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The role of circular economy in EU entrepreneurship: A deep learning experiment

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A B S T R A C T

Fostering innovation is one of the key roles of the Circular Economy (CE) that applies also to European Union (EU) firms, because entrepreneurs are persistently seeking new ways and means to create values, contributing with significant market opportunities, and depicting large potential for EU sustainable growth. This study explores the effects of firms' investments in using highly disruptive technologies in the energy sector on the Eurozone (EU-27) in the last two decades (1990–2019). An Artificial Neural Networks (ANNs) experiment through a Deep Learning (DL) approach is implemented to test this hypothesis. The empirical findings show that investments in highly disruptive technologies, especially by large digitally qualified companies, boost economic growth. They are also a crucial driver of digitalization not only because they enhance a wide strategic change implying a radical innovation in business models, but they completely transform markets, from energy to food production, water resources, pollution, connectivity, and plastic waste. These expected benefits represent a possible policy measure to offset the decline in global activity due to the impact of the Russia-Ukraine war on global energy markets. In addition, a positive association between trade and output is confirmed. Finally, promising policy actions are discussed.

1. Introduction

The necessity to live in a sustainable socio-economic system is a priority of all countries since the current production and consumption patterns highly depend on raw materials that are only to some extent reused, and/or recycled, but generate endless waste with a never-ending demand for virgin raw materials. In this no-longer sustainable scenario, some firms and entrepreneurs move towards more sustainable transition models that involve these new socio-eco values. The linear economic model of "take-make-dispose" is now facing the concept of Circular Economy (CE) which has gained increasing attention in the last years, mainly for the

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negative crashes of the traditional model. CE is a potential, and promising, answer to introduce and address environmental changes, networking with the traditional linear economic model.

It is one of the new techno-economic paradigms that has attracted the interest of various stakeholders who envision intriguing socio-economic opportunities. It aims to decouple economic growth from resource depletion and environmental degradation by designing out waste and pollution, maintaining products and materials in use, and regenerating natural systems. To apply this new construct, it is necessary to have an open mind attitude and/or a circular entrepreneur willing to adopt circular domain strategies, but aware of undefined ecological and social sustainability outcomes in the short run. This leader protects the natural capital, increases resource productivity, and states a more efficient system. According to Zucchella and Urban (2019), "circular entrepreneurship consists in processes of exploration and exploitation of opportunities in the circular economy domain", based on a double step: the design of the value proposition and the development of a new circular business model (Suchek et al., 2022; Cullen & De Angelis, 2021).

At the core of the CE concept lies the goal of maximizing resource productivity while minimizing waste. This new vision emphasizes increasing productivity and seeks to reconcile the consumption and final life impacts externalities of the production process. In this way, it is possible to create a closed-loop system founded on sustainability (renewing and preserving natural systems, designing out waste and pollution), and reusability (keeping materials in use). Bocken et al. (2016) highlighted that CE models want to achieve the highest elements' utility compressing production cycles, a mechanism that requires time and resilience and explicates social and environmental benefits in the medium time.

CE has emerged as a fundamental framework channeling entrepreneurial endeavors encapsulating a paradigm shift towards sustainable production and consumption. The European Union (EU) – more slowly than its member countries - has shown a strong interest in it, recognizing CE as one of the main strategies to address challenges related to environmental sustainability, resource efficiency, and economic competitiveness. This EU attention has been reflected in several initiatives and policies aimed at promoting and supporting the single countries' transition to a CE. In 2015, the first Circular Economy Action Plan (CEAP),[1] supported by over €650 million under Horizon 2020 and €5.5 billion under the structural funds, settled, through 54 actions, key objectives to reduce resource consumption, increase recycling, and promote innovation in the circularity domain. This strategy provided the first long-term framework for integrating circular principles across various sectors and policies (EC, 2015). In 2020, the EC adopted a new CEAP[2] as a key component of the European Green Deal, which outlines Europe's agenda for sustainable growth. Its goals, crucial for achieving the EU target of climate neutrality by 2050 and for halting biodiversity loss, are to facilitate the transition to a CE, reducing pressure on natural resources while fostering sustainable growth and job creation (EC, 2020).

This strategy includes specific attention to resource efficiency and waste reduction across various sectors, including packaging, electronics, plastics, and textiles, by emphasizing the importance of maximizing resource efficiency and minimizing waste generation. The CEAP promotes also eco-design principles to ensure that products are designed with durability, reparability, and recyclability in mind, encouraging the adoption of sustainable materials and manufacturing processes to lessen the environmental impact throughout the product's long-lifecycle. It encourages the adoption of circular business models (i.e., product-*as*-a-service, sharing and leasing, and remanufacturing), to extend product lifecycles and promote resource efficiency, specifically supporting innovative approaches to value creation that prioritize reuse, repair, and recycling over traditional linear consumption models.

Moreover, the strategy emphasizes the need for increased investment in research, innovation, and infrastructure to support the transition to a CE, calling for public and private partnerships to develop and scale up circular solutions, technologies, and business models. It proposes, as well, a mix of market incentives, regulatory measures, and standards to drive the transition to a CE, including actions to promote sustainable product design, improve waste management and recycling infrastructure, and incentivize the use of recycled materials in manufacturing. In this framework, this strategy highlights the importance of international cooperation and collaboration to address global challenges related to resource depletion and environmental degradation. It calls for dialogue with international partners to promote CE principles, culture, and practices globally.

According to Eurostat, in 2022, 11.5% of the resources used in the EU came from recycled materials, confirming the average figure for the period 2012–2022, albeit with significant disparities persisting among countries. This "circularity rate", indicating the proportion of new material resources derived from recycled waste reintegrated into the production cycle, shows a slight growth compared to previous years. Among EU countries with the highest propensity for recycling are the Netherlands (27.5%), followed by Belgium (22.2%), France (19.3%), and Italy (18.7%); conversely, circularity rates were very low in Finland (0.6%), Romania (1.4%), and Ireland (1.8%). The prospect of increasing product recycling gains further importance considering that these materials could then be subject to exportation. The EU exported 6.4 million tonnes of recyclable products (paper, plastic, and glass) to non-EU countries, an 8.4% increase compared to 2021, against imports of 4.0 million tonnes, up by 4.2% from 2021. The main export destinations were India for recyclable paper (29% of total extra-EU paper exports), Turkey for plastic (29% of total extra-EU plastic exports), and the United Kingdom for recyclable glass (46% of total extra-EU glass exports), with Switzerland (11%) and Brazil (9%) following behind. Back to 2010, total exports of recyclable products to non-EU countries decreased by over a third (−35.2%, from 9.8 to 6.4 million tonnes). Total imports, however, increased by 23.9% (from 3.2 to 4 million tonnes).

At its core, providing a fertile ground for innovation, the CE concept aims to decouple economic growth from resource depletion by promoting the regenerative use of materials and resources throughout their lifecycle. In other words, it involves a closed-loop system where resources are utilized, reused, and recycled, generating added value across multiple lifecycles. Goods reaching the end of their useable lifespan are transformed into resources for others, creating a closed loop and minimizing waste (de Jesus et al., 2018).

[1] https://environment.ec.europa.eu/topics/circular-economy/first-circular-economy-action-plan_en.

[2] https://eur-lex.europa.eu/resource.html?uri=cellar:9903b325-6388-11ea-b735-01aa75ed71a1.0017.02/DOC_1&format=PDF.

EU entrepreneurs have embraced this model as a pathway to foster innovation, cost-efficiency, and environmental stewardship. By prioritizing principles of reuse, recycling, and waste reduction, businesses are not only minimizing their environmental footprint but, also, unlocking new avenues for profitability (Huang et al., 2024). Through initiatives like product lifecycle extension, resource recovery, and remanufacturing, entrepreneurs are pioneering novel business models that prioritize longevity and efficiency over the traditional linear approach of "take-make-dispose". This shift not only addresses pressing environmental concerns such as climate change and resource scarcity but, also, promotes resilience in the face of global economic challenges.

Furthermore, the CE fosters collaboration across sectors, encouraging partnerships between businesses, policymakers, and civil society to co-create solutions for a sustainable future. In this context, EU entrepreneurship is not merely about profit maximization but, also, about societal and environmental value creation. By embedding circularity into the fabric of entrepreneurship, the EU action plans are fostering a culture of innovation that not only drives economic growth but, also, promotes environmental integrity and social well-being, thereby laying the groundwork for a more sustainable and prosperous future.

Moreover, sustainability and reusability ask for innovation and the adoption of digital tools of Industry 4.0 (I4.0) (Dantas et al., 2021; Morelli et al., 2020; Rosa et al., 2020). The increasing utilization of digital technologies and their ongoing adaptation also entails entrepreneurial and managerial decision-making. In the past, leadership decisions were based on rationality and the uncertainty of the design-connected risk, while today, with the use of digital tools and the need to invest in them, there are no well-defined boundaries, due to digital interoperability (Chalmers et al., 2021). However, this implies that the digital manager has a smart capability suitable for allowing venture investments in previously unimaginable areas. Therefore, the classic vision of an entrepreneur solely dealing with the aftermath of a decision is replaced by a broader concept of someone who embraces new technologies, invests in them, and readjusts business decisions in response to the rapid changes demanded by technology itself.

Globalization pushes managers to increase investments and strengthen commercial agreements with geographically co-localized (i.e., friend-shoring, reshoring, and nearshoring practices), economically credible partners who share common values.

The adoption of technologies, particularly circular ones, is primarily an entrepreneurial decision. Thus, in a company the entrepreneur's role is crucial for its life; his/her decisions conditionate the firm's performance. The entrepreneur is a key driver for the introduction and adoption of CE ideas (Jansen et al., 2020) due to their ability to innovate both by identifying new eco-opportunities and generating new circular business models (Centobelli et al., 2020). Henry et al. (2020) stated that only big companies, with high financial capital, can adopt CE paradigms and determine new business models. Notwithstanding, small and medium firms and start-ups may, due to their natural flexibility and the low presence of mechanical links, apply CE elements. They can offer their competencies to sustainable consumers by exploiting new peculiar chances. Start-ups usually offer a strong ethical motivation, which represents the social and emotional value (firms' social responsibility) of their entrepreneurs. The managers have an eco-intuition, create a circular value, and offer a sustainable output. The real limit is connected with costs, but the entrepreneur's Cost-Benefit Analysis (CBA) puts ambition above all.

Circular entrepreneurs are more credible than traditional firms since their innovative and green characters inspire much competence in solving environmental problems. Thus, a CE leadership must face uncertainty and many risks (financial and reputation), but its capacity to be innovative and green could offer the ability to realize that environmental market failures and inefficiencies can evolve into new green opportunities. A circular entrepreneur is also a social agent involved, with sustainability, in the strategies of the CE paradigms.

In this scenario, circular entrepreneurs are credible agents because they have huge capital and I4.0 skills or users and promoters of new technologies. The new digital entrepreneur is a global subject, constantly evolving and capable of creating a digital-value proposition, in which the entrepreneurial capital is of the high-digital-intangible type.

Technological and circular entrepreneurs still seem to be the only ones able to guarantee and sustain a global value chain even if, during the last energy crisis, also firms' production negatively reacted to final demand shocks. CE implementations are more present in the end-use and design procedures phases of the value chain (Cristoni & Tonelli, 2018). Also, the institutional environment has an impact on the entrepreneurs' options to adopt CE practices. Zamfir et al. (2017) and García-Quevedo et al. (2020) highlighted the great importance of the region where firms are located. The higher the level of local economic development, the higher the possibility of introducing CE paradigms. Legal and normative barriers, in this case, have less importance because public and private interests progress in the same direction. Public support for CE creation and implementation is relevant for the territory since it builds the culture and the ethic substratum (i.e., collaborations, networks, green facilitators).

A broader idea of CE should comprise wider links that certainly include the adoption and implementation of green technologies, also through public and private policies and funding but, above all, a deep cooperation between different stakeholders. This way of understanding the CE helps entrepreneurs to have a socio-economic-green capital in which every revolution is part of a puzzle of long-term resilience. Public entrepreneurship (policies of innovation and public incentives) and private one (own financial capital and specific institutional and local incentives for renewable energies) can support sustainable innovation and diffuse CE culture.

To offset the decline in global activity in the EU major economies, we propose to measure the effect of firms' investments in highly disruptive technologies, as profiled by the I4.0 paradigm – namely Big Data (BD) – and check their influence on economic growth. Households and firms might benefit from this policy action since they could accelerate the Gross Domestic Product (GDP) positive response in large areas, primarily in Europe.

The recent energy crisis is further strengthening the position of some digitally qualified companies while challenging many traditional firms, emphasizing the increased reliance on new business models based on digital platforms and services. Digital technologies and new business models have allowed some companies, more than ever, to avoid a complete shutdown of general activities, accelerating the transition to a digitalized society (Magazzino & Mele, 2022; Maroufkhani et al., 2022).

Addressing sustainability challenges through entrepreneurial endeavors is an urgent imperative in the face of escalating environmental crises and resource depletion. Entrepreneurs wield the agility, innovation, and drive necessary to catalyze transformative change across industries. Their ventures not only offer innovative solutions to pressing sustainability issues but also drive economic growth, create jobs, and foster resilience in the face of climate-related risks. With time running short to curb emissions, preserve ecosystems, and ensure equitable access to resources, entrepreneurial action is indispensable in paving the way toward a sustainable future for current and future generations.

Xu et al. (2019) clarified how BD and green economic development are linked; nevertheless, there is a need for additional empirical research to sustain this argument. In this paper, through a Deep Learning (DL) approach with Artificial Neural Networks (ANNs), we aim to show if managers' decision to invest in BD and related technologies in the energy sector can generate a positive GDP acceleration in EU economies. In addition to generating the NN, a proxy able to synthesize firms' investments in BD and the current digitalization process in the EU-27 has been designed. By addressing this question, we aim to develop a more comprehensive framework that depicts the effectiveness of the I4.0 paradigm from the perspective of firms using an advanced Artificial Intelligence (AI) analysis.

This paper contributes to the literature in several ways. First, to the best of our knowledge, no previous study empirically assesses the nexus between firms' investments in BD for the energy sector and the GDP growth rate. Moreover, this study integrates the still limited literature on digitalization and BD, in particular on its capacity to serve as an enabler of the new entrepreneurial model; to this extent, a DL algorithm is implemented to analyze this relationship. The applied results highlight the crucial role that investments in BD played in the economic growth process. Moreover, our results confirm the importance of the openness degree as a viable tool to sustain economic activity.

ANNs and DL play a fundamental role in understanding the effects of disruptive technologies on economic growth in the EU by analyzing vast and complex datasets with unprecedented efficiency. By leveraging these advanced computational techniques, researchers can discern intricate patterns and correlations within multifaceted economic systems, elucidating how disruptive technologies such as automation, AI, and biotechnology impact productivity, employment dynamics, and market structures. Moreover, ANNs enable the modeling of dynamic relationships over time, offering insights into the long-term implications of technological disruptions on economic resilience and competitiveness within the EU market.

The paper proceeds as follows. Section 2 presents a critical review of previous studies and suggests a scientific framework that emphasizes firms' capabilities in enforcing the I4.0 paradigm. Section 3 explains the theoretical model, the methodology, and the dataset, while Section 4 shows the empirical findings and the discussion. Finally, Section 5 concludes by suggesting some policy evaluations helpful in the present worldwide scenario of profound and rapid changes.

2. Theoretical background

Circular entrepreneurs pursue the sustainability and efficiency of natural resources, sharing and spreading an eco-social-economic culture. Through the use and enhancement of digital technologies, the entrepreneur can create new business models for CE.

Entrepreneurs play a vital role in adopting and implementing the principles of CE. They create new markets and foster a culture of innovation and sustainability, leading to a circular transition.

A circular entrepreneur must plan and direct decisions in order to create a sustainable and efficient structure (Kuzma et al., 2021). This supposes a strong change from a linear model to a circular one, in which innovation and the use of digital tools represent the link between the past and the present world. It is the creation of sustainable digital value that must be included in new business models. Several studies (Holzer et al., 2021; Mura et al., 2020; Prieto-Sandoval, Torres-Guevara, Ormazabal, & Jaca, 2021) investigate the use and implementation of CE paradigms in European small and medium firms and the common elements are the manifest entrepreneurs' attitude to use CE tools, and that incremental innovations (García-Quevedo et al., 2020) require deeper attention. Rizos et al. (2016) underline how circular managers seek both an external appreciation and appeal, and also a financial return.

Moreover, it is Information and Communication Technologies (ICT): if the civic green culture is diffused and it is strong, then entrepreneurs are more motivated to be circular. So, in the entrepreneurial process, the decision to integrate CE elements encounters various barriers, including technological, social, and financial constraints (Jaeger & Upadhyay, 2020; Morelli et al., 2022; Sharma et al., 2021). Technological barriers stem from the requirement for innovative processes and technologies that facilitate resource efficiency, waste reduction, and product lifecycle extension. Social barriers may arise from a lack of awareness or acceptance of circular practices among consumers, stakeholders, or employees. Additionally, financial barriers may include high initial investment costs for implementing circular solutions, uncertainty about returns on investment, especially in the short-run, and limited access to funding or incentives for circular initiatives.

I4.0 tools, from blockchain to the Internet of Things (IoT), are already being used to foster CE practices (Wang et al., 2020). Reike et al. (2018) showed the benefits and advantages of the introduction of CE paradigms for a country and its positive effects on economic growth.

Starting from these considerations, we aim to determine whether firms' investments in BD, as decisions made by entrepreneurs, within the energy sector, might influence the economic growth process within the EU-27.

Although BD has been the subject of multiple studies under different perspectives in recent years, the empirical literature on the relationship between investments in BD and economic growth needs to be more present. The globalization and digitalization process, in which firms are deeply involved, favors the introduction of several instruments (enterprise resource planning, operations excellence, manufacturing execution systems, and so on), besides enabling technologies, for supporting and improving economic activity and growth. This scenario could push firms to increase investments in I4.0 technologies. According to Kondratieff (1925) waves theory, high and low economic growth levels are tied to the rise and fall of waves of technological innovation, which generates cyclical dynamics with a long period of prosperity and economic decline. The nature of digital tools displays characteristics of generality, originality, and longevity, independently they are taken together and/or individually (Martinelli et al., 2021).

The existence of digital technologies affects the classic idea whereby an entrepreneur recognizes a new opportunity and, as a consequence, the new business model is formed and spread. Digital technologies add value in themselves because they are enablers, and the phases of the value chain are getting closer and closer. Naturally, this means that the entrepreneur must be increasingly attentive because being technological also means being readily adaptable. In practice, digital technologies impose fluid business models that can be easily reprogrammed because they require radical and sometimes all-encompassing adaptations.

The unceasing and rapid development of these technologies and the potential for disruptive changes also have significant implications for barriers to entry, market concentration, and the organization of value chains between incumbents and new entrants that firms are more likely to offset. Managers have a natural ability to use-adapt and manage enabling technologies. Consequently, they are more easily able to exploit the induced and consecutive effects of digitalization.

The relationship between the I4.0 paradigm and smart investments could boost economic performance. However, to the best of our knowledge, only a few studies have investigated this topic regarding enabling technologies as a strong driver of growth.

In the economic growth literature, Solow's residual is strategic for technological investments in the development process, and it is the base for understanding the role of investments in boosting growth (Solow, 1956): the innovation-growth relationship has a positive sign. The productivity paradox has a one-time effect on the real understanding of the technological outcomes, measurement fragilities (since empirical methods do not always catch input and output data properly), and a general loss of total productivity.

On the other hand, technological advantages are only sometimes fairly distributed and completely converted into an increase in productivity; thus, they require specific enabling skills. The time-inconsistent preferences theory (Machado et al., 2014) and the loss of productivity (the engine of growth) following the absorption of innovation (Gordon, 2016) believe ICT might be harmful to growth. On the opposite, several studies show the positive nexus between these two variables, mainly empirically tested in the US, highly explained by the distinguished human capital formation (Kretschmer, 2012). Stanley et al. (2018) highlighted that ICT positively contributed to economic growth for both industrialized and developing countries, taking into account the peculiarities of the geographical area as well as the different types of ICT. As a result, empirical studies provide evidence of the positive nexus of enabling technologies on growth.

The introduction of I4.0 tools should overcome the stabilization/absorption gap of the initial positive effect, and the consequent loss of productivity, as a circular chain of connected and consequential innovation. Moreover, this digital change implies the continuous and gradual creation of complementarities (digital innovations), linked to the territory's economic development: the higher the skill levels of a country, the greater the possibility that the effects described are explicated, but the greater the risk of social inequalities. Therefore, a positive link between I4.0 instruments and growth might exist, and the newly created well-being effect could push toward new smart investments in digital complementarities, enhancing the CE (Ajwani-Ramchandani et al., 2021; Ghobakhloo, 2020). Muhammad et al. (2022) explored the impact of the fintech industry on environmental efficiency across EU countries. Data Envelopment Analysis (DEA) and Generalized Method of Moments (GMM) show that the overall environmental efficiency of EU countries has improved over the years.

As underlined by Hajek and Abedin (2020), BD requires special attention. In addition to the traditional factors of consolidation of market power (i.e., economies of scale, economies of scope, network effects), advantages derive from the exploitation of the information extrapolated from the data generated by the single user (Gandomi & Haider, 2015; Ji-fan Ren et al., 2017). Innovative business models are deeply characterized by data-driven network effects that support growth through digital innovation. It allows companies to improve their advertising, leading to high profits and, confidently, new investments which, in turn, enhance the level of global welfare. Like all technological investments, investments in BD determine faster access to information, being a value indicator.

Entrepreneurs of large companies, being interested in implementing rapid technological changes and developing new markets, retain all the capabilities and financial resources to play a pivotal role in this scenario since they are the most skilled to introduce smart investments in digital technologies and BD quickly. However, the uncertain, volatile, and complex set-up where they operate, automatically generates a bundle of information to be processed. Thus, implementing in their operational strategies the I4.0 paradigm, being part of the productive environment, could surge the international leader position.

Underpinning the circular-smart capability, there is an I4.0 culture, consisting not only of technological abilities but, also, of a strong proclivity towards what is new and disruptive. This culture-action includes a new vision and new strategies, which rely on virtual components and global value chains, based on blockchain (Qader et al., 2022), open to new social and organizational practices (new business models).

The entrepreneurs' investment decision process follows the same path as all other companies, expecting an economic return since it faces a partially calculated risk. It adopts incremental investment strategies that, according to Kogut (1991), create a different path of future growth options (Bowman & Hurry, 1993). Investing in smart technologies before making whatever different type of investment option is relevant for the decision-making process, since it could help to reduce the level of risk. In fact, I4.0 enabling technologies might be viewed as incremental strategies suitable for delimiting the risks of the investment itself, generating new information.

Regarding the localization process, Lee (2019) noted that a positive relationship might emerge between innovation and technologies in enhancing the development of a specific territory, helping to solve regional lock-in, producing smart spillovers usually co-localized, and generating social and income inequalities.

Circular firms are cyber entities with an advanced adaptable culture, showing a path of smart dependence strictly connected with the geographical context. The suggested theoretical model supports the hypothesis that smart investments by companies could foster the economic growth process and, according to Van der Wouden (2020), regions with high GDP, such as the EU-27, are more suitable to attract and develop smart technologies.

3. Data and methodology

The empirical strategy implements a DL approach with a production function to test the effects of firms' investments in digital transformation and BD on EU economic growth. Oryx protocol 2.0.8 is used on a dataset that exemplifies the variables that generate a positive GDP acceleration. The variables cover the period from 1990 to 2019 for EU-27 member countries.

The selected variables are *GDP* for per capita GDP (in constant 2010 US$),[3] *K* for the Gross Fixed Capital Formation (in constant 2010 US$),[4] *L* for the Labor Force,[5] *Open* for the degree of openness of the country measured by the energy trade balance (as a share of GDP),[6] and *Public Spending* for government expenditure (% of GDP).[7] The variable *BigData* represents firms' investments in the energy sector with BD (see Table 1). This infrastructure has large spillovers, and it can be considered in some respect as a very unusual public good, non-rivalrous but excludable, since data is reusable, and non-discriminatory access can maximize its value. Thus, BD is becoming an added value generator, whose distinctive features, from an economic point of view, are a widespread presence (data can be collected anywhere), non-rivalry (its possession by a subject does not preclude the same by others), and material inconsistency.

Because of the absence of homogeneous sources, this variable has been generated *ad hoc*, using data from the Digital Economy and Society Index (DESI)[8] and the EU Industrial R&D Investment Scoreboard[9] related to the energy sector. It is a good indicator of firms' investments in R&D, since it covers companies with headquarters mostly in industrialized and emerging countries, with investment for a total amount equivalent to 90% of the world's business-funded R&D. The result is a proxy capable of catching EU countries' investments in BD for the energy sector.

DL offers several advantages over traditional econometric analysis, particularly in handling complex and nonlinear relationships within economic data. Unlike traditional econometric models that rely on predefined functional forms and assumptions, DL algorithms can automatically learn intricate patterns and correlations from vast and unstructured datasets. This flexibility enables DL models to capture nonlinearity, heterogeneity, and interactions among variables more effectively, thus providing more accurate and robust predictions. In addition, DL excels in handling high-dimensional data, such as images, texts, and long time series with high-frequency data, allowing economists to incorporate diverse sources of information into the analyses. Furthermore, DL models can adapt and evolve, making them suitable for dynamic economic environments characterized by evolving trends and uncertainties (Lantz, 2023).

Following Minsky and Papert (1987), we use a multilayer Neural Network (NN) model with a definition of perceptrons. These are feedforward networks with layers of units between inputs and outputs, which do not directly interact with the external environment. For this reason, these nodes are called "hidden units", and they are the key point for overcoming the limits of computational systems. In fact, they allow the elaboration of an internal representation of the input vectors, useful for realizing non-linearly separable transformations between input and output units (Mele & Magazzino, 2020).

As highlighted by Minsky and Papert (1987), a multilayer network with a single layer of hidden units is able to carry out the transformation required for any Boolean function to be computed. The general architecture of a multilayer network, also called "generalized perceptron", contains multiple layers of hidden units, where the interconnections are unidirectional, and they range from the units of a particular layer to those of a higher-level layer, i.e., closer to the output layer. The *x* state of a neuron belongs to the range (0, 1) and the activation function is given by:

$$x_j = g\left(\sum_{k}^{n} w_{jk} x_k\right) \qquad [1]$$

where the function *g* is differentiable.

For each configuration *x* of the input layer, the network calculates a configuration *y* of the output layer. Therefore, a transformation *f* is established between the input configurations and those of exit. Random initial weights are also set. By way of providing the network with a sequence of stimuli $[x_k]$, it changes the weights of the connections so that, after a finite number *N* of so-called learning steps, the network function, i.e., the output y_k, coincides with $f\,[x_k]$ for each $k > N$, with the desired precision. The logical step allows the weights to be modified to minimize the discrepancies between the network response and the pursued one.

Therefore, following the theoretical settings of a multilayer NN and Magazzino et al. (2021), we generated an NN in the dataset containing the list of variables explained in Table 1. In addition, we increased the number of data (according to the postulation of a DL model), and generated several transformations of the original series (logarithms, variations, growth rates). In this way, the NN can process *n* combinations of inputs concerning a target. Overall, the model generated 1,764,322,560[10] possible combinations.

3 https://fred.stlouisfed.org/series/EUNNGDP.

4 https://fred.stlouisfed.org/tags/series?t=europe%3Bfixed+capital+formation%3Bgross%3Bquarterly.

5 https://fred.stlouisfed.org/series/LNS11300012.

6 https://ec.europa.eu/eurostat/web/energy/data/energy-balances.

7 https://data.imf.org/?sk=a0867067-d23c-4ebc-ad23-d3b015045405.

8 https://ec.europa.eu/digital-single-market/en/desi.

9 https://iri.jrc.ec.europa.eu/scoreboard/2021-eu-industrial-rd-investment-scoreboard.

10 Result $= DR_{n,k}$. In this case, *k*, a positive integer, can also be greater than or equal to *n*.

Table 1
Data description.

Variable	Definition	Source
GDP_p	GDP per capita in 2000 US$ (converted at Geary Khamis PPPs)	FRED Data
K	Gross Fixed Capital Formation (constant 2010 US$)	FRED Data
L	Labor Force	FRED Data
Open	Exports + Imports (in the energy sector)/GDP (%)	EUROSTAT
Public Spending	Government Expenditure (% of GDP)	IMF
BigData	Firms' investments in the energy sector using BD	DESI and IRI Scoreboard

Source: authors' elaboration.

4. Empirical findings

The statistical neural analysis produced 16 Inputs concerning a single Target, with no omitted variables. Out of 15 variables combined by them, one variable (which does not appear) represents the substrate (Fig. 1).

The use of all instances in the dataset is shown in detail in Fig. 2.

The result has been divided into three subsets for a total number of instances equal to 30. The number of training instances is 18 (60%), and they are the design of the model through various settings. In other words, we built models with different architectures and, then, compared their performances. The number of selection instances is 6 (20%). Instead, these instances choose the NN with the best generalization properties. The number of testing instances is 6 (20%). These instances validate the operation of the model. Finally, the number of unused instances is 0 (0%). This result is highly significant since it highlights that no outliers in the data can alter the NN's functioning. After observing the dataset's behavior regarding the ML processing, we can analyze the ANNs results as shown in Fig. 3.

The ANNs graph in Fig. 3 contains a scaling layer, a NN, and an unscaling layer. The complexity, represented by the number of hidden neurons, is 16:10:8:6:1. Each neuron is interconnected with the other, and between the perceptrons of the subsequent networks. The absence of anomalous values allowed a pyramid interconnection without the presence of anomalous perceptron networks such that they were more significant than the first NN.

From the ANNs results, the pre-set target was *dGdp*, which is the best choice, compared to $DR_{n,k}$ possible combinations of inputs, to generate a target necessary for the analysis.

As shown in Table 2, the Confusion Matrix corroborates the previous results gained through ANNs analysis.

Compared to the actual positive values, the expected values cause a change in the target 90.69 times every 100 combinations between the inputs (predicted positive/total predicted). Therefore, compared to the actual positive values, there is only a 9.31% probability of choosing a different target than the one selected in the ANNs analysis (*dGDP*). We obtain the same result by observing, in the Confusion Matrix, the ratio between the actual negative values and the predicted positive and negative. In this case, the probability of obtaining a different target is lower (9.11%).

Finally, to check for errors in the prediction process, we test the model through the Quasi-Newton method, although it does not require the calculation of second derivatives (Fig. 4). Instead, the Quasi-Newton method computes an approximation of the inverse Hessian at each iteration of the algorithm by only using the gradient information.

The blue line represents the training error, and the orange line is the selection error. The initial value of the training error is 4.15595, and the final value after ten epochs is 0.051782. The initial value of the selection error was 6.81115, and the final value after 11 periods was 0.057160. Again, this analysis, confirming the previous findings, highlights how the NN's exclusive selection and training process presents (almost) a cancellation of errors as the eras increase.

Furthermore, to check this algorithm's goodness of fit, we performed the ANNs Error test, which analyses the result of four different errors concerning the three main instances of the NN model.

Table 3 presents four alternative scenarios of the prediction errors related to training, selection, and testing. According to the ANNs theory, the obtained statistics should be lower than unity. Here, the results confirm the hypothesis of the test since all the errors of the three main components of the ANNs are <1. In addition, the training errors are lower than the selection errors, which are lower than the testing errors. Thus, the test confirms how the latest architecture of the ANNs is in line with the hypothesis of the slightest prediction error and that numerous combinations between the inputs correctly influence our generated target.

Afterwards, we analyze the final ANNs architecture through an additional test. A standard method to test the loss of a model is to perform a linear regression analysis between the scaled NN outputs and the corresponding targets for an independent testing subset (Fig. 5). If the correlation coefficient is equal to 1, then there is a perfect correlation between the outputs from the NN and the targets in the testing subset. Graphically, the prediction line (concerning the target, *dGdp_p*) significantly confirms the goodness of the elaboration about the algorithm on the final architecture: in fact, the interpolating line crosses the point cloud, and the two are almost perfectly superimposable.

Finally, since the ANN analysis has revealed a large quota of 60% relationship between the investigated variables, we evaluate which is the most significant on the Target (*dGdp_p*). To this end, we performed the Importance test on the ANNs algorithm (Fig. 6). Only nine variables were considered in the test since the remaining variables were poorly related to the Target. As we can see, the change in the prediction of *dBigData* represents the variable that generates the most significant effect in the change in *dGdp_p* (43.20%). However, also the Open variable has a high value in the test (29.03%), reassuring the positive impact of trade on GDP changes (Arif et al., 2020; Guei and Le Roux, 2019). This result underlines how, at the level of predictive influence, the international business's

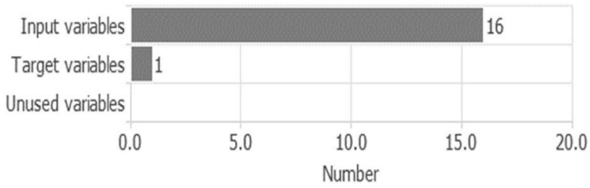

Fig. 1. Variables bars chart.
Source: authors' elaborations in Oryx.

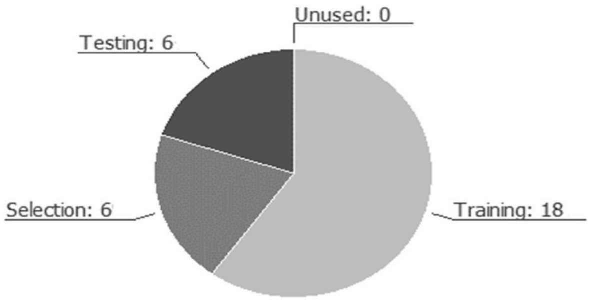

Fig. 2. Instances pie chart.
Source: authors' elaborations in Oryx.

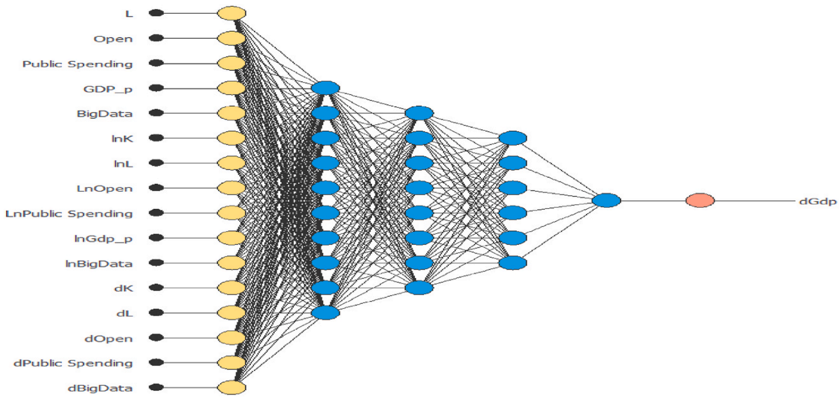

Fig. 3. ANNs graph.
Source: authors' elaborations in Oryx.

Table 2
Confusion matrix.

	Predicted Positive	Predicted Negative
Actual Positive	8547	877
Actual Negative	851	8531

Source: our elaborations in Oryx.

opening rate impacts the acceleration of GDP for about one-third.

Therefore, these results are open to two essential interpretations. Primarily, an economic policy action that chooses public and private investments in BD could be the best initiative to face the economic crisis. In other words, the EU should use its own BD ability to promote recovery and growth in the medium-long term. It could pass precisely from the innovation of data to the software of electricity information systems, a sector that has been severely affected by the present crisis. Secondly, policies capable of influencing EU international trade would be a good driver for economic growth (Frankel & Romer, 1999; Grossman & Helpman, 1991). Observing the Importance Test results, we can affirm how these two variables can most likely assist each other.

If we look at the so-called megatrends, investments in digitalization would be essential and enabling factors to accelerate markets'

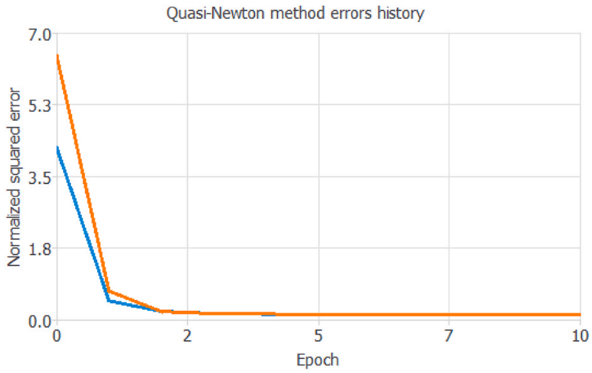

Fig. 4. The training process test.
Source: authors' elaborations in Oryx.

Table 3
ANNs error test.

Error	Training	Selection	Testing
Sum Squared	6.57604e-06	0.000398861	0.00113685
Mean Squared	2.2676e-07	4.43179e-05	0.000126317
Root Mean Squared	0.000476193	0.00665717	0.0112391
Normalized Squared	0.000172109	0.0351309	0.0454978

Source: authors' elaborations in Java and Oryx.

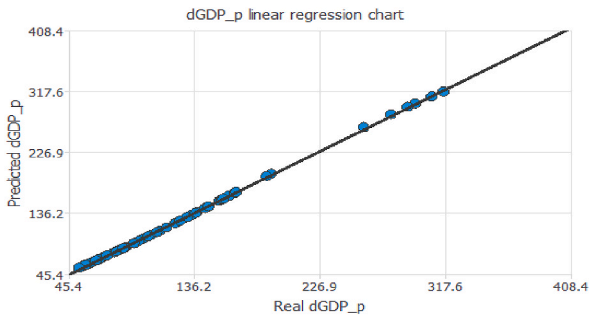

Fig. 5. Predicted regression test.
Source: authors' elaborations in Oryx.

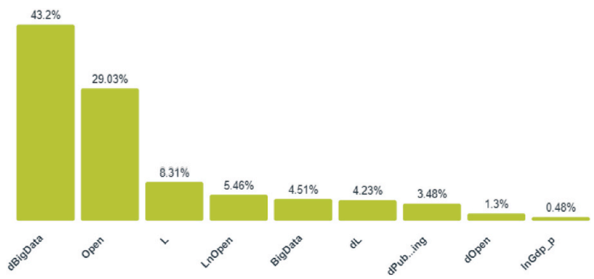

Fig. 6. Importance test.
Source: authors' elaborations in BIGM.

growth and foster product innovation toward a more sustainable environment. This last factor would represent an element of the new international trade theory traceable to the Verdoorn (1949) model. Therefore, a strong investment in BD could support the growth of EU international trade. The positive surpluses in the balance of payments current account could be finalized to finance projects precisely in BD policies.

According to Fosso-Wamba et al. (2015) and Byers (2015), BD holds the potential to generate billions of values across various sectors, which can lead to enhanced productivity for economies, identify new leaders in the private sector, and offer benefits and conveniences to consumers, confirming that businesses that use BD *effectively hold a potential competitive advantage over the others since* their ability to make faster and more informed decisions. Xie et al. (2021) posited that BD development encourages emerging market firms to diversify strategies and increase competitive advantages. They found that firms' international diversification significantly enhances their innovation performances, which in turn positively affects economic growth. Wang et al. (2022) highlighted that BD promotes the development of a green economy and plays a greater role in facilitating technological progress and boosting efficiency. From a microeconomic perspective, Intizar Ali et al. (2021) suggested that BD can enhance firm performance by gaining competitive advantages. El-Kassar and Singh (2019) found that BD raises green innovation in enterprises, thereby encouraging green growth.

Regarding the effect of trade openness on economic growth, among others, Marelli and Signorelli (2011) for China and India, Fetahi-Vehapi et al. (2015) for ten Southeast European countries, Khalid (2016) for Turkey, Keho (2017) for Cote d'Ivoire, and Huchet et al. (2018) for a panel of 169 countries showed that trade openness exerts a positive impact on economic growth both in the short- and long-run.

5. Concluding remarks and policy implications

Fostering innovation is one of the key roles of CE that also applies to EU entrepreneurship, since entrepreneurs are persistently seeking new ways and means to create values, contributing with significant market opportunities, and depicting large potential for an EU more sustainable growth.

Our results show that investments in highly disruptive technologies have a positive nexus with economic output in the EU-27. The empirical findings suggest that countries investing more in BD technologies tend to experience higher levels of economic growth and innovation. Additionally, such investments contribute to enhancing productivity, competitiveness, and job creation within the entire region. Overall, the relationship underscores the importance of leveraging disruptive technologies to drive economic development and prosperity across the EU-27.

These findings can inform policy measures to address global economic challenges in several ways. First of all, they ask the policymakers to put more effort into the diversification of energy sources: investing in disruptive technologies, such as renewable energy and energy storage, can help diversify energy sources and reduce reliance on fossil fuels, thereby mitigating the impact of disruptions in energy markets caused by geopolitical conflicts like the Russia-Ukraine one. Next, emphasizing investments in innovative technologies enhances the resilience and adaptability of economies to external shocks (i.e., geopolitical conflicts, natural disasters, pandemics, terrorism, financial crises, trade barriers and tensions between countries, and technological disruption). They highlight the interconnectedness and vulnerability of the global economy to various risks and uncertainties, stressing the importance of resilience, awareness, and cooperation in mitigating their impact. Thus, by promoting technological innovation and digitalization, EU countries can build up more robust and flexible economic systems capable of withstanding and recovering from disruptions even in energy markets. Moreover, in terms of efficiency and sustainability, BD often leads to improvements in these respects across various economic sectors. Policies that encourage investments in these technologies can drive economic growth while reducing environmental impact, contributing to long-term sustainability and resilience in the face of global economic challenges. Then, addressing these issues requires strong international collaboration and cooperation. Our results highlight the importance of collaborative efforts among EU-27 and with global partners to accelerate the adoption of disruptive technologies and develop innovative solutions to mitigate the impact of geopolitical events on energy markets. Last but not least, policymakers can use the insights from the relationship between disruptive technologies and economic output to align policy measures with long-term economic goals. This might involve fostering and funding more R&D investments, providing funding for technology adoption and deployment, and encouraging a supportive regulatory environment to facilitate innovation and entrepreneurship in disruptive technology sectors.

By leveraging the findings on the relationship between large firms' investments in disruptive technologies and economic output, policymakers can develop proactive strategies to address the challenges posed by global exogenous events, like the war in Ukraine on energy markets, while simultaneously promoting sustainable economic growth and resilience.

There exists widespread confidence that by using digital technologies and BD, economies under pressure can accelerate their efforts to boost the digitalization process. Therefore, most countries are focusing on digital policies to sustain economic recovery in the medium term, though significant uncertainties remain due to the conflict between Russia and Ukraine (Magazzino et al., 2023).

This paper aims to empirically test how firms' investments in the energy sector on BD may affect the economic growth process. To this extent, a dataset over the 1990–2019 period has been built for EU-27 economies. An experiment based on a DL model with ANNs has been performed to test the relationship between firms' investments in digital technologies, such as BD, and the economic output. The results confirm the endogenous growth theory, showing the potentially positive role of enabling technologies to produce significant competitive advantages and new knowledge-based capital among member countries. It will enhance innovation and sustainable growth across the EU economies, helping the recovery from the present energy crisis.

Because of the geo-political and energy crisis with an uncertain recovery, the European public debt and labor market might be negatively affected. European households' disposable income is forecasted to experience minimal growth in 2024 after the strong reduction observed until early 2023, although policy emergency responses to the energy crisis were put in place to alleviate the impacts. Policy interventions at a large scale, particularly through the European Recovery Package and the Next Generation EU Plan, could still absorb a significant share of the economic and social shock. Among these actions, we recommend stressing public and private investments, especially to large companies, more talented at introducing quickly smart investments in digital technologies and BD. Temporary measures such as income subsidies, tax rebates, and unemployment benefits will not offset the long-run energy turmoil.

To test this proposal, we have developed a model to assist policymakers in implementing effective economic policies to face the ongoing energy crisis. Starting from a production function that considered some determinants of economic growth, we built a variable able to represent potential large firms' investments in BD as a driver for growth. The results of the ANNs are consistent with the premises, confirming that a significant change in overall investments in digital technologies and BD turns into a GDP-positive variation. Firms' investments in BD represent the variable with the highest importance score in the tested model, holding great potential to inform policy measures addressing global economic challenges, including the impact of the Russia-Ukraine war on energy markets. By harnessing vast datasets on energy production, consumption, and market trends, firms can employ advanced analytics and AI algorithms to forecast supply chain disruptions, price fluctuations, and geopolitical risks. These insights enable policymakers to formulate agile and targeted responses, such as diversifying energy sources, enhancing energy security measures, and promoting renewable energy investments to mitigate the impact of geopolitical instability on energy markets. However, the barriers that must be overcome are as significant as the potential impact. Merely investing in technology will not be adequate to realize this impact.

This outcome advises policymakers to use forthcoming public and private resources from the European Recovery Funds and the Next Generation EU Plan to accelerate the EU economies' digital transformation by investing in potential long-term actions for more sustainable development, anticipating future energy use patterns, and consequent environmental impacts. Further, we have observed that the openness degree to international trade in the energy sector also returns to the NN signal (from the inputs to the target) with a very high value. This result would represent a glue with the one obtained from the BD variable. Consequently, higher investments in policy innovation and BD would produce positive externalities to international trade and EU competitiveness.

Firms' investments in BD have profound policy implications for economic growth, necessitating agile regulatory frameworks to harness their full potential. By leveraging huge datasets, firms can optimize operations, enhance productivity, and drive innovation, fostering competitiveness and dynamism within economies. However, the concentration of data among large firms raises concerns regarding market power, data privacy, and inequality. Policymakers must strike a balance between promoting innovation and safeguarding consumer rights through measures such as antitrust enforcement, data protection regulations, and investment in digital infrastructure. Effective policies can harness the transformative power of BD to stimulate inclusive and sustainable economic growth while mitigating potential risks and disparities.

Brynjolfsson and McAfee (2014), more than others, emphasize the transformative impact of digital technologies, particularly highlighting the exponential growth of technological capabilities and the need, for businesses and individuals, to adapt to a rapidly changing digital landscape. They highlight the potential for digital technologies to drive productivity gains, reshape industries, and fundamentally alter economic and social structures.

At the national level, the capacity to accumulate, process, and utilize vast amounts of data will become a new landmark of a country's strength. Nevertheless, because of their extensive nature, these technologies are mostly difficult to process and often lead to misleading conclusions if not adequately evaluated (Ardagna et al., 2016). By using advanced analytics techniques, organizations within EU countries might use BD in developing innovative products, insights, and services and smoothing turbulent economic waves.

It is highly reliable that future economic and political competitions among countries will be based on exploiting the potential of BD. It offers a great opportunity and massive risk simultaneously, although the latter did not receive enough political attention between EU countries. Verma and Bridges (2018) state that organizations gain in different domains, such as security, e-commerce, health, electricity, and e-government, when they use data in their decision-making process. Shen et al. (2018) affirm that BD is a source of innovative industry services, products, and opportunities. Information about people is also critical in increasing the efficiency and effectiveness of business operations (i.e., optimization of supply chain flows, error minimization, and quality improvement, identification of the best price for products and services, and selection of the best workers for specific tasks) (Bilgin, 2017). Above all, BD might negatively influence individuals whose data have been collected, sometimes misusing personal information. Therefore, BD has pushed the scientific community to re-examine its research methodology and has triggered a revolution in thinking and methods (Jin et al., 2015).

So, overcoming barriers to CE culture requires proactive strategies where BD might be determinant, as well as collaboration, and support from stakeholders, policymakers, and the broader community to foster a conducive environment for circular entrepreneurship. In a real-world business setting, entrepreneurs are encouraged to prioritize designing products with durability, reparability, and recyclability in mind. This entails embracing eco-design principles to minimize material waste and environmental impact. Consequently, investing in R&D becomes imperative to innovate new materials and manufacturing processes that support circular production. By adopting circular business models, entrepreneurs can explore new revenue streams and bolster customer loyalty. They can achieve this by forging partnerships and collaborations to develop and scale up these models, leveraging digital technologies to optimize resource use and maximize value creation.

Moreover, optimizing supply chains to procure sustainable materials, minimize waste, and enhance resource efficiency is crucial for CE adoption. Implementing traceability and transparency measures can bolster accountability and foster trust with consumers. Additionally, educating consumers about the advantages of circular products and services is pivotal for generating demand. Entrepreneurs can engage customers through marketing campaigns, product labeling, and interactive platforms that underscore the environmental and economic benefits of circularity. Furthermore, incentivizing sustainable behavior through initiatives like discounts for returning or recycling products can further encourage consumer participation in circular practices.

Limitations of the papers are related to the difficulty of defining and measuring firms' investments in BD. Some of these concerns are hard to focus through public policy. However, data protection laws are fundamental to address ethical concerns. Regarding technical issues, Hilbert (2016) highlights the relevance of financial incentives and subsidies to spur investments in data repositories and scientific data management systems. A way to consider the BD unreliability may be to supplement them with national statistics. Furthermore, a strategy to solve data access weaknesses is the expansion of "open data", considering it a very unusual public good.

Because of the declining costs along the data value chain, BD remains a significant driver of the increased use of data and the accelerated migration of socio-economic activities to the Internet. It allows rapid and lasting growth, the only limits being the saturation of the available information (correlated to a finite number of potential users) and the achievement of quality levels that cannot be further improved.

In line with this observation, future research may explore the impact of BD on economic growth through alternative empirical strategies using dynamic panel data models, a time-varying causality approach, or wavelet analysis to confirm our results. Furthermore, there needs to be more consensus on whether digitalization can replicate the same geographical disparities as innovation. The disruptive digitization structure opens dynamic areas/sectors, determining a new territorial configuration where regions with less technological intensity could emerge. Moreover, future research could explore this relationship through standard econometric analyses, comparing regression and causality results with those obtained in this study.

Ethical approval

Not applicable.

Availability of data and materials

The data that support the findings of this study are available from the Corresponding Author upon reasonable request.

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CRediT authorship contribution statement

Giovanna Morelli: Conceptualization, Investigation, Supervision, Writing – original draft, Writing – review & editing. **Cesare Pozzi:** Conceptualization, Supervision. **Antonia Rosa Gurrieri:** Conceptualization, Project administration, Resources, Writing – original draft. **Marco Mele:** Data curation, Resources, Software. **Alberto Costantiello:** Resources. **Cosimo Magazzino:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, 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. The datasets used during the current study are available from the website and are available on request.

Data availability

Data will be made available on request.

Abbreviations

AI	Artificial Intelligence
ANNs	Artificial Neural Networks
BD	Big Data
CE	Circular Economy
CEAP	Circular Economy Action Plan
DEA	Data Envelopment Analysis
DL	Deep Learning
EC	European Commission
EU	European Union
GDP	Gross Domestic Product
GMM	Generalized Method of Moments

ICT	Information Communication Technologies
IoT	Internet of Things
I4.0	Industry 4.0
ML	Machine Learning
R&D	Research and Development

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