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Digitalisation dynamics in SMEs: An approach from systems dynamics and artificial intelligence

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ABSTRACT

This paper addresses the study of digitalisation dynamics in SMEs. Improving on existing research and its methodological limitations, we provide an understanding of the digital transformation in SMEs by approaching the research from a non-linear and complex perspective. We empirically test our hypotheses using the Eurostat Flash Eurobarometer No. 486 data set, with a final sample of 16,365 SMEs. Our first contribution shows that an adequate understanding of digital transformation not only implies the identification of drivers of digitalisation but also a grasp of how these drivers act, highlighting the differential effect that internal capabilities and external support of the company in interaction have on digital transformation. Moreover, the results show that the effect of interactions between variables is transferred to the output variable in a non-linear process, which may contain an optimum produced by a differential combination of input variables. Second, the paper extends the research methodology, emphasising the importance of combining classic regression analysis with machine-learning techniques. Thus, using a systemic approach, we conclude that the combination of the explanatory power of regression models and machine learning allows us to quantify and explain how variables act, solving complex and non-linear problems.

1. Introduction

Digital transformation in companies involves the implementation of digital technologies to transform production systems, work organisations, and strategic decision-making (Guandalini, 2022; Díaz-Chao et al., 2021; Frank et al., 2019; Vial, 2021). This digitalisation process is fundamentally based on companies embracing emerging technologies such as big data, cloud computing, artificial intelligence/machine learning (AI/ML), robotics, data analytics, and blockchain (Schönfuß et al., 2021; Masood and Sonntag, 2020; Kiel et al., 2017), which allow them to increase the efficiency and quality of both their firms and supply chains (Al Mashalah et al., 2022; Brenner and Hartl, 2021; Agrawal et al., 2020; Bai et al., 2020).

While previous literature has recognised the relevance of digital transformation, it has also noted the difficulties of this transformation for companies (Türkeş et al., 2019; Orzes et al., 2018). For instance, lack of knowledge and skills, financing problems, and resistance to change are the main difficulties that companies encounter (Sebastian et al., 2020; Singh and Hess, 2020; Orzes et al., 2018). This is especially evident in small and medium enterprises (SMEs), where, due to limited resources, the challenges are exacerbated (Ardito et al., 2021; Pfister and Lehmann, 2021). Therefore, a primary concern has been the need to develop conditions that facilitate the digital transformation of companies, creating a framework of relationships and factors that encourage and support the development of this change (Barber et al., 2022; de Sousa et al., 2018). Thus, from an institutional point of view, administrations have understood this need and implemented actions, mainly regulation and financial support. This is especially evident in the industrial sector, where we can find important initiatives such as *Industry 4.0* (I4.0), *smart manufacturing* in the US, *Made in China 2025*, *The Future of Manufacturing* in the UK, and *Smart Factory* in South Korea (Ghobakhloo, 2020; Bai et al., 2020; Galati and Bigliardi, 2019; Frank et al., 2019).

From a theoretical point of view, resource-based view (RBV) or stakeholder approaches have not only considered the importance of factors internal to companies in the development of digital

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transformation (Barber et al., 2022; Zhu et al., 2021; Liao et al., 2017) but also the need for firms to establish relationships with stakeholders as critical agents in creating an adequate institutional framework to facilitate and promote digital development (Agrawal et al., 2020; Manesh et al., 2020). However, although the literature has made important contributions to the identification of factors, obstacles, and barriers that have influenced the implementation of the digitalisation process, there are limitations in understanding how these factors act to promote its development. The main limitation arises from the fact that previous research has analysed the relationship between drivers and digitalisation without considering that this process is dynamic and complex, where non-linear processes and the interaction between variables determine the dynamics of digitalisation.

A first gap in the literature is that most research has approached the study of the digitalisation process from an external perspective, considering how input variables (drivers) directly affect digitalisation, forgetting the effect that interactions between drivers may have on the digitalisation process. The importance of these interactions has been highlighted, especially in recent management and business research, which has pointed out the importance of investigating interactions between processes, as generators of synergistic and complementary effects able to produce surprising impacts on output variables (Arranz et al., 2019; Ballot et al., 2015). Therefore, investigating how drivers interact in the digitalisation process, facilitating it or generating synergistic processes, is important and must be considered.

The second gap arises from the limitation that econometric models have in modelling complex relationships. Previous research has highlighted the problems of classical econometric models in determining the interactions and non-linearity between variables, which have led to the low explanatory power of these models. The question of quantifying and prioritising how drivers affect digitalisation has not been resolved, which is an important issue from the perspective of business decisions and the development of policies (Barber et al., 2022; Agrawal et al., 2020; Arranz et al., 2019), considering the limited resources and the need to identify what the critical factors are in digitalisation.

Therefore, the study of the digitalisation of companies will require the solving of previous limitations and approaching the research from non-linear and complex perspectives,[1] which will allow adequate modelling of these systems. In this context, our paper addresses this gap. First, the theoretical framework used in this paper is dynamic capabilities theory (Sterman, 2000; Barney, 2001; Zahra et al., 2006). Following Eisenhardt and Martin (2000), we assume that firms have the ability to digitalise, deploy resources and capabilities, and use organisational processes to achieve these objectives. In this context, we consider that a firm's decision to develop digitalisation is driven by factors external and internal to the company (Horváth and Szabó, 2019; de Sousa et al., 2018). Moreover, in line with Arranz et al. (2019) and Ballot et al. (2015), we assume that these factors interact, being able to produce a synergistic or complementary effect by stating that it derives from shared competencies, resources, and routines, through the generation of economies of scale and learning processes.

Second, as an analytic framework, we use a systems approach (Teece, 2018; Mercure et al., 2016; Simonovic, 2012; Bergek et al., 2008). Under this framework, we consider drivers as input variables and the digitalisation process of companies as an output variable. Moreover, in line with Wu and Marceau (2002), we consider that drivers interact in non-linear and dynamic processes towards digital transformation. To do this, following Sterman (2000, 2001), we use the theory of dynamic systems, which, combined with simulation methods, will allow us to understand the interaction between the drivers.

Third, from an instrumental point of view, we will combine regression analysis with machine learning, using artificial neural networks (ANNs) and tree regression in our modelling. Thus, to the explanatory power of regression models we can add the capacity of ANNs in the analysis of complex problems, determining all interactions through learning algorithms. This will allow us to solve previous limitations of regression models, providing a higher level of explained variance, which will result in a better understanding and quantification of how various drivers affect the development of eco-innovation systems (Minbashian et al., 2010; Somers and Casal, 2009).

Lastly, our study addresses the digital transformation of SMEs. SMEs are the backbone of Western economies; however, they have been overlooked by previous research, which has mainly focused on large companies. Our study employs the Flash Eurobarometer No. 486 database from Eurostat (Eurostat, 2022), containing a sample of 16,365 SMEs.

2. Theoretical and analytic framework

2.1. Digital transformation of SMEs

An adequate contextualisation of the digital transformation of companies must be carried out under the umbrella of Industry 4.0. Sanders et al. (2016, p. 816) consider that Industry 4.0 is the fourth industrial revolution, where internet and intelligent systems transform human–machine interaction, applying the principles of cyber-physical systems. From an operational point of view, Masood and Sonntag (2020) point out that Industry 4.0 is made up of different technologies such as the internet of things (IoT), cloud computing, additive manufacturing, cybersecurity with blockchain, artificial intelligence (AI), big data, and autonomous robots. In this context, digitalisation is occurring in all countries at many levels in companies (Bai et al., 2020; Kiel et al., 2017), transforming economies, societies, and forms of communication (Da Silva et al., 2020; Singh and Hess, 2020; Horváth and Szabó, 2019). It is in this setting that companies implement these digital technologies, transforming production systems, work organisation, and strategic decision-making (Ciarli et al., 2021; Díaz-Chao et al., 2021).

Digital techniques have the ability to improve the utilisation of energy, equipment, and human resources (Brenner and Hartl, 2021). For example, smart devices help companies continuously monitor machine and energy needs. Digitalisation is transforming the supply chain into a smart supply chain, where the use of IoT and AI-ML allows companies to receive information from the supply chain, analyse this information, and make proactive business decisions. In the field of logistics, we can find applications for container control with blockchain, allowing companies like IBM and Maersk to track container shipments (Papathanasiou et al., 2020). In healthcare, traditional software focused on clinical history and document management, but this is being replaced by cloud computing with instant access to patient data (Chen et al., 2012). In this context, SMEs are recognising the impact of Industry 4.0, incorporating digital technologies into their processes either to increase productivity or, encouraged by the supply chain, to meet the requirements of business development (Masood and Sonntag, 2020; Wang and Bai, 2021). However, this process is not exempt from barriers and challenges (Orzes et al., 2018; Masood and Sonntag, 2020; Horváth and Szabó, 2019; Yu and Schweisfurth, 2020; Schönfuß et al., 2021; Zhu et al., 2021). Previous studies point out that SMEs have greater limitations on financial resources and knowledge, which makes it difficult to tackle the

[1] Following Mercure et al. (2016) and Arranz et al. (2019), complex systems are those whose behaviour is intrinsically difficult to model due to dependencies, relationships, or other types of interactions. Sterman (2000) finds the features of complex systems to be dynamic, tightly coupled, with feedback, non-linear, dependent, self-organising, and adaptative. Therefore, to fully understand the impact of digitalisation on companies, we must consider the interactions between various factors, which may include both internal and external elements. These interactions are often non-linear, meaning that small changes in one area can lead to significant consequences in others. Furthermore, the interactions may be complex, with feedback loops and multiple causal relationships that cannot be easily reduced to a simple cause-and-effect relationship (Sterman, 2000; Pruyt, 2013; Grösser, 2017).

digitalisation process (Horváth and Szabó, 2019). Matt and Rauch (2020) point out that financial difficulties limit investments in digital technologies. For their part, Türkeş et al. (2019) suggest the lack of general knowledge about Industry 4.0 as a key barrier for SMEs. Orzes et al. (2018) identify the following barriers to digitalisation in SMEs: economic and financial, cultural, competence and resources, legal, technical, and implementation processes.

2.2. Theoretical framework: Dynamic capabilities perspective

The paper is framed within dynamic capabilities theory (Eisenhardt and Martin, 2000; Teece, 2018). Dynamic capabilities consist of a set of higher-level activities that allow firms to orient their ordinary activities to high pay-off. Teece (2018) consider dynamic capabilities as firms' abilities to integrate and reconfigure capabilities to address rapidly changing environments. This requires managing and coordinating firms' resources to address these quickly evolving business environments (Teece, 2018). Dynamic capabilities not only encompass capabilities but also firms' processes and routines. In this context, the digital transformation of companies constitutes an example of the development of dynamic capabilities (Díaz-Chao et al., 2021). Helfat and Raubitschek (2018) have pointed out that the digitalisation process, which encompasses the introduction and implementation of digital technologies, is a disruptive one, where internal and organisational processes must change to adapt to new needs. To explore how companies implement digital transformation, we consider three factors: *innovation capabilities*, *digital capabilities*, *and environmental support*.

Cohen and Levinthal (1990) introduce the concept of innovation capability, outlining it as a series of processes and organisational routines that allow a company to seek out, acquire, assimilate, and use resources. These innovation capabilities manifest themselves in firms' innovation processes, that is, the capabilities of organisations to successfully adopt and implement new ideas, processes, and products. Following Teece (2018), who states that firms' capabilities enable the development of innovation processes, we consider the ability to develop certain processes as internal to organisations, conceptualising them as drivers of digitalisation.

Moreover, digital transformation has its peculiarities. Carcary et al. (2019) suggest the need for specific skills and capabilities related to digital transformation. Nwankpa et al. (2021) emphasise the role of information technology (IT) capabilities, arguing that these drive digital transformation. Warner and Wäger (2019) identify a set of digital capabilities, such as digital sensing, digital capture, and digital transformation, for digital transformation in a traditional industry. Mendonça and Andrade (2018) identify the relationship between digital technologies and dynamic capabilities, suggesting that the implementation of AI-ML, big data, and IoT influences the capture capacity of an organisation as a component of a traditional dynamic capability. Therefore, in line with the dynamic capabilities perspective, which considers that firms' capabilities result from learning, organisational resources, and organisational histories (Teece, 2018), we consider that the possession of digital capabilities is an outcome that arises from practice, experimentation, and learning.

Finally, Sussan and Acs (2017) have highlighted the interaction of firms with their environment as a driver of the digital transformation of companies. Thus, stakeholders have pushed and facilitated companies to increase competitiveness, introducing digital technologies in an interconnected world. In particular, companies immersed in the business environment can find process facilitators. Thus, financial and regulatory support, such as the availability of adequate digital competencies and managerial skills, as well as an adequate IT infrastructure, among others, facilitates the digital transformation process (Guandalini, 2022; Sussan and Acs, 2017).

2.3. Analytical framework: System dynamics theory

As pointed out in the introduction, for our modelling, we are going to use system dynamics theory. The system dynamics approach presents a means to describe and simulate dynamically complex problems through the structural identification of feedback and lag processes that drive system behaviour (Sterman, 2000; Pruyt, 2013). This method itself has been used for a wide spectrum of applications, including the modelling of complex ecological and economic systems (Costanza and Gottlieb, 1998; Costanza and Voinov, 2001), many of which address, to some extent, the social implications of the behaviour of the system (Wu and Marceau, 2002; Bossel, 2007; Ford, 1999). In this context, Sterman (2000) points out that the system dynamics approach describes and simulates dynamically complex problems, and allows the identification of interactions between variables and processes which drive the behaviour of the system. Sterman (2000) and Pruyt (2013) point out that the process of developing system dynamics models is generally based on the identification of factors and their dynamic interaction, followed by the simulation and interpretation of the model.

System dynamics theory considers that a complex system is composed of elements, parts, or subsystems, and emphasises the interaction between the elements and a system's evolution (Russell and Smorodinskaya, 2018; Zhao et al., 2018; Sterman, 2001). Interaction between components is defined as a process by which two or more variables affect each other, implying the idea of a bidirectional effect as opposed to a unidirectional causal effect (Sterman, 2000, 2001). Input variables interact in a dynamic process, where the interactions between components produce an effect on their initial value. Sterman (2000) models the dynamic interaction between components, conceptualising it as a feedback loop in which the effect of a variation in any component propagates through the loop and returns to the component, affecting the initial value. This author distinguishes between a reinforcing loop, in which a reinforcement of the initial value occurs, and a balancing loop, in which a weakening of the initial value occurs. Two consequences can be derived from the effect of the dynamic interaction between components: first, a strengthening/weakening in the components as a consequence of the interaction; and, second, the output variables of the system are left strengthened/weakened as a consequence of the interaction of the input variables, with respect to the non-existence of interaction.

2.4. Research model and hypotheses

In our modelling, we propose that the development of digitalisation in SMEs is fostered and promoted/facilitated by a series of factors (drivers). We take a systems approach to digitalisation, where input variables are the drivers and the output variable is digitalisation. Thus, digitalisation will involve a dynamic process where input variables (drivers) interact with each other to achieve the output variable. Fig. 1 shows the causal loop diagrams (CDL) of digitalisation systems.

2.4.1. Interaction between internal drivers and the impact on the digital transformation of SMEs

From an internal point of view of the company, we have considered two drivers of SMEs in the development of the digitalisation process: innovation capabilities and digital capabilities. Following a system dynamics approach, it is expected that these internal drivers will interact with each other in a reinforcing loop. First, Arranz et al. (2019) and Pfister and Lehmann (2021) point out that the digitalisation of companies can mean changes in products, processes, and organisations, where the possession of innovation capabilities also facilitates its development. Hence, SMEs must make digital competencies compatible with innovation capabilities, with the aim of facilitating the digital transformation. That is, under the logic of dynamic systems (Sterman, 2000), in this interaction process, digital capabilities might be affected by their interaction with the innovation capabilities of the organisation,

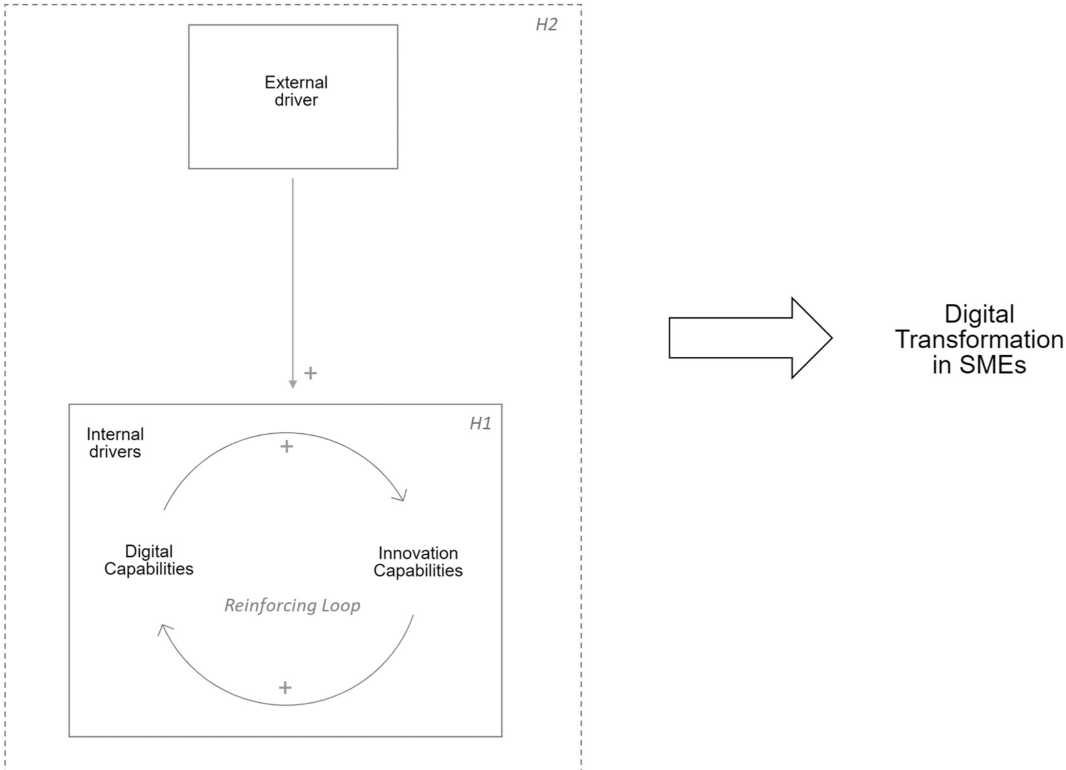

Fig. 1. Model of digitalisation in SMEs.

reinforcing the digital capabilities. From the perspective of dynamic capabilities, the possession of innovation capabilities should affect SMEs, increasing the control of firms' activities and the creation of new organisational routines in the process of digital transformation (Eisenhardt and Martin, 2000; Teece, 2018). Second, it is to be expected that the existence of innovation capabilities in a company will be reinforced by the implementation of digital capabilities. Innovation capabilities are expected to be strengthened when interacting with digital capabilities. Innovation capabilities require digital competencies in the digital transformation process (Ciarli et al., 2021; Pfister and Lehmann, 2021; Bharadwaj et al., 2013).

Moreover, from the point of view of dynamic capabilities, especially in the context of innovation studies, extensive research explains the reinforcement or synergistic effect of the interaction between technological and non-technological innovation and its effect on firm performance (Ballot et al., 2015; Arranz et al., 2019). For example, Camisón and Villar-López (2014) report a complementary effect between organisational and process innovations and their impact on firm performance. Doran (2012) justifies that the interaction between resources and capabilities arises as a consequence of the need to develop tasks and previous routines or the affinity between them. Fagerberg (2018) highlights the positive and synergistic effects of the integration of various strategies through the shared value created by knowledge management systems and the influence on organisational performance. Arranz et al. (2019) have highlighted that the innovation process in organisations involves mobilisation of resources, capabilities, and organisational routines, emphasising the synergies produced in this process. In this sense, the interaction of digital and innovation capabilities leads to processes that can produce complementarities in the development of digitalisation, through the generation of economies of scale and learning processes.

Digital and innovation capabilities individually have a positive effect on the digital transformation of companies (Ardito et al., 2021). We postulate that the interaction of internal drivers (digital and innovation capabilities) creates a reinforcement effect in a feedback loop, where the two drivers are mutually reinforcing, which will result in a greater probability of digitalisation than if the drivers did not interact. Hence, we propose:

Hypothesis 1a. Internal drivers (digital and innovation capabilities) interact with each other, forming a reinforcing interaction, which positively affects the digital transformation of SMEs more than if they do not interact.

Nevertheless, previous research also highlights the difficulties of this transmission as a consequence of problems in the compatibility and development of both capabilities, especially in SMEs. Moeuf et al. (2019) and Ardito et al. (2021) point out that, based on the limited resources of companies, there are difficulties in integrating some strategic orientations. That is, the knowledge and human resources necessary to implement digital innovation can be different and addressed with varying objectives. More particularly, SMEs have a limited number of employees, so considering both digital and innovation capabilities can expose these employees to a variety of tasks and skills. Therefore, both capabilities might be difficult to absorb and assimilate, and employees may not be committed to dedicating the necessary effort and time to diverse activities and distant opportunities (Ardito et al., 2021; Ocasio, 2010). Additionally, the interaction of both capabilities can produce a paradoxical organisational situation, where managers have to face too many competing tasks and objectives when managing digital and innovative capabilities (Kim et al., 2013). In this sense, Ocasio (2010) notes the problem of attention distribution, arguing that attention is a limited resource and that managers need to concentrate their energy, effort, and full attention on a limited number of items to achieve performance. Moreover, Ardito et al. (2021) indicate that this problem is aggravated in the case of SMEs as managers do not usually delegate the implementation of a strategy and will probably be overwhelmed by the complexity of integrating both strategies and combining resources, identifying the probability of generating conflict situations.

However, our position suggests that both capabilities can coexist with different levels of integration. Yet, Adams et al. (2019) emphasise that the implementation of strategic orientations is a dynamic process characterised by various levels of integration: from proactivity, where companies take the initiative and address the objectives and actions to implement these strategic orientations, to reactivity, where, due to market, stakeholder, or regulatory pressures, firms implement strategies without a high level of commitment. This is consistent with the literature that highlights that a characteristic of SMEs, in addition to flexibility, is reactivity in the implementation of strategic orientations (Ardito et al., 2021), allowing different levels of integration of the various orientations. In this context, Masood and Sonntag (2020) highlight that the digitalisation process itself is complex, requiring high levels of resources from SMEs, as a consequence of the need to integrate various digital technologies simultaneously. For example, cloud computing coexists with smart devices and IT infrastructure, implying the connectivity of companies through IoT (Masood and Sonntag, 2020), or, in the case of manufacturing companies, collaborative robotics connect with smart supply chains through the industrial IoT (IIoT) (Da Silva et al., 2020), or analytical tools of machine learning combined with big data provide information on trends, markets, and consumers (Masood and Sonntag, 2020; Frank et al., 2019). Furthermore, in certain sectors, the digitalisation of companies is not only key to their competitiveness but is also imperative to the supply chain of the firm (Al Mashalah et al., 2022; Moeuf et al., 2019). All this will force SMEs to focus fundamentally on developing digital competencies and using innovative capabilities in a complementary way. Moreover, based on these perspectives, we postulate that the relationship between the integration of both capabilities and the digital transformation of the SME follows a U-inverse shape function. This is derived from the paradoxical situation of the integration of both capabilities. This means that for high levels of integration of both capabilities, the digital transformation of SMEs can be weakened. Thus, the interaction of digital and innovation capabilities has a positive effect on digital transformation; however, when the level of integration of both capabilities is high, resource allocation and management problems might arise, producing a decrease in the effect that both have on the digitalisation of SMEs. Hence, we propose two more hypotheses:

Hypothesis 1b. The impact of digital capability is higher than the impact of innovation capabilities in the digital transformation of SMEs.

Hypothesis 1c. The relation between digital and innovation capabilities and digital transformation in SMEs follows a U-inverse shape.

2.4.2. *Interaction between external and internal drivers, and the impact on the digital transformation of SMEs*

In our model, we propose, as external drivers, the existing environmental framework suitable for the development of digitalisation in SMEs. Unlike the interaction between internal drivers that we consider reciprocal (bidirectional), in this case, we postulate a unidirectional interrelation, where external drivers reinforce internal drivers.

First, dynamic capabilities theory points out that the possession of resources affects firms' capabilities, through the development of competencies and capabilities, increasing the control of firms' activities and permitting the creation of organisational routines (Eisenhardt and Martin, 2000; Teece, 2018). In this context, we postulate that the creation of adequate environmental support based on access to financial aid, regulation, and standardisation of activities, among others, will have a significant effect on the internal capabilities of the organisation in the digital transformation of SMEs, affecting both digital and innovation capabilities. In particular, the existence of regulation can be seen as a facilitator of internal capabilities in a firm. In line with Arranz et al. (2022), regulations and standards increase the digital and innovative competencies of organisations through the introduction of procedures and organisational routines, mitigating the uncertainty of the digitalisation process. Therefore, regulations and standards will have a positive effect on increasing internal capabilities in organisations. Furthermore, financial resources have been recognised as an incentive for the development of digital and innovation capabilities (Díaz-Chao et al., 2021). Digitalisation requires companies' investment, for which sources of financing must be sought either internally, withdrawing them from other investments, or externally, for example, coming from the administration (Ardito et al., 2021). Moreover, the existence of financial support will be postulated as a reinforcement impulse of internal drivers in the digital transformation of companies. Siguaw et al. (2006) point out that the existence of external funding will encourage capabilities and competencies in a firm. In addition, financial resources allow for increasing the innovative competencies of a company, through, for example, training programmes (Sussan and Acs, 2017; Teece, 2018), and the consequent impact on internal capabilities in the digitalisation of SMEs.

However, this reinforced loop between a favourable environment and internal capabilities is not known as it translates to the digital transformation of SMEs. Martínez-Román et al. (2011), Lichtenstein (2000), and Antoniou et al. (1997) have pointed out that this positive effect follows a non-linear behaviour derived from administrative complexity. For example, Emara and Zhang (2021) have indicated that digitalisation policies can be implemented in the form of regulations and standardisations, which can have a non-linear effect. Hence, as policies and the level of regulation increase, the effect on companies diminishes. This can be especially critical in the case of SMEs, which, due to either a small number of staff or the scarce tendency of managers to delegate, excessive regulation can be a disincentive to digital transformation. Similarly, the literature contains contradictory arguments regarding the financial support of the administration (Abe et al., 2015). That is, access to financial support can be administratively complex and tedious, especially for SMEs, becoming a disincentive for companies to resort to public financing. Hence, we propose:

Hypothesis 2. The relation between the interaction of internal and external drivers and the digital transformation of SMEs is non-linear, and follows a U-inverted shape.

3. Empirical study

3.1. *Database*

To empirically test the hypotheses, we use the database from the Eurostat Flash Eurobarometer No. 486, which is conducted for the European Commission (Eurostat, 2022). The FL486 survey on "SMEs, start-ups, scale-ups and entrepreneurship" was conducted in the EU27 and an additional 12 non-EU countries and territories, and focuses on the barriers and challenges that SMEs in Europe face when growing, transitioning to more sustainable business models and digitalisation. The survey collected responses from >16,000 telephone interviews with enterprises employing one or more persons between 19th February and 5th May 2020. Interviews were conducted by phone in their respective national language, providing a final sample of 16,365 SMEs.

Regarding the distribution based on size, we see that 62 % of the companies are microenterprises (one to nine employees), 22.5 % are small companies (ten to 49 employees), and, finally, 15.5 % are medium-sized companies (50 to 249 employees). Regarding the sectoral distribution, the companies are included in 16 business sectors, corresponding to manufacturing at 19.5 %, retail firms at 27.7 %, and scientific and technical activities at 9.3 % (Table 1). Moreover, in Table 2, we present the distribution by country.

3.2. *Measures*

The output variable measures the intention to plan for future *digital transformation* in SMEs. The question posed is: which of the following options best describes your enterprise's approach to digital technologies? The question contains these multi-item options: i) your enterprise is planning to adopt basic digital technologies such as email or a website

Table 1
Distribution of SMEs by sector (NACE-Sections).

Sector	Frequency	Percent
B - Mining and quarrying	90	0.5
C - Manufacturing	3184	19.5
D - Electricity, gas, steam and air conditioning supply	100	0.6
E - Water supply, sewerage, waste management/ remediation activities	167	1.0
F - Construction	1576	9.6
G - Wholesale and retail trade, repair of motor vehicles and	4532	27.7
H - Transportation and storage	929	5.7
I - Accommodation and food service activities	919	5.6
J - Information and communication	625	3.8
K - Financial and insurance activities	344	2.1
L - Real estate activities	376	2.3
M - Professional, scientific and technical activities	1524	9.3
N - Administrative and support service activities	720	4.4
P - Education	383	2.3
Q - Human health and social work activities	622	3.8
Arts, entertainment and recreation	274	1.7
Total	**16,365**	**100.0**

Table 2
Distribution of SMEs by country.

Countries	Frequency	Percent
FR - France	503	3.1
BE - Belgium	500	3.1
NL - The Netherlands	500	3.1
DE - Germany	500	3.1
IT - Italy	500	3.1
LU - Luxembourg	200	1.2
DK - Denmark	500	3.1
IE - Ireland	500	3.1
GB - United Kingdom	502	3.1
GR - Greece	500	3.1
ES -Spain	502	3.1
PT - Portugal	500	3.1
FI - Finland	501	3.1
SE - Sweden	500	3.1
AT - Austria	500	3.1
CY - Cyprus (Republic)	201	1.2
CZ - Czech Republic	501	3.1
EE - Estonia	500	3.1
HU - Hungary	500	3.1
LV - Latvia	500	3.1
LT - Lithuania	500	3.1
MT - Malta	201	1.2
PL - Poland	500	3.1
SK - Slovakia	503	3.1
SI - Slovenia	503	3.1
BG - Bulgaria	500	3.1
RO - Romania	500	3.1
TR - Turkey	300	1.8
HR - Croatia	500	3.1
MK - Makedonia/FYROM	202	1.2
RS - Serbia	200	1.2
NO - Norway	300	1.8
IS - Iceland	201	1.2
JP - Japan	300	1.8
US - USA	501	3.1
BR - Brazil	344	2.1
BA - Bosnia and Herzegovina	200	1.2
RS-KM - Kosovo	200	1.2
CA - Canada	500	3.1
Total	**16,365**	**100.0**

but not advanced digital technologies; ii) there is a need to introduce advanced digital technologies but your enterprise does not have the knowledge, skills, or financing to adopt them; iii) there is a need to introduce advanced digital technologies and your enterprise is currently considering which of them to adopt; and iv) there is a need to introduce advanced digital technologies and your enterprise has already started to adopt them.

Regarding the input variables and, more specifically, the internal drivers (*innovation and digitalisation capabilities*), we consider, in line with the dynamic capabilities perspective, that a firms' capabilities result from learning, organisational resources, and organisational histories (Teece, 2014). Therefore, the possession of digital and innovation capabilities is an outcome that arises from practice, experimentation, and learning. In this context, we measure digitalisation capabilities by the level of experience and digitalisation acquired by an SME. To do this, we pose a multi-item question, using a relation of emerging technologies such as big data, cloud technology, AI/ML, robotics, data analytics, and blockchain. The question posed is: which of the following digital technologies has your enterprise adopted? The question contains multi-item options: i) AI, e.g. machine learning or technologies identifying objects or persons, etc.; ii) cloud computing, i.e. storing and processing files or data on remote servers hosted on the internet; iii) robotics, i.e. robots used to automate processes, for example, in construction or design, etc.; iv) smart devices, e.g. smart sensors, smart thermostats, etc.; v) big data analytics, e.g. data mining and predictive analysis; vi) high-speed infrastructure; and vii) blockchain. Additionally, following Arranz et al. (2021), the variable *digital capabilities* was formed as a cumulative index of the seven types of digital technologies (AI, cloud computing, robotics, smart devices, big data analytics, high-speed infrastructure, and blockchain), measuring the level of digitalisation of SMEs (Cronbach alpha: 0.682).

In line with the previous variable input, we measure the innovation capabilities, considering them by the level of experience and development of innovations in the SME. The proposed question is: during the past 12 months, has your enterprise introduced any of the following types of innovations? The question contains multi-item options: i) a new or significantly improved product or service to the market; ii) a new or significantly improved production process or method; iii) a new organisation of management or a new business model; iv) a new way of selling your goods or services; and v) an innovation with an environmental benefit, including an energy or resource efficiency benefit. As with the previous variable, we create a new variable *innovation capabilities* as a cumulative index of the five items (Cronbach alpha: 0.610).

The last input variable measures the support given by the business environment to SMEs (external drivers). The question posed is: how would you rate your business environment in terms of: i) access to private and public finance; ii) quality of support services for businesses provided by private and public actors; iii) access to and collaboration with business partners, including other enterprises, the public sector, educational institutions, research organisations, etc.; iv) availability of staff with the right skills, including managerial skills; v) legal and administrative environment; and vi) infrastructure for businesses, such as available office space, internet connectivity, etc. The *external driver* variable is created as a cumulative index of previous items (Cronbach alpha: 0.717).

3.3. Methodology

In the modelling, we follow the analytical framework of systems theory, considering the input variables as internal drivers (digital and innovation capabilities) and an external driver (environmental framework), and the output variable as planning the future digitalisation transformation. Furthermore, under the systemic approach, an important aspect is the dynamics of the interaction and possible synergistic/ complementary effects that occur between the input variables and the output variable. Regarding the existence of synergistic effects in the output variable, we conceptualise complementarity across activities when two types of activity simultaneously result in greater returns than engagement in either of these forms separately. Milgrom and Roberts (1990) point out that doing more than one activity increases the returns compared to doing more of another. In the simplest case, in which two variables x and y take two values, 0 and 1, the complementarities are expressed by the following condition on the objective function *f (x, y)*, where *f (1,1)* corresponds to the presence of both variables x and y, and *f (1,0)* the presence of x and the absence of y:

$$f(1,1) - f(1,0) \rangle f(0,1) - f(0,0)$$

Such a function is said to be strictly super-modular in x and y, with existing complementarity between both variables.

3.3.1. Statistical models for estimation

In this paper, we combine regression analysis with ANN and tree regression. We propose a simulation of the effect of the three drivers on digitalisation with ANN and tree regression.

Regarding the simulation using ANN architecture, we use the typology of ANN known as multilayer perceptron (MLP) (Fig. 3). This architecture is known as a supervised network in the sense that the predicted results can be compared against known values of the dependent variables. The network architecture of an MLP has an input layer, hidden layers, and an output layer. The hidden and output layers' neurons, with their associated weights, are connected, which allows for analysing the interaction between input variables.

In order to design the ANN-MLP architecture, we follow Wang (2007) and Arranz et al. (2022). Table 3 shows the design procedure of the ANN-MLP architecture. In this procedure, we can distinguish two key points: i) the choice of the number and size of the hidden layer, and ii) the choice of the learning algorithm. First, while the number of inputs and outputs of the proposed network is given by the number of available input and output variables, the number and size of hidden layers are determined by testing several combinations of the number of hidden layers and the number of neurons,[2] using a trial-and-error approach (Arranz et al., 2022; Ciurana et al., 2008; Mohrotra, 1994). That is, the selected architectures are tested with diverse activation functions, finding that the best architecture is one that minimises the error. Second, for the choice of the learning algorithm, in this case, we use a back-propagation algorithm. This learning algorithm determines the connection weights of each neuron, readjusting the weights and minimising the error.[3] The equation for modifying the algorithm weights is shown below:

$\Delta wji(n+1) = \mathcal{E} \bullet \mu_{pi \cdot} - x_{pi} + \beta \Delta w_{ji}(n)$	Being, w_{ji} = weight neuron i and j n = number of interactions $\mathcal{E}$ = learning rate μ_{pi} = neuron j error for pattern p x_{pi} = output of neuron i for pattern p β = momentum

From the equation, we can see that there are three critical variables: the number of interactions, the learning rate, and the moment. Regarding the number of interactions (n), we have used 10,000.[4] As for the value of the learning rate (β), which controls the size of change of the weights in each iteration,[5] this is usually between 0.05 and 0.5. Finally, the moment factor (α) accelerates the convergence of the weights. Yegnanarayana (2009) points out that a value close to 1, for example, 0.9, is a good value.

The analytical equation of our simulation with ANN-MLP takes the following form:

$Digitalisation =$ $h\left[\sum_{k=1}^{6} \alpha_k \bullet g\left(\sum_{j=1}^{6} \beta_{jk} \bullet X_j\right)\right]$	with X_j being the input variable; j the number of input variables; *h(.)* and *g(.)* the activation functions; α_k and β_{jk} the input and hidden network weights, respectively; and k the number of hidden layers.

4. Analysis and results

Before the analysis of the hypotheses, we tested the robustness of the questionnaire, answers, and variables. Regarding this, we have analysed the common method variance (CMV) and the common method bias (CMB), following Podsakoff et al. (2003)' method. This analysis reveals eight distinct latent constructs that account for 76.75 % of the variance. The first factor accounts for 14.064 % of the variance, which is below the recommended limit of 50 %. This result suggests CMV and CMB are not a concern in our results.

Regarding Hypotheses 1a and 1b, which point out how the interaction between digital and innovation capabilities affects the development of digitalisation in SMEs, we previously carried out an initial test using regression analysis. Table 3 (Models 1 and 2) shows the results of the regression analysis, demonstrating that digital ($\beta = 0.443$; $p < .001$) and innovation capabilities ($\beta = 0.197$; $p < .001$) have a positive effect on the future digitalisation of SMEs. We also observed that the joint capabilities variable ($\beta = 0.010$; $p < .001$) has a positive effect on the digitalisation. The last column of regression analysis shows the VIF (variance inflation factor) scores, which indicate the absence of collinearity issues between the variables' digital capabilities, innovation capabilities, and external drivers. Additionally, Durbin-Watson results indicate the absence of autocorrelation problems in the regression analysis, suggesting that the residuals are independent and do not exhibit a pattern of correlation. Overall, based on the VIF scores and the results of the Durbin-Watson test, it appears that there are no collinearity or autocorrelation issues in the regression analysis involving the variables mentioned. This strengthens the reliability of the regression model and the interpretation of its results. However, due to the high correlation between the joint variables and the variables acting independently, it is not possible to obtain a single model including the three variables.

To solve this problem of collinearity, and to analyse the interaction of the input variables, in Table 3 (Models 4 and 5), we show the regression analysis using categorical variables. As dependent variables, we use the variable *digitalisation*, and in Model 4, three categories with reference to digital capabilities. The first category corresponds to when SMEs do not have digital capabilities, the second to when they have digital capabilities, and the third to when they have digital capabilities together with innovation capabilities. For the analysis of the results, the various regression coefficients must be interpreted as follows: the

[2] The choice of an appropriate number of hidden neurons is extremely important: if few are used, few resources would be available to solve the adjustment problem, and too many neurons would increase the training time in addition to causing an overfit. Ciurana et al. (2008) and Mohrotra (1994) point out that for function approximation, a two-layer neural network is usually sufficient to accurately model.

[3] The backpropagation algorithm works as follows: an input is set as a stimulus for the first layer of neurons in the network; this stimulus spreads through all the layers until it generates an output. The result obtained in the output neurons is compared with the actual output and an error value is calculated for each output neuron. These errors are then transmitted backwards, starting from the output layer, to all the neurons in the intermediate layer that contribute directly to the output, receiving the approximate error percentage of the participation of the intermediate neuron in the original output. Based on the value of the error received, the connection weights of each neuron are readjusted. This process is critical for network optimisation and error minimisation.

[4] Normally, the number of iterations ranges from 1000 to 10,000, and a trial-and-error process is recommended (Arranz et al., 2022).

[5] Two extremes should be avoided: too little a learning rate can cause a significant decrease in the speed of convergence and the possibility of ending up trapped in a local minimum; however, too high a learning rate can lead to instabilities in the error function, which will prevent convergence from occurring because jumps around the minimum will be made without reaching it. Therefore, it is recommended to choose a learning rate as large as possible without causing large oscillations (Arranz et al., 2022).

Table 3
Regression analysis for complementarity effect.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5	VIF
	Estimate	Estimate	Estimate	Estimate	Estimate	
Digital capabilites	0.443***					1.178**
Innovation capabilities	0.197***					1.164*
External driver	0.016***					1.044
Digital & innovation		0.010***				
Digital & innovation & external			0.008***			
Digital capabilites				1.043***		
Digital & innovation				1.063***		
Innovation capabilites					0.678***	
Digital & innovation					1.388***	
−2 Log Likelihood	6264.530	3011.151	2127.392	180.403	122.223	
Chi-square	1921.817	1137.767	1120.518	1195.223	974.420	
Sig.	0.000	0.000	0.000	0.000	0.000	
Cox and snell	0.142	0.086	0.085	0.091	0.074	
Nagelkerke	0.155	0.095	0.093	0.099	0.082	
McFadden	0.062	0.037	0.036	0.039	0.032	

Durbin-Watson test: 1.917.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

regression coefficient value 0 reflects the reference category (digital capabilities =0), and the rest of the regression coefficients obtained correspond to the various categories, which reflect the probability of digitalising with respect to the first category. That is, H0: $ß \leq 0$ means there is a lower probability of digitalising than the reference category, and H1: $ß > 0$ entails there is a greater probability of categories than the reference category. The results show a complementarity effect when both capabilities act together with respect to individual performance. In Model 4, we see that the regression coefficient of digital capabilities ($\beta = 1.043$; $p < .001$) is lower than that of digital capabilities and innovation capabilities together ($\beta = 1.063$; $p < .001$). Model 5 shows similar results for the case of innovation capabilities. Thus, innovation capabilities have a positive regression coefficient ($\beta = 0.678$; $p < .001$), but are lower than the joint variables of both capabilities ($\beta = 1.388$; $p < .001$). We can conclude that there is complementarity between both capabilities in digitalisation, corroborating Hypothesis 1a.

Regarding Hypothesis 1b, which examines the type of capability that has the greatest impact on the digitalisation of SMEs, previous analysis shows a differential contribution, since digital capabilities have a greater contribution than innovation capabilities, as shown by the difference in the regression coefficients obtained. With the aim of testing these results, we have performed a complementary analysis using tree regression. The econometric models for this analysis are as follows:

$$\text{Digitalisation} = f(\text{digital capabilities}; \text{innovation capabilities})$$

In Fig. 2, we find the results of this analysis, using CHAID as a method and showing the possible combinations of both capabilities with different values. Firstly, we see two levels of the decision tree, the first corresponding to digital capabilities, which is the one with the greatest impact (Chi-square: 1832.911; df: 12; sig.: 0.000), and the second to innovation capabilities, showing a lower impact on the probability of developing digitalisation in SMEs (Chi-square: 51.722; df: 6; sig.: 0.000). To proceed with the analysis, we identified the branches that are more likely to digitalise. On the first level, we found that node 5 has a higher digitalisation value, with the estimated value being the maximum for the digitalisation variable in 68 % of cases (see Fig. 2). In this node, there are values of digital capabilities >4 (digital capabilities range: 0 to 7), with a very wide range of innovation capabilities values (range: 0 to 5), as shown by node 18, with a range of the variable from 2 to 5, and node 19, with a range from 0 to 1. Second, node 1 shows a high probability of obtaining a maximum digitalisation value, with medium digital capabilities values (3; max range: 7) and significant variability of the innovation capabilities variable, as shown by node 6 (values: 1 and 2), node 7 (values: 0), and node 8 (values: 4 to 5). The rest of the branches of the tree model show a low probability of obtaining high digitalisation values. Therefore, we see that the digital transformation of SMEs is more probable with high values of digital capabilities, combined with moderate values of innovation capabilities, corroborating Hypothesis 1b.

Regarding Hypothesis 1c, which establishes a relationship between digital and innovation capabilities and the digital transformation of SMEs, we performed pre-testing beforehand (see Table 4). Using regression analysis and the independent variables as categorical (digital capabilities and innovation capabilities), we obtained the marginal effects of each independent variable. In both variables, the maximum value has been used as the reference variable; hence, in this case, the regression coefficients are negative. Regarding the digital capabilities variable, with a range from 0 to 7, we observe that the values increase up to the value of 3; from there, the values are not significant, having no impact on digitalisation (Model 1). In the same way (Model 2), we see that innovation capabilities monotonically increase up to the value of 3, being non-significant up to the maximum value of the variable (5). Therefore, we see that when the capabilities variables act independently, the impact increases up to a certain value, from which we cannot assess this impact since it is not significant.

After this pre-testing, we carried out modelling with ANN-MLP in order to compare the interaction between the input variables and their effect on the output variable. The econometric models include the two input variables and the joint variable.

$$\text{Digitalisation} = f(\text{digital capabilities}; \text{innovation capabilities}; \text{digital*innovation})$$

The results of the architecture for the model are shown in Table 5. Thus, the architecture for digitalisation is 3–4-1, which means that there are 3, 4, and 1 neurons in the input, hidden, and output layers, respectively. In the case of the hidden layer, the activation function used was the hyperbolic tangent and the SoftMax function was used for the output layer.

Previously, we tested the robustness of the analysis, and we can point out that the robustness of the simulation is high, considering the various tests performed. First, we tested the fitting of the ANN-MLP design, performing a level of the fitting up to 70 %. Second, we checked the predictability of our models, using the receiver operating characteristics (ROC) curve, which is a figure of sensitivity versus specificity, showing the classification performance (Arranz et al., 2022). That is, if the curve moves away from 45 degrees, the accuracy of the model is higher. In our case, the ROC curve shows that the chosen architecture can predict >60 % of the values of the output variable (Fig. 3). Moreover, we have

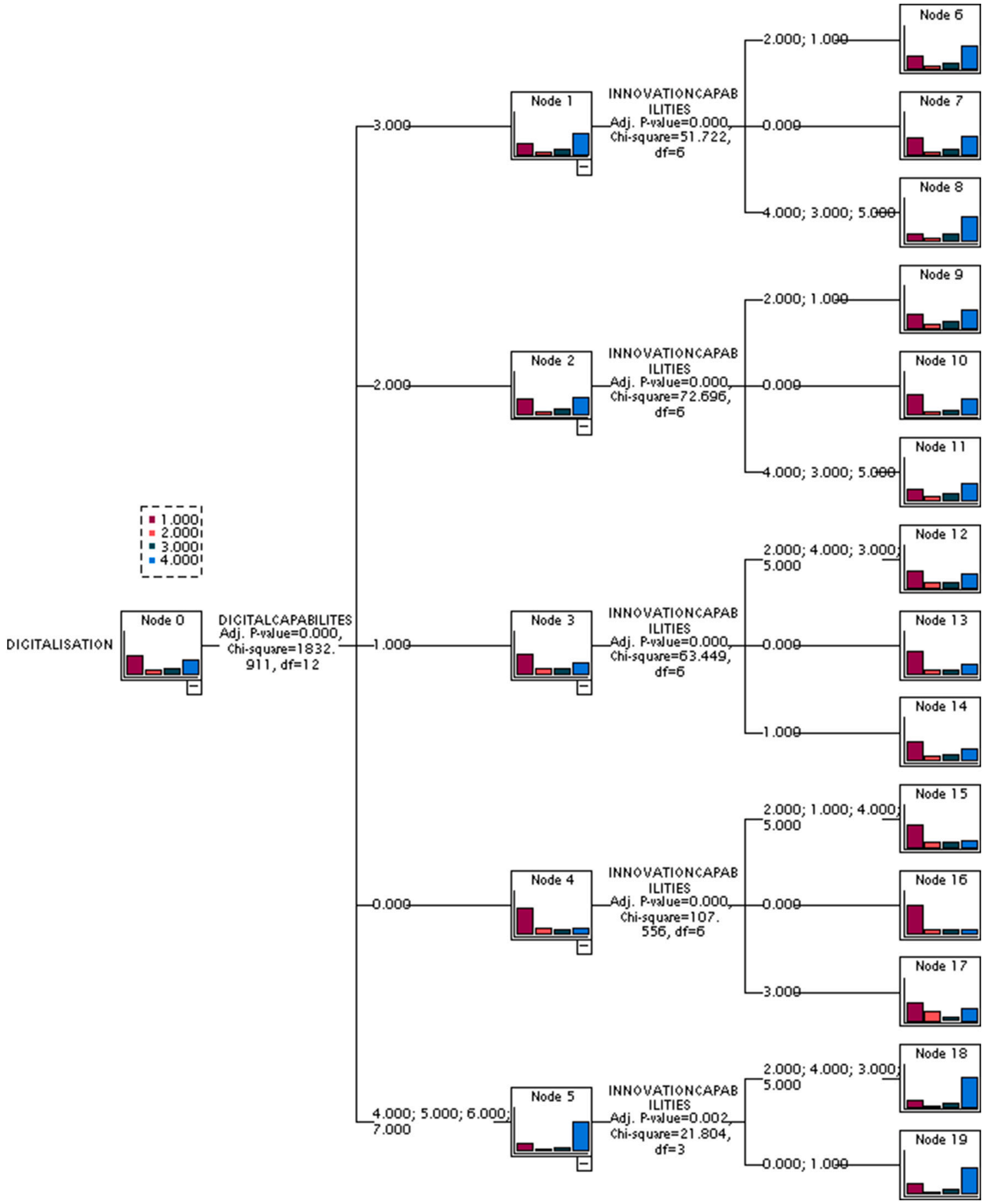

Fig. 2. Tree regression analysis with digital and innovation capabilities.

included the cumulative gains curve[6] and lift charts in Fig. 3, showing that the robustness of the simulation is high.

Fig. 4 displays the relationship between digitalisation and the two input variables (digital and innovation capabilities). In both cases, we notice that the results show a maximum value, from which increases in the input variables do not generate increases in the digitalisation variable. Furthermore, Fig. 4 shows the relationship between the joint digital and innovation capabilities variable with respect to digitalisation, showing a decrease at high values, corroborating Hypothesis 1c.

Additionally, Fig. 5 shows the normalised importance of each input variable on the output variable. The normalised importance of each

[6] The cumulative gains curve is the presence of correct classifications obtained by the ANN model against the correct classifications that could result by chance (i.e. without using the model). Lift charts, as well as gain charts, are visual aids for evaluating performance of classification models.

Table 4
Regression analysis with marginal effects.

Model 1		Model 2	
Variable	Estimate	Variable	Estimate
DIGITALCAPABILITES = 0.00	−2.206***	INNOVATIONCAPABILITIES = 0.00	−1.284***
DIGITALCAPABILITES = 1.00	−1.565***	INNOVATIONCAPABILITIES = 1.00	−0.751***
DIGITALCAPABILITES = 2.00	−1.060**	INNOVATIONCAPABILITIES = 2.00	−0.352***
DIGITALCAPABILITES = 3.00	−0.572**	INNOVATIONCAPABILITIES = 3.00	−0.103***
DIGITALCAPABILITES = 4.00	0.024*	INNOVATIONCAPABILITIES = 4.00	0.139
DIGITALCAPABILITES = 5.00	0.154	INNOVATIONCAPABILITIES = 5.00	0[a]
DIGITALCAPABILITES = 6.00	0.457		
DIGITALCAPABILITES = 7.00	0[a]		
−2 Log Likelihood	290.917		138.740
Chi-Square	1738.790		798.723
Sig.	0.000		0.000
Cox and Snell	0.129		0.061
Nagelkerke	0.141		0.067
McFadden	0.057		0.026

[a] Baseline group.
* $p < .10$.
** $p < .05$.
*** $p < .01$.

Table 5
ANN-MLP architecture for investment in cybersecurity analysis.

Output variable	ANN architecture	Activation Functions	Error function
Digitalisation	3-4-1	● Hyperbolic tangent ● Identity (SoftMax)	Cross-entropy

input variable[7] is based on Garson's algorithm, which uses the absolute values of the final connection weights when calculating variable contributions. In more detail, the relative importance of neuron x is represented by the sum of the product of the connection of the final weight from input neurons to hidden neurons with the connections from hidden neurons to output neurons. We observe that digital capabilities have the highest effect on digitalisation (digital capabilities: 0.482; 100 % normalised value), followed by innovation capabilities (innovation capabilities: 0.271; 56.3 % normalised value), and, finally, the variable joint digital and innovation capabilities (digital and innovation capabilities: 0.247; 51.2 % normalised value), reinforcing the analysis with tree regression.

Regarding Hypothesis 2, which addresses how the existence of an adequate environment framework (external driver) together with the digital and innovative capabilities of a company (internal drivers) affect the development of digitalisation in SMEs, we have combined, for the analysis, tree regression with ANN-MLP.

The first analysis performed is with tree regression, using the following model:

$$\text{Digitalisation} = f(\text{external driver; digital and innovation capabilities})$$

Fig. 6 shows the results of the analysis with tree regression (CHAID method).[8] Regarding the results, we obtain two levels in the tree regression, observing that the variable that has the most impact on digitalisation are the internal drivers (digital and innovation capabilities) compared to the environment support (external driver), shown in the second level. Considering that the digital and innovation variable has a range between 0 and 35, we observe that the highest probabilities of obtaining the highest level of digitalisation are in nodes 1, 6, and 7 (Chi-square = 96.129; df = 9; $p < .000$). Regarding the environmental support variable (external driver), we observe that it has a lower impact. In particular, the highest probabilities of digitalisation are found in nodes 6 (73.4 %) and 7 (63.4 %), combined with nodes 12 and 13. For example, in node 6, we see that digital and innovation capabilities values are between 8 and 28, combined with a medium value of environmental support of 17 (environmental support range: 0 to 40), in nodes 12 and 13. However, in node 1, with a 48.7 % probability of obtaining a maximum digitalisation value, this is not combined with the environmental support variable. Therefore, we can conclude, first, that the impact of internal drivers (capabilities) is greater than the effect of the external driver (environmental support). Second, the functional relationship between digitalisation and the input variables has a maximum value.

Moreover, we have carried out an analysis with ANN-MLP to deepen the tree regression analysis findings. For this, we have performed a simulation, following the equation of Model 8. The results of the architecture for the model are shown in Table 6. Fig. 7 shows the ROC curve, which tests the robustness of the simulation. Moreover, we have included the cumulative gains curve and lift charts in Fig. 7, showing the robustness of the simulation is high.

Fig. 8 shows the relationship between the external driver (environmental support) and digitalisation in SMEs, resulting from simulation. Furthermore, the results of the analysis with ANN-MLP show that the joint variable of digital and innovation capabilities (digital and innovation: 0.769; 100 % normalised value) has greater normalised importance in the digitalisation of SMEs than environmental support (environmental support: 0.231; 30 % normalised value) (see Fig. 9). These results reinforce and complement the tree regression findings, highlighting that internal drivers, in the form of digital and innovation capabilities, have a greater impact than the external driver (environmental support) and that the relationship between the input and the output is not linear, corroborating Hypothesis 2.

5. Discussion

This paper analysed the dynamics of digitalisation in SMEs. Thus, from the perspective of dynamic capabilities, this study considered three factors that drive digitalisation, such as the possession of digital capabilities and innovation capabilities (internal drivers) and the existence of

[7] Ibrahim (2013) revises some methods for assessing the relative importance of input variables in artificial neural networks. These methods are based on Garson's algorithm, which uses the absolute values of the final connection weights when calculating variable contributions. $RI_x = \sum_{x=1}^{n} \frac{|w_{xy}\ w_{yz}|}{\sum_{y=1}^{m} |w_{xy}\ w_{yz}|}$ where RI_x is the relative importance of neuron x. $\sum_{y=1}^{m} w_{xy}\ w_{yz}$ represents the sum of the product of the final weights connection from input neurons to hidden neurons with the connections from hidden neurons to output neurons.

[8] Before conducting the analysis, we checked the robustness of the model, which is significant (Chi-square = 1446.762; df = 18; $p < .000$).

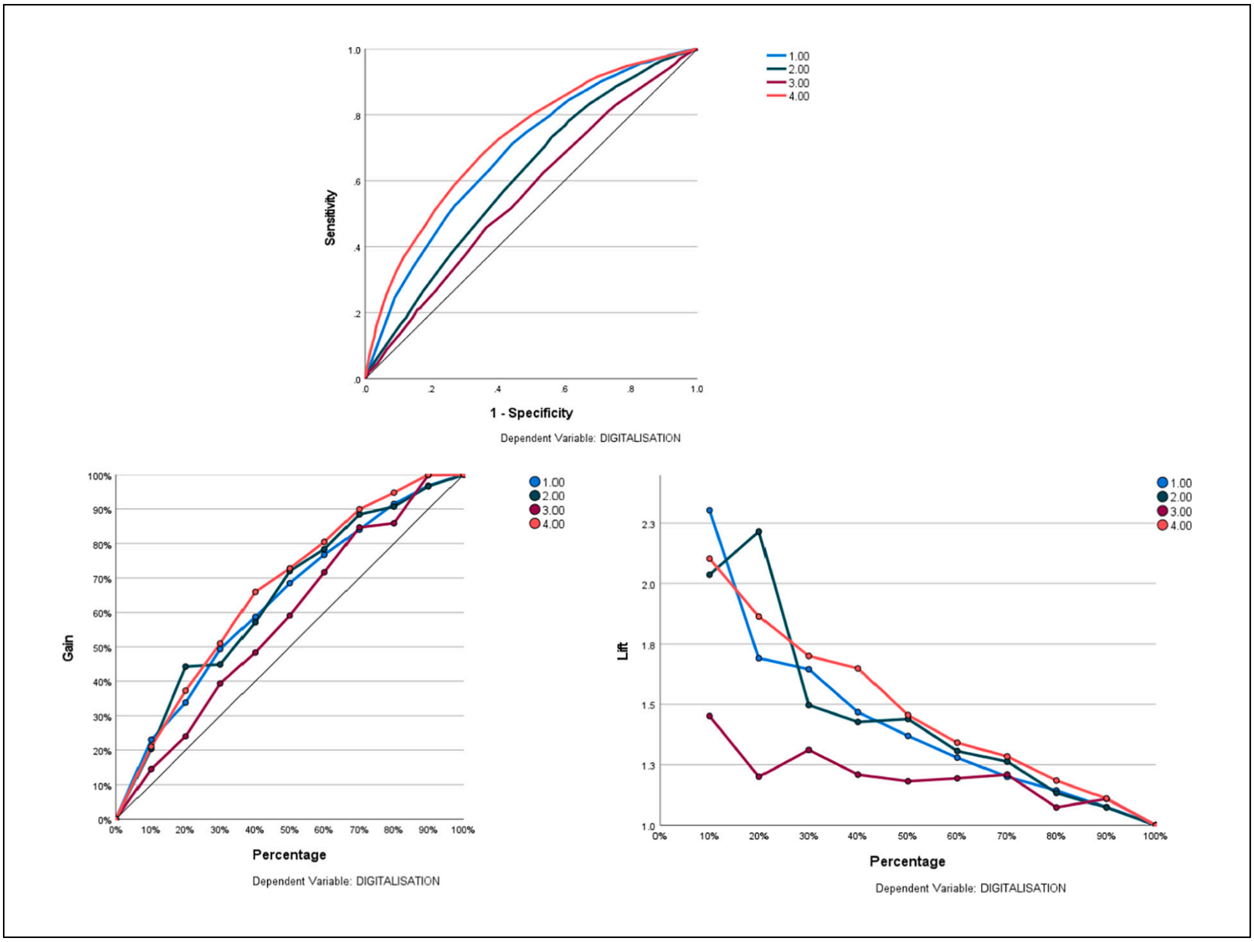

Fig. 3. Robustness of ANN-MLP: ROC curve, cumulative gains, and lift charts.

an adequate environment that supports digitalisation (external driver). Furthermore, from a system dynamics perspective, we assumed a systemic approach to this research, where the factors that drive digitalisation interact and produce synergistic effects in the digitalisation process of SMEs. For this research, we used a database with 16,365 SMEs.

Regarding Hypotheses 1a and 1b that analyse how digital and innovation capabilities (internal drivers) impact the digital transformation of SMEs, the results show that the interaction of both capabilities has a synergistic effect, which is transferred to the digitalisation process of SMEs. Thus, unlike previous studies that exclusively analysed the direct effect of input variables in the digitalisation process, our results show that in order to fully understand how the digitalisation process occurs, it is necessary to consider the effect of the interaction between variables. Additionally, our results are in line with previous research that has highlighted the reinforcement or synergistic effect of the interaction between technological and non-technological innovation and its effect on firm performance (see, for example, Ballot et al., 2015; Arranz et al., 2019), emphasising the importance of the interaction between variables, and indicating that doing more than one activity increases the returns compared to doing more of another. In more detail, our results show significant differences between digital and innovation capabilities in their impact on the digital transformation process. Unlike previous studies that indicated whether the variables were significant or not, our results allow quantification of the impact. Thus, we extend previous literature that highlighted the role of digital capabilities as a key element in the digital transformation of companies (Kiel et al., 2017; Liao et al., 2017; Da Silva et al., 2020; Barber et al., 2022) by showing that these capabilities have a greater effect on the digital transformation of SMEs than innovation capabilities. Therefore, we can point out that while digital capabilities are the key element for digital transformation, innovation capabilities encourage and compliment them.

Regarding Hypothesis 1c, our analysis examined in detail the relationship between internal drivers (digital and innovation capabilities) and digital transformation in companies. This was in line with previous research in the field of management (Emara and Zhang, 2021; Mercure et al., 2016), which highlights how the relationship between two variables can follow a non-linear function. That is, in the first stages, as input variables increase the output increases as well, but decreases for high levels of input variables. In our case, both the digital capabilities and the innovation capabilities have a non-linear effect on the digital transformation, which means that increases in innovation capabilities and digital capabilities produce a non-uniform impact, producing a decrease at the high values of both variables. In more detail, the results show that the greatest boost in digital transformation in SMEs occurs with a differential combination of digital capabilities and innovation capabilities, prioritising digital capabilities over innovation capabilities. Our results provide further empirical evidence that reinforces the findings of Ocasio (1997), Moeuf et al. (2019), and Ardito et al. (2021), which, based on the limited human and management resources in SMEs, point out that integrating some strategic orientations simultaneously has a negative impact on the performance of companies. That is, the high-level development of both digital and innovation skills can mean that the two capabilities compete for resources, negatively affecting the digitalisation process within a firm. More specifically, the knowledge and competencies to implement digital capabilities (such as collaborative robotics, smart devices, machine learning, analytic tools, IIoT) and innovation capabilities can be different and address different objectives, which is

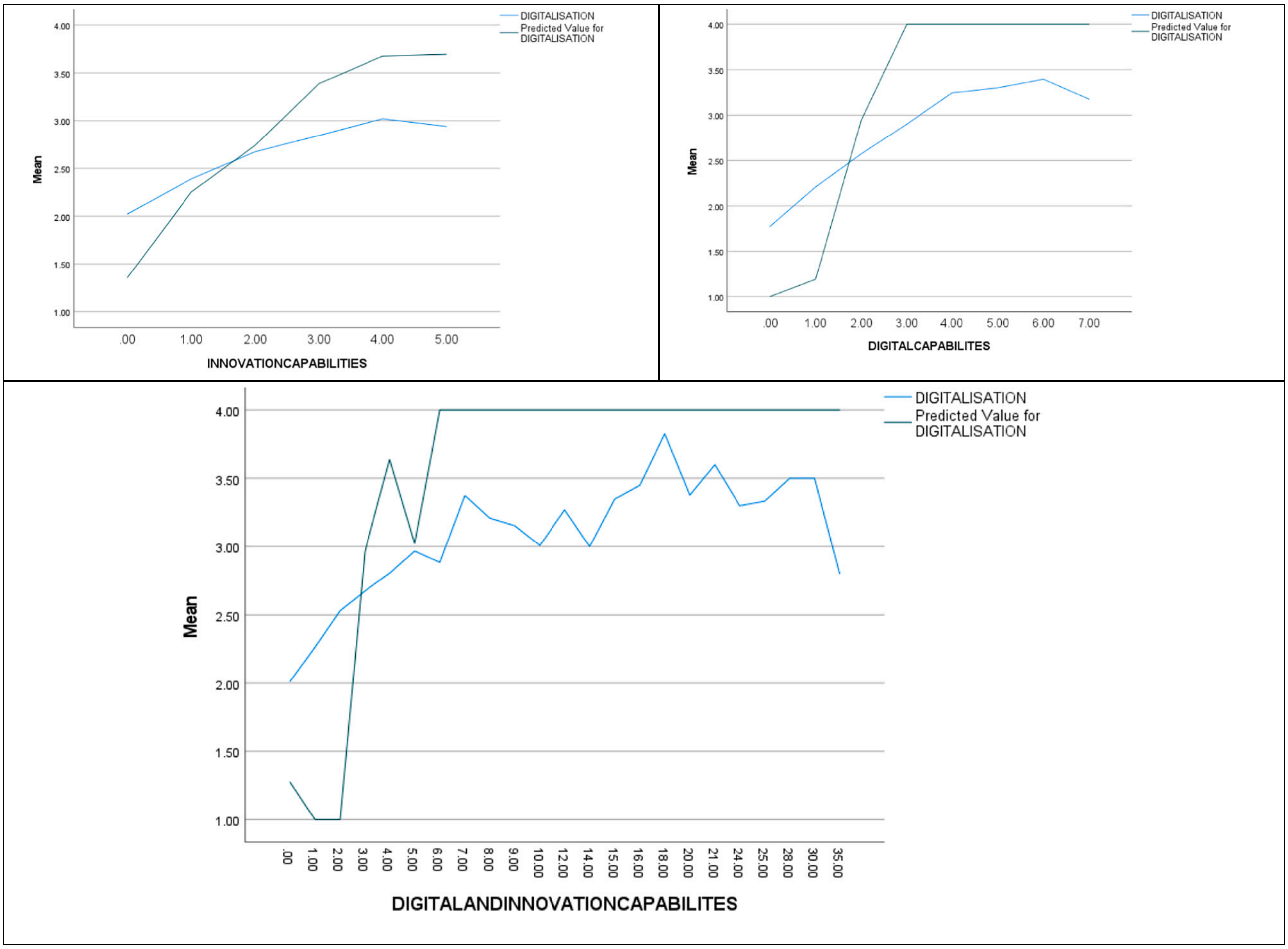

Fig. 4. ANN-MLP simulation relationship of digital transformation and digital and innovation capabilities.

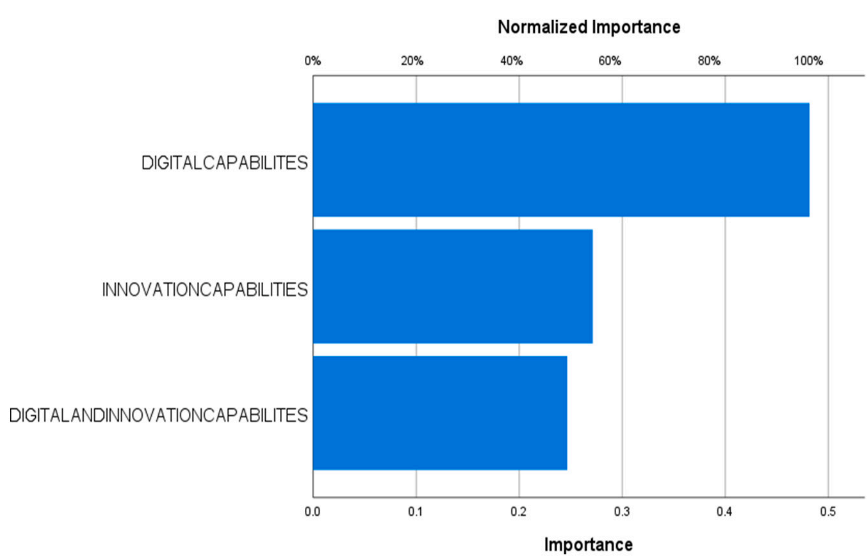

Fig. 5. ANN-MLP simulation of the normalised importance of digital and innovation capabilities.

especially critical for SMEs as a consequence of their limited level of resources. Furthermore, as indicated by Ardito et al. (2021), SME managers do not usually delegate the execution of a strategy and will probably be overwhelmed by the complexity of integrating both strategies and combining resources, which may generate conflict situations. Therefore, our results show that an adequate combination of both capabilities, where priority is given to the development of digital capabilities, accompanied by a moderate development of innovation capabilities, has a high probability of promoting the digital transformation of SMEs.

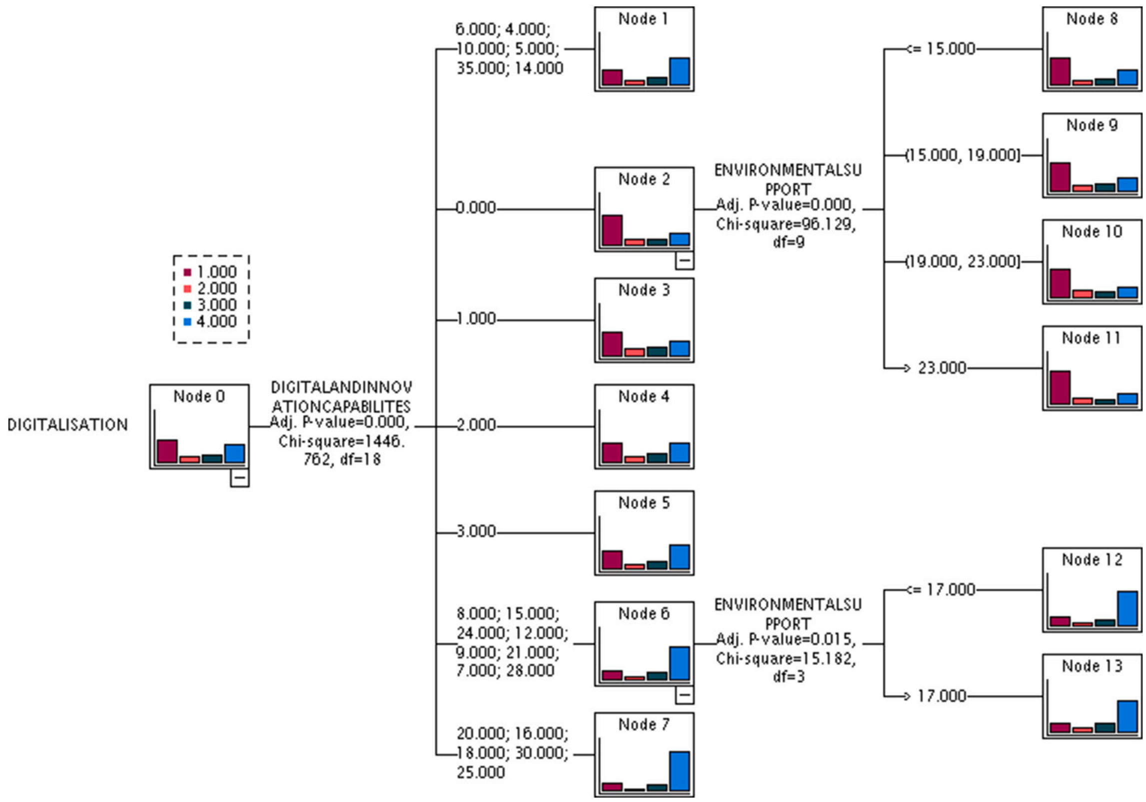

Fig. 6. Tree regression analysis of joint digital and innovation capabilities and environmental support.

Table 6
ANN-MLP architecture for investment in cybersecurity analysis.

Output variable	ANN architecture	Activation functions	Error function
Digitalisation	2-4-1	● Hyperbolic tangent ● Identity (SoftMax)	Cross-entropy

Regarding Hypothesis 2, which explores how external drivers in the form of environmental support affect the digital transformation of SMEs, our results extend previous literature (de Sousa et al., 2018; Díaz-Chao et al., 2021; Pfister and Lehmann, 2021; Barber et al., 2022). That is, while the literature has emphasised that an adequate business environment facilitates innovative development, for example, through regulations and financial support, our results show that environmental support (external driver) has a residual effect compared to the internal capabilities of SMEs. In particular, we have found that a high level of internal capabilities (digital and innovation), with a moderate level of support from the environment (external driver), increases the probability of developing digitalisation in SMEs. Therefore, our results support the view of Abe et al. (2015), which highlights that an excess of regulation or administrative difficulties in accessing financial support has a negative impact on the innovation of companies.

6. Conclusion

This paper has focused on examining the dynamics of digitalisation in SMEs. By overcoming the limitations of existing research and methodologies, we aimed to enhance our understanding of digital transformation in SMEs through a non-linear and complex perspective. The paper yields significant theoretical, methodological, and managerial implications, which contribute to the field of study.

This paper makes a *first theoretical contribution* in the field of dynamic capabilities and their application to the digital transformation of companies (see, for example, Helfat and Raubitschek, 2018). The results show that an adequate understanding of digital transformation not only implies an identification of drivers of digitalisation but also an understanding of how these drivers act. Therefore, it is necessary to consider the synergistic effects that occur in the interaction of these drivers. The study extends previous research in the field of dynamic capabilities, which highlights how the interaction of the capabilities of companies can produce complementary effects (Arranz et al., 2019; Teece, 2018), extending them to the field of digitalisation, highlighting the differential effect that internal capabilities of a company in interaction has on digital transformation. In this line, an adequate digital transformation of a company must highlight the priority role of the possession of digital capabilities and the complementary character of innovation capabilities. Furthermore, the contribution extends previous research that highlights how the ecosystems of companies affect internal capabilities (Díaz-Chao et al., 2021; Ghobakhloo, 2020; de Sousa et al., 2018). Previous studies point out the importance of creating an adequate environment that provides companies with resources to develop internal capabilities; however, our study shows the residual character of a company's external resources in the digitalisation process, concluding that the digital transformation of firms is fundamentally based on their internal capabilities. The last contribution of this paper addresses the gap that exists in the understanding of how SMEs have digitalised, compared to the extensive literature on the digital transformation of large companies (Ardito et al., 2021).

The second theoretical contribution revolves around the engagement of SMEs in digital transformation. SMEs are increasingly recognising the significance of Industry 4.0 and are incorporating digital technologies into their processes. This integration is driven by the desire to enhance productivity, revenue, and market positioning, as well as the influence of supply chain requirements related to Industry 4.0 development (Horváth and Szabó, 2019; Masood and Sonntag, 2020). Although there has been some research on the digitalisation of SMEs, particularly regarding barriers, challenges, and benefits (Orzes et al., 2018; Stoldt et al., 2018; Masood and Sonntag, 2020), there remains a substantial gap

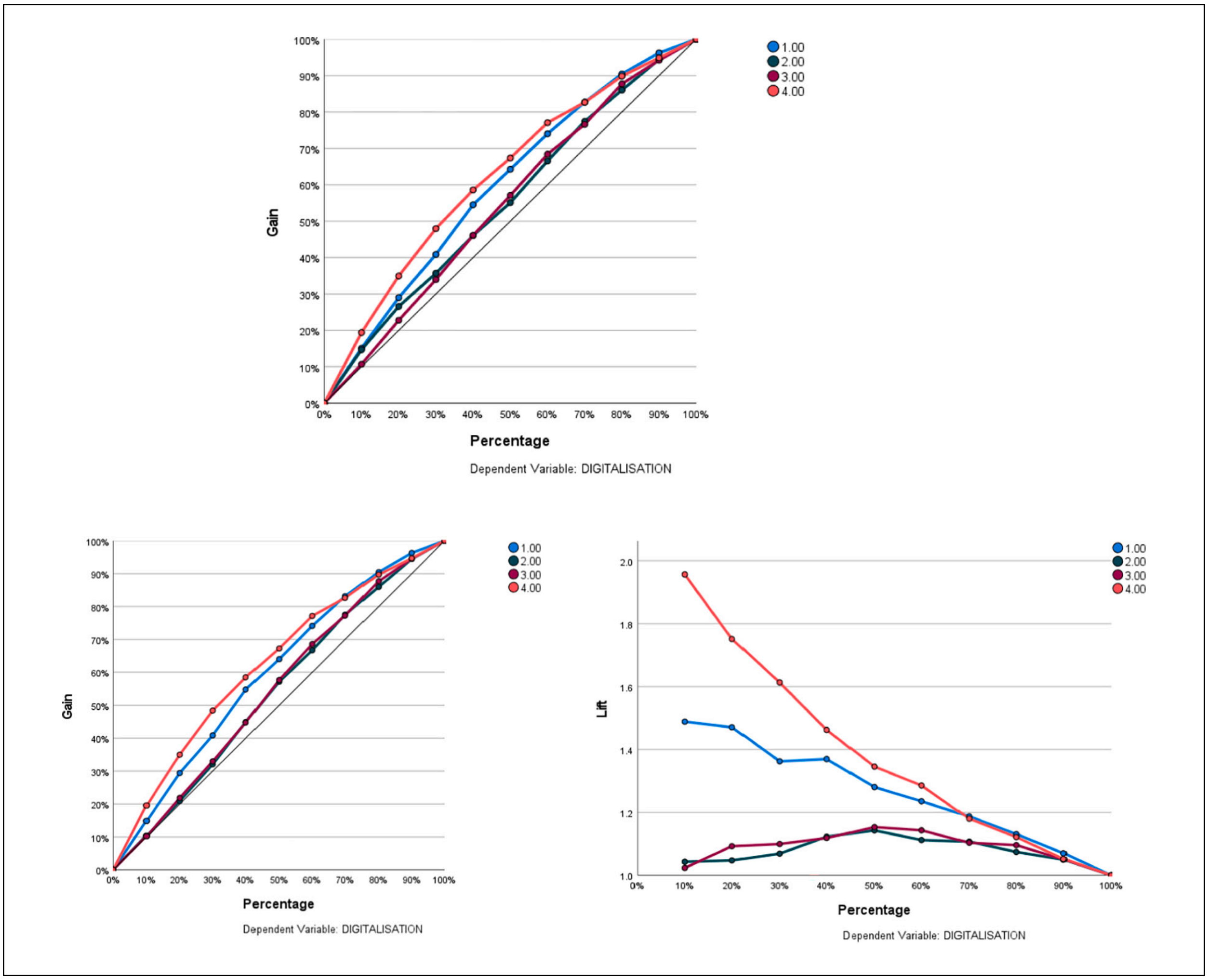

Fig. 7. Robustness of ANN-MLP: ROC curve, cumulative gains, and lift charts.

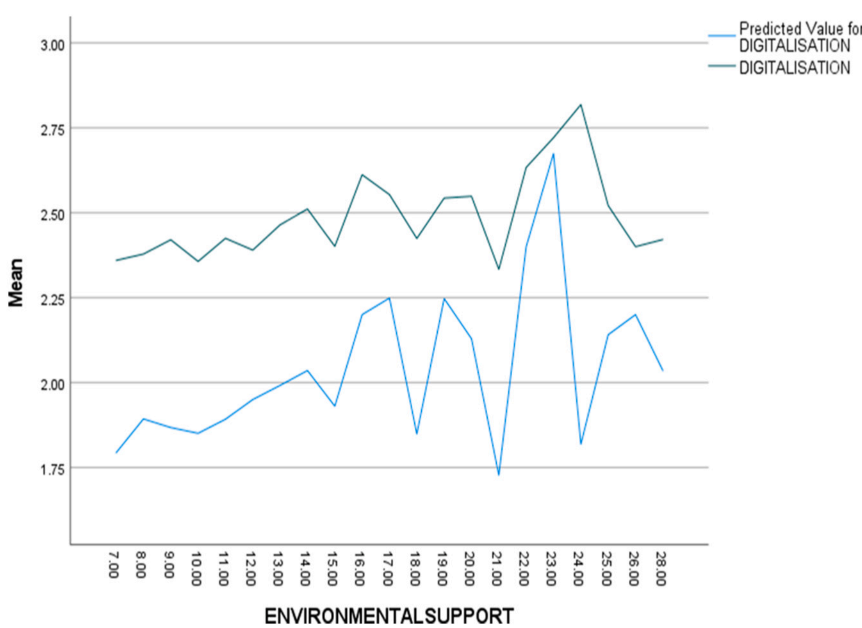

Fig. 8. ANN-MLP simulation relationship of digital transformation and the external driver (environmental support).

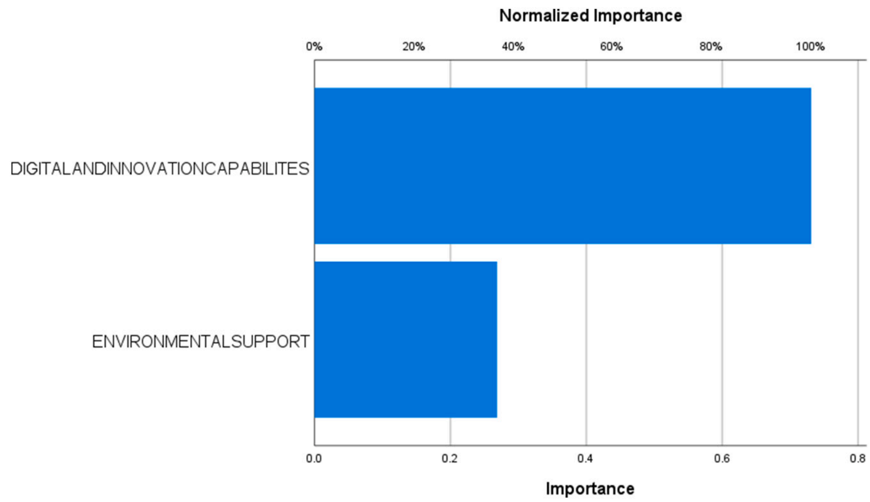

Fig. 9. ANN-MLP simulation of the normalised importance of joint digital and innovation capabilities (internal drivers) and environmental support (external driver).

in understanding the ongoing development of this digitalisation. Academic studies on Industry 4.0 predominantly focus on large companies, with limited attention given to SMEs (Horváth and Szabó, 2019; Masood and Sonntag, 2020; Yu and Schweisfurth, 2020; Schönfuß et al., 2021). Therefore, our research expands upon existing literature by revealing that the implementation process of digital transformation in SMEs is facilitated by a combination of internal and external drivers, thus enabling a smooth transition from the intention to digitalise to its actual implementation. In examining the dynamics of this process, it is crucial to consider both the digital and innovation capabilities of SMEs.

From a *methodological point of view*, the paper contributes to the understanding of the dynamics of digitalisation. First, our study extends previous research on the digital transformation of companies (Guandalini, 2022; Díaz-Chao et al., 2021; Frank et al., 2019), highlighting the need to approach it from a systemic perspective, where interactions and non-linear processes are the main characteristics of digitalisation. Thus, our research reinforces previous literature in the area of system dynamics, highlighting that the interaction between input variables produces reinforcement loops between variables (Sterman, 2000; Teece, 2018). Furthermore, our work extends this perspective by stressing how this interaction is transferred to output variables. From our study, we see that the effect of interactions between variables is transferred to the output variable in a non-linear way, which may contain an optimum, which is produced by a differential combination of input variables. Therefore, adequate modelling of the interaction requires an estimation of the combination of input variables with different levels of contribution of the variables. Second, our paper extends the research methodology, emphasising the importance of combining classic regression analysis with machine-learning techniques (Da Silva et al., 2020; Horváth and Szabó, 2019; Kukreja et al., 2016; Mercure et al., 2016). Thus, the combination of the explanatory power of regression models and machine learning allows us to quantify and explain how variables act, solving complex and non-linear problems. Likewise, machine-learning tools allow the solving of collinearity and endogeneity problems, increasing the robustness of the regression models.

Furthermore, the paper contributes some key *managerial implications* for SMEs. In this sense, we emphasise that the digital transformation of SMEs requires differential efforts and resources allocated to digitalisation. In line with previous strategies and implementation processes in organisations, we note the importance of capabilities in a company. In particular, our research emphasises the importance of digital and innovation capabilities in the digital transformation of companies. Moreover, it is necessary to prioritise where these resources should be allocated due to the limited resources of SMEs. Thus, from our results, we observe that digital capabilities have a greater impact than innovation capabilities in the digital transformation process of SMEs. Thus, SMEs should focus on developing digital competencies in order to develop their digitalisation management. Also, managers should consider the U-inverted shape effect of the combination of digital and innovation capabilities acting together, implying that there is no linear pathway between investment in developing capabilities and its effect on the digitalisation of SMEs. Moreover, our results show the limited impact of external resources. In this line, managers must pay relative attention to the external resources existing in the ecosystems of SMEs. Finally, our paper is not exempt from limitations typical of a survey. Thus, while the geographic scope of the sample is large, and the robustness of the survey is high, future research could extend in different lines. First, future work should consider diversifying the drivers used in the study and increasing the number of variables to better understand the digitalisation of SMEs. Second, future research should deepen the identification of how variables interact, considering a dynamic perspective.

Author statement

All authors contributed equally.

Data availability

Data will be made available on request.

Appendix A. Appendix

Table A1
Digital implementation Level.

Implementation of Digital Technologies	Companies	
Your enterprise has adopted/is planning to adopt basic digital technologies but not advanced digital technologies	5475	33.5 %
There is a need to introduce advanced digital technologies but your enterprise does not have the knowledge	1259	7.7 %
There is a need to introduce advanced digital technologies and your enterprise is currently considering	1605	9.8 %
There is a need to introduce advanced digital technologies and your enterprise has already started to adopt them	4256	26.0 %
Your enterprise does not need to adopt any digital technologies	2751	16.8 %
Missing Value	1119	6.3 %
Total	**16,365**	**100.0**

Table A2
Descriptive analysis of digitalisation capabilities variables.

Digitalization level	Companies	
1. Artificial intelligence, e.g., machine learning or technologies identifying objects or persons, etc.	1252	7.7 %
2. Cloud computing, i.e., storing and processing files or data on remote servers hosted on the internet	7836	47.9 %
3. Robotics, i.e., robots used to automate processes for example in construction or design, etc.	1403	8.6 %
4. Smart devices, e.g., smart sensors, smart thermostats, etc.	4549	27.8 %
5. Big data analytics, e.g., data mining and predictive analysis	2368	14.5 %
6. High-speed infrastructure	5521	33.7 %
7. Blockchain	541	3.3 %
Total	**16,365**	**100.0 %**

Table A3
Descriptive analysis of innovation capabilities variables.

Innovation level	Companies	
A new or significantly improved product or service to the market (*Product*)	4561	27.9 %
A new or significantly improved production process or method (*Process*)	3231	19.7 %
A new organisation of management or a new business model (*Organisational*)	2665	16.3 %
A new way of selling your goods or services (*Commercial*)	3440	21.0 %
Innovation with an environmental benefit, including innovations with an energy or resource efficiency benefit (*Environmental*)	3615	22.1 %
Total	**16,365**	**100.0 %**

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