	26-50%	12
	More than 50%	15
Innovation	Product	78.5
	Process	76.5
	Organisational	61.5
	Marketing	58.5
	Incremental	42
	Radical	59
Eco-innovation	Eco-innovation	52.5

Section A. AGRICULTURE, FORESTRY AND FISHING		
Group		%
01.1	Growing of non-perennial crops	13,00
01.2	Growing of perennial crops	8,00
01.3	Plant propagation	0,50
01.4	Animal production	18,00
01.5	Mixed farming	2,50
01.6	Support activities to agriculture and post-harvest crop activities	7,50
Section C. MANUFACTURING		
Group		
10.1	Processing and preserving of meat and production of meat products	10,50
10.2	Processing and preserving of fish, crustaceans and mol·luscs	0,50
10.3	Processing and preserving of fruit and vegetables	6,50
10.4	Manufacture of vegetable and animal oils and fats	2,50
10.5	Manufacture of dairy products	3,50
10.6	Manufacture of grain mill products, starches and starch products	2,50
10.7	Manufacture of bakery and farinaceous products	5,50
10.8	Manufacture of other food products	9,00
10.9	Manufacture of prepared animal feeds	1,00
11.0	Manufacture of beverages	9,00
	Total	100,00

for new technologies. Senior management must stimulate organisational change, communicating the right vision for the company (Kandil et al., 2018). Continuous learning and global dissemination of the need for technology is vital to ensure success in this endeavour (Maroufkhani et al., 2020).

In summary, the differences in the scores given to internal and external drivers of digitalisation mark the difference between Strong and Emerging Adopters, with Management support and Competitive pressure being the most notable discrepancies.

These results coincide with those reported by (Annosi et al., 2020), who concluded that among the different factors associated with DT adoption, organisational variables are the most important, and those of Lioutas et al. (2021), who highlighted that management support is decisive in promoting, leading and being willing to take the risks required for successful digitalisation. External support, with lower scores and little difference between clusters, is a driver that still has some room for improvement.

Having determined the internal and external drivers that mainly differentiate the clusters from one another, we establish a ranking based on the drivers, to identify and characterise the best and worst companies. This will allow us to answer the second research question.

Q2. Is the position of agri-food companies in the ranking produced using the SI conditioned by their innovation and/or eco-innovation orientation?

Before constructing the SI, the drivers must be classified into inputs and outputs. For this purpose, a PCA has been carried out, identifying two factors (Bartlett, p-value = 0.000 and KMO = 0.848), with a total variance explained of more than 60 % (Table 3). In addition, the rotated component matrix shows a clear grouping of the variables. Factor 1 is composed of internal drivers that represent the needs of the firm when adopting DTs (compatibility, complexity, and capability), related to business and cultural practices, technological infrastructure, and skills. Factor 2 defines the outcome of digitalisation and includes two internal drivers (benefits and relative advantage) and two external drivers (competitive pressure and external support). Considering these results, Factor 1 is assigned to inputs and Factor 2 to outputs, as required for the application of CE.

The SI constructed by means of CE makes it possible to produce a ranking of agri-food companies, which can then be divided into quartiles. Table 4 shows the statistics of the relationships between belonging to each quartile of the ranking and the variables described.

The results reveal that product innovation, radical innovation and eco-innovation are associated with the position in the SI (Chi-sq presents a p-value < 0.05), but no association is found with the other innovation options (p-value greater than 0.05). The associations between types of DT and companies' position in the ranking are all significant, except for the most accessible technology (internet access and use) and the most disruptive (Blockchain). Thus, IoT, big data and cloud computing show the strongest connection between ranking position and implementation, shaping the degree of digitalisation of the sector.

The contingency tables below show the percentage of companies in each quartile of the SI and each of the variables analysed (Table 5). (SeeTable A1.Table A2.).

The best positioned companies in the ranking (first SI quartile) were mostly in CL1 (strong adopters) with some in CL2 (moderate adopters). The worst ranked companies are mainly in CL3 (emerging adopters).

A large percentage of the top-ranked companies are product innovators. Different skills are required for technology adoption and for innovation: product innovation requires the company to assimilate customer needs to design new products, while technology adoption requires technical skills to facilitate its application (Oltra-Mestre et al., 2021). It has been shown that the adoption and use of DTs in firms is associated with the ability to introduce new products into the markets, giving firms a competitive advantage. Ali et al. (2021), in their study of Indian agri-food firms, suggest that greater depth of technology adoption is needed to diversify product innovations. Oltra-Mestre et al. (2021) describe how the DTs implemented in Spanish agri-food companies improved functionality to respond to customers' needs with products featuring better aesthetics. The results obtained by Blichfeldt and Faullant (2021) relating to process industries show that companies with higher levels of product innovation are associated with a higher degree of DT implementation.

The relationship between SI position and radical innovation indicates that the percentage of firms that carry out radical innovations is higher in the first quartile. These types of innovations lead to fundamental changes and present opportunities to respond to major disruptions; they are therefore often associated with the development and use of new technologies (Blichfeldt and Faullant, 2021). Pichlak and Szromek (2021) found that the most innovative companies in Poland have higher technological capabilities and are mainly engaged in radical innovations. Linnan et al. (2021) indicate that the leadership-innovation relationship is stronger for radical than for incremental innovations

Table A2
Description and mean values of the digitalisation variables.

Variable	Description	Mean values
Adoption degree	1. Known or not known, but not currently adopted	44 %
	2. In planning	7 %
	3. In installation	3 %
	4. Recently installed	4 %
	5. Installed more than a year ago	40 %
Benefits	Mean Value	3.83
	a) Improvements in planning and management	4.15
	b) Improvements in problem identification	4.04
	c) Improved decision-making	4.02
	d) Improved communication and cooperation with suppliers and customers.	4.10
	e) Improvements in product quality	3.28
	(f) Productivity gains	3.75
	(g) Increased benefits	3.50
Relative advantage	Mean Value	4.01
	a) Helps to reduce costs	4.11
	b) Improves the productivity of the company	4.26
	c) Helps to identify new opportunities (products or services)	3.97
	(d) Facilitates access to new customers or markets	3.93
	e) Allows the company to be more sustainable and environmentally friendly.	3.80
Compatibility	Mean Value	3.74
	(a) It is consistent with the company's current business practices.	3.76
	b) It is compatible with the company's culture and values.	3.89
	c) It is compatible with the company's current technological infrastructure (hardware and software).	3.56
Complexity	Mean Value	3.66
	a) Using new DTs is easy for the company	3.37
	(b) It would be possible to use new DTs in the company	4.35
	c) Employees could quickly learn how to use new DTs.	3.25
Management support	Mean Value	3.71
	a) Promotes and expresses support for the use of new DTs	4.00
	b) Is actively involved in and leads the process of adopting new DTs in the company.	3.80
	c) Is willing to take risks or takes risks to drive the process of adopting new DTs in the company.	3.56
	(d) Adoption of new DTs is a strategic priority	3.51
Company capacity	Mean Value	3.47
	a) Adequate technological infrastructure to be able to implement new DTs	3.40
	(b) Adequate technological infrastructure to be able to operate or manage new DTs	3.40
	c) The talent or skills needed in the company to implement new DTs	3.55
	d) The talent or skills needed in the company to operate or manage new DTs.	3.52
Competitive pressure	Mean Value	3.55
	a) The use of new DTs is a strategic necessity to compete in the agri-food sector because it improves the company's image in the market.	3.71
	(b) General operating practices in the sector make it necessary to adopt new DTs.	3.52
	(c) Competition is an important factor in the decision to adopt new DTs.	3.43
External Support	Mean Value	3.18
	a) Government policies enhance the digitalisation of the agri- food sector	2.71
	(b) Aware of the existence of government agencies that provide services, advice or financial support for the adoption of new DTs.	3.37
	c) The support of technology providers is a factor in the decision to adopt new DTs.	3.45

because decisive management support for modernisation encourages the introduction of more complex developments requiring more technological resources. Acemoglu et al. (2022) show that companies that are more "open to disruption" are more likely to engage in radical innovation.

Regarding the connection between digitalisation and eco-innovation, Table 5 shows a higher concentration of eco-innovating firms in the first two quartiles of the SI. Half of the top-ranked companies align their activities with eco-innovation; therefore, two areas that can progress together, digitalisation and sustainability, are beginning to gain ground. Both concepts support the objectives of the European Commission's Eco-Innovation Action Plan, which focuses mainly on innovative SMEs introducing technological advances in their production systems to bring about a circular economy (European Commission, 2022). The most active companies in innovation development are those that create technological solutions that enable the optimisation of the production process and the creation of competitive advantages that must be aligned with eco-innovation to ensure the successful implementation of the circular economy (ben Amara and Chen, 2022; Pichlak and Szromek, 2021).

Finally, the relationship between the position in the ranking and each of the DTs in the portfolio analysed shows that the higher the complexity of the technology, the lower the percentage of companies that use it in all quartiles. In addition, big data, IoT and artificial intelligence are the technologies that make the most notable difference: in fact, more than 40 % of the companies that use them are in the first quartile. These results are in line with Blichfeldt and Faullant (2021), who found that in the most technological companies there is a direct effect of DT adoption on competitive advantage, while the effect is less clear in the less technological ones. These technologies are associated with the use of information that requires cloud-based data storage, which generates a large digital footprint. The collection and analysis of this information may shift the decision-making power of farm management from farmers to private companies. In a case study of a farmer analysed by Kayad et al. (2022), the accumulated data were found to have doubled approximately every 16 months over the last two decades. The authors call for governments and farmers' associations to raise farmers' awareness about such concerns and protect their data. In addition, the adoption of blockchain throughout the food supply chain requires a well-organised and standardised supply chain between all major (internal and external) stakeholders, but design and deployment is a complex and costly activity (Cao et al., 2021). The results show that this technology is not fully developed in this sector, which limits its adoption by companies.

6. Conclusions

This study sheds light on the internal and external drivers of the degree of digitalisation of agri-food companies, and the relationship between the companies that are best and worst at meeting this digitalisation challenge and their orientation towards innovation and/or eco-innovation. Jointly analysing an entire DT portfolio offers a more detailed and comprehensive view of the situation for making business and policy decisions. Therefore, the study analyses the implementation of both the simpler DTs (internet, e-commerce, business management systems, cloud computing) and the more complex and disruptive ones (big data, IoT, artificial intelligence and blockchain), collecting primary information from 200 companies in the agri-food sector.

The results reveal that DT implementation is conditioned by both internal and external drivers. Management support, which is internal, and competitive pressure, which is external, make the biggest differences between the companies. External support, on the other hand, yields the smallest differences. This indicates that companies with a higher degree of digitalisation have implemented these technologies to cope with competitive pressure, which mainly requires management support to promote, lead and be willing to take risks, rather than

Fig. A1. Territorial distribution of the sample.

external support from government policies or company suppliers. The compatibility of DTs with the company's practices, values, culture and infrastructure and the ability to operate and manage the technologies are the internal drivers that mark the difference between the most digitally advanced group and the rest. Moreover, the results point to a high percentage of companies in the sector that are holding back the digitalisation process due to lack of investment in skills and technology infrastructure. Of the internal behavioural drivers, the evaluation of the benefits of DTs is lower in the less technological companies, reducing their interest in implementing these technologies.

The digitalisation process of agri-food companies is related to their innovation orientation as well as to eco-innovation. Specifically, the position in the ranking based on internal and external drivers is related to companies' product innovation, but there is no evidence that it is related to the rest of the innovation types—process, marketing, and organisational. The top-ranked companies are more proactive in the introduction of radical innovations, while there are no such differences among companies when it comes to the introduction of incremental innovations. It can also be seen that DTs are increasingly aligned with measures that foster sustainability, as confirmed by the greater percentage of companies that carry out eco-innovation activities in the top-ranked group of companies.

Finally, the results indicate that the digitalisation of the sector is marked by the degree of complexity of the technologies. Thus, the percentage of top-ranked companies increases significantly with the degree of complexity, specifically in IoT, big data and artificial intelligence technologies. Blockchain technology is currently implemented by only 22 % of companies and does not make a difference in the digitalisation of the sector.

In short, the research emphasises the importance of understanding the evolution of digitalisation in a sector as strategic as the agri-food sector, which relies on the use of natural resources for its growth. The information obtained can help steer the sector towards modernisation, to which end company management must be aware of the importance of competitive pressure in this sector and promote and lead a digitalisation strategy. Furthermore, both public and private policies should seek to strengthen the sector with well-trained, competitive professionals, who are proficient in the application disruptive technologies. Such measures can help companies that are lagging catch up with the top-ranking companies, allowing a joint development of the sector oriented towards radical innovations and sustainable actions.

However, there are some limitations to the study that must be borne in mind for a proper understanding of the implications. One is the geographical scope: repeating the survey in other countries could reveal different realities. It may also be worth extending the questionnaire to capture characteristics of the digitalisation adopter, such as age, education, digitalisation training, etc. Furthermore, although the present study analyses and describes the position of the companies in the ranking, it could be extended with other methods, such as partial least squares structural equation modelling (PLS-SEM) or fuzzy set qualitative comparative analysis (fsQCA) to identify the necessary and sufficient conditions for the result to occur, in this case, the implementation of digital technologies in the sector.

CRediT authorship contribution statement

C. Calafat-Marzal: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Supervision, Visualization, Writing – original draft, Writing – review & editing. **M. Sánchez-García:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Project administration, Resources, Supervision, Validation, Writing – review & editing. **L. Marti:** Data curation, Formal analysis, Methodology, Software, Supervision, Visualization, Writing – review & editing. **R. Puertas:** Data curation, Formal analysis, Methodology, Software, Supervision, Validation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

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

Data availability

Data will be made available on request.

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Appendix 1. .

Characterisation of the sample and description of digitalisation variables and their mean values.

(SeeFig. A1.)

Appendix 2. .

Description of the digitalisation variables and their mean values.

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