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Identifying necessary conditions to deep-tech entrepreneurship

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Abstract

Purpose – This paper aims to address which resources provided by an entrepreneurial ecosystem (EE) are necessary for deep technology entrepreneurship.

Design/methodology/approach – The authors used a novel approach known as necessary condition analysis (NCA) to data on EEs and deep-tech startups from 132 countries, collected in a global innovation index and Crunchbase data sets. The NCA makes it possible to identify whether an EEs resource is a necessary condition that enables entrepreneurship.

Findings – Necessary conditions are related to political and business environment; education, research and development; general infrastructure; credit; trade; diversification and market size; and knowledge absorption capacity.

Research limitations/implications – The results show that business and political environments are the most necessary conditions to drive deep-tech entrepreneurship.

Practical implications – Policymakers could prioritize conditions that maximize entrepreneurial output levels rather than focusing on less necessary elements.

Social implications – Some resources require less performance than others. So, policymakers should consider allocating policy efforts to strengthen resources that maximize output levels.

Originality/value – Studies on deep-tech entrepreneurship are scarce. This study provides a bottleneck analysis that can guide the formulation of policies to support deep-tech entrepreneurship, as it allows to identify priority areas for resource allocation.

Keywords Entrepreneurial ecosystems, Emerging technology

Paper type Research paper

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1. Introduction

The works by Spilling's (1996) and Van De Ven's (1993) who, at that epoch, did not use the term entrepreneurial ecosystem (EE) but described things like entrepreneurial system (former) and industrial infrastructure for entrepreneurship (latter) as well as some on the business ecosystem literature (Iansiti & Levien, 2004; Moore, 1993), served as a foundation for Cohen's (2006) seminal work, which coined the term EE (Shi & Shi, 2021). However, the term gained greater notoriety only with Isenberg's (2010) seminal article on EEs. Since then, the interest of researchers in the EE subject has grown, as this concept is a relevant approach to analyzing entrepreneurship from a systemic perspective (Ács et al., 2014; Feldman, Siegel, & Wright, 2019; Spigel & Harrison, 2018; Wurth, Stam, & Spigel, 2021). Some researchers who use the EEs lens to assess the Brazilian context stand out, such as Alves et al. (2021) who based themselves on Isenberg's framework to analyze knowledge-intensive EE configurations. Other researchers focused on studying other aspects of EEs, such as the university ecosystem (Moraes et al., 2021; Silva et al., 2021), proposing indicators (Rovere et al., 2021) and/or theoretical frameworks to measure Brazilian EEs (Gimenez, 2022).

The EEs provide key resources for new ventures, which typically have limited resources (Miller & le Breton-Miller, 2021), to exploit economic opportunities (Ács et al., 2017). These resources can be allocated for new businesses' value creation and innovation processes (Barney, 1991; Wernerfelt, 1984), with knowledge (Tallman, Jenkins, Henry, & Pinch, 2004), talent (Spigel & Vinodrai, 2020) and technologies (Qian, Ács, & Stough, 2015) standing out among them. Also, resources are both non–firm-specific and firm-specific. Non–firm-specific resources, known as classical "Penrosian" resources (Penrose, 1995), can be acquired via the formal economic exchange (Dyer, Singh, & Hesterly, 2018), whereas firm-specific resources can be acquired by any entrepreneur inside of an EE (Pitelis, 2012) via a simple acquisition process (Thompson, Purdy, & Ventresca, 2018).

Furthermore, regional entrepreneurship literature cites "untraded interdependencies," which refer to "nontraded" resources, which include the "labor markets, public institutions, and locally- or nationally-derived rules of action, customs, understandings, and values" (Storper, 1995, p. 205). These interdependencies refer to the availability of human resources (Thompson et al., 2018), financing (Vedula & Kim, 2019), a friendly institutional environment (Minniti, 2008) and cultural support for entrepreneurship (Bogatyreva, Edelman, Manolova, Osiyevskyy, & Shirokova, 2019) that can drive or inhibit entrepreneurship.

Providing resources, therefore, is the main function of EEs (Autio, Nambisan, Thomas, & Wright, 2018; Feldman & Zoller, 2012; Spigel & Harrison, 2018). A suitable EE provides critical resources to entrepreneurs that facilitate running their businesses and exploiting economic opportunities (Ács et al., 2017; Autio et al., 2018; Stam, 2015).

The EEs are understood as geographically delimited systems that allocate assets and resources to enable economic activities (Ács, Autio, & Szerb, 2014; Cao & Shi, 2021). In this sense, EEs are resource-providing systems that allocate these resources to entrepreneurs and latent actors who aim to exploit economic opportunities by developing new entrepreneurial firms, which eventually can lead to added value for the entire ecosystem (Wurth et al., 2021).

In recent years, studies (Dealroom, 2021; Start-up Genome, 2020) have drawn attention to the growth of deep technology ventures (e.g. artificial intelligence, big data, robotics, nanotechnology, among others), i.e. startups based on exploring opportunities from emerging technologies (Rotolo, Hicks, & Martin, 2015), e.g. blockchain, quantum computing and other technologies related with Industry 4.0, which offer a substantial advance over established technologies in terms of solving existing problems (Siegel & Krishnan, 2020).

Deep-tech ventures, as they require longer/slower cycles of research and development (RD) for an aspect of emerging technology to be translated into commercial solutions for consumers (Dealroom, 2021), are usually developed by highly qualified entrepreneurs (PhDs or postgraduates). In this sense, this type of entrepreneurship relates to concepts such as scientific/academic entrepreneurship (Etzkowitz, 1998; Sapir & Oliver, 2016; Stuart & Ding, 2006) and knowledge-intensive entrepreneurship (Malerba & McKelvey, 2020; Salles-Filho, 2022), as the science, technology and innovation structure of a country makes it possible.

However, deep-tech entrepreneurship is limited to exploring emerging technologies, not established technologies (Siota & Prats, 2021). Also, as it is a new concept of entrepreneurship and is associated with emerging technologies, studies on the subject and the conditions to enable this activity are still scarce (Romansanta, Ahmadova, Wareham, & Priego, 2022). In this sense, to contribute to the EEs' studies, in this article, we seek to answer the question:

Q1. What are the necessary conditions inherent in EEs that drive deep-tech entrepreneurship?

The purpose of this research is twofold. First, we seek to identify what EE' resources are necessary conditions for deep-tech entrepreneurship (if the condition does not happen, the outcome will not realize [1]). Second, we scrutinize the level of necessity of each condition to obtain different entrepreneurial output levels. To achieve these goals, we apply a novel technique known as necessary condition analysis (NCA). The NCA makes substantial contributions to identifying whether a resource offered by an EE is a necessary condition for entrepreneurship.

The remainder of the article is organized as follows: Section 2 reviews the related literature on deep-tech entrepreneurship and EEs resources, Section 3 describes the methodological step, Section 4 contains the results of the application of the NCA approach, Section 5 discusses the empirical findings, and finally, Section 6 concludes and highlights future research.

2. Theoretical background

To develop the theoretical framework for both subsections of deep-tech entrepreneurship and EE resources, we do not follow a systematic literature review protocol but use the snowball method (Wohlin, 2014), whose assumption is to find a relevant set of papers that lead to other related and/or complementary studies. Among them are the articles on deep-tech entrepreneurship by Pujol Priego et al. (2021) and the studies on ecosystems by Cao and Shi (2021), Shi and Shi (2021) and other references throughout the section.

2.1 Deep-tech entrepreneurship

The term "deep-tech" has been used to refer to technologies related to 4th Industrial Revolution/4.0 Industry such as artificial intelligence (AI), big data, drones, quantum computing and robotics, among others. For example, digital-enabled unicorns are based on consumer-driven business models where new technologies are not critical to their success (Urbinati, Chiaroni, Chiesa, & Frattini, 2019) and receive much more attention from researchers and funding organizations (Aldrich & Ruef, 2018). Digital unicorns are feasible by a digital architecture, normally based on pre-established technologies (de Massis, Frattini, & Quillico, 2016). In contrast, businesses based on deep technologies did not receive attention from funding programs, venture capitalists and policymakers until recently (Different Funds, 2020; Gigler, 2018).

The term was introduced in 2015 by Swati Chaturvedi, CEO of venture capital company Propel(x). Chaturvedi (2015, p. 1) defines deep tech as "companies founded on a scientific discovery or meaningful engineering innovation." Chaturvedi proposes a distinction of deep-tech companies from digital-enabled unicorns, considering the role of technology and competitive advantage. Currently, most digital-enabled unicorns are innovative business models based on existing or pre-existing technologies. In contrast, the deep-tech companies' business model creates value by proposing a technological solution to existing problems. As they are based on scientific-technological discovery, the business models of deep-tech companies are more difficult to copy (Chaturvedi, 2015).

In this sense, instead of business model innovation, deep-tech startups use deep technologies (e.g. AI, Big Data, robotics, etc.) as a source of competitive advantage. Thus, many deep-tech startups are spin-offs or collaborators in facilities and research infrastructure (Scarrà & Piccaluga, 2020). However, as deep technology is difficult for many investors to understand, these entrepreneurs must find early supporters to secure funding for their innovative projects (Fisher, Kotha, & Lahiri, 2016; Vossen & Ihl, 2020).

In contrast to digital startups, deep technology requires complex integration between software and hardware (Siegel & Krishnan, 2020). This means that deep-tech startups can deliver unique innovative solutions, but also that finding compatible existing technology architectures is difficult (Adner & Kapoor, 2010; Thomas, Autio, & Gann, 2014).

Unlike many digital startups that use the lean approach, fast and iterative development cycles to improve their products according to consumer requirements, deep-tech startups require long/slow and sequential development cycles (Dealroom, 2021). Furthermore, unlike digital technologies that provide direct solutions to the market, deep technologies represent basic and intermediate components, i.e. enabling technologies that feed the creation of application or facilitate the delivery of solutions to end-users (Bresnahan & Trajtenberg, 1995). Thus, entrepreneurs' role is to identify the uses of creating deep technologies for end-users (Garud, Gehman, & Giuliani, 2018). These characteristics lead to the assumption that these companies are associated with high risk and uncertainty.

2.2 Entrepreneurial ecosystem resources

Promoting entrepreneurship is associated with public policies and context (Autio et al., 2014). Entrepreneurship generates added value in the form of economic growth and jobs (Haltiwanger, Jarmin, & Miranda, 2013; Ordeñana, Vera-Gilces, Zambrano-Vera, & Amaya, 2019). Therefore, governments, whether by subsidies, creating a favorable regulatory framework, or implementing supportive policies, often encourage entrepreneurial activity (Autio & Rannikko, 2016).

At last, the country's business environment, i.e. the costs, requirements and procedures to start a business, can represent an obstacle to business creation and a discouragement (Chowdhury, Audretsch, & Belitski, 2019; Dutta, Sobel, & Roy, 2013). However, excessively reduced costs and procedures can increase the number of noninnovative entrepreneurs (Bailey & Thomas, 2017). In this sense, establishing a regulatory framework that does not discourage innovators without encouraging noninnovative entrepreneurs' entry is necessary (Darnihamedani, Block, Hessels, & Simonyan, 2018).

Human resources represent the knowledge, competencies and skills acquired by individuals (Schultz, 1961). Entrepreneurs who have received formal education, especially tertiary education, are more likely to create innovative ventures (Michelacci & Schivardi, 2020). Thus, education in science, technology, engineering and mathematics (STEM) facilitates the adoption of deep technologies (Delera, Pietrobelli, Calza, & Lavopa, 2022) and, consequently, entrepreneurship (Colombo & Piva, 2020). The STEM education is not restricted to the tertiary level, some countries have overhauled secondary education systems by implementing STEM education models (Hiğde & Aktamış, 2022; Kutnick, Lee, Chan, & Chan, 2020).

Knowledge is also generated in knowledge-intensive business (KIBS) and therefore incorporated by knowledge-intensive workers. The KIBS can provide solutions and support services for early-stage entrepreneurs, acting as an innovative entrepreneurship driver (Badulescu, Badulescu, Sipos-Gug, Herte, & Gavrilut, 2020).

Also, RD are essential for knowledge creation. The knowledge spillover theory of entrepreneurship assumes that knowledge generated by RD activities by universities and incumbent companies can create entrepreneurial opportunities (Tavassoli, Obschonka, & Audretsch, 2021). Entrepreneurs can interact with universities, research institutes and RD companies, using the research infrastructure to develop innovations. These interactions can represent a driving factor for developing innovative ventures (Malerba & McKelvey, 2020). Therefore, knowledge flows and the ability of individuals/entrepreneurs to absorb these flows and transform them into innovations is fundamental for creating innovative ventures (Ganotakis, D'Angelo, & Konara, 2021).

Physical infrastructure is fundamental for connecting the economic agents and, therefore, crucial for entrepreneurial activity (Audretsch, Heger, & Veith, 2015). Digital infrastructure, i.e. information and communication technologies (ICTs), also enables digitalization, promotes the growth of the digital economy and generates entrepreneurial opportunities (Ganotakis et al., 2021; Jafari-Sadeghi, Garcia-Perez, Candelo, & Couturier, 2021). Finally, physical infrastructure also is important for the environment and the need to implement sustainable corporate practices, as well as the creation of sustainability startups (Tiba, van Rijnsoever, & Hekkert, 2021).

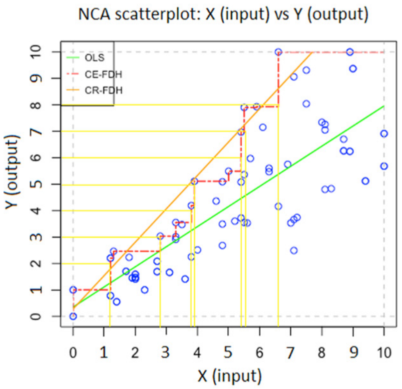
Access to credit is one of the major obstacles to the venture creation, as most early-stage entrepreneurs deal with a lack of financial resources to make their respective businesses viable (Dutta & Meierrieks, 2021). Studies indicate that financing is fundamental for entrepreneurship, especially for innovative ventures, and the lack of investment funds is one of the main barriers to the EEs' improvement (Ács et al., 2017; Spigel & Vinodrai, 2020). Besides, the demand is essential for entrepreneurs, as selling novel goods will only be viable if the population has the material conditions to acquire them (Leendertse et al., 2021). Researchers show that growing markets increase the firms' entry (Eckhardt & Shane, 2003; Sato, Tabuchi, & Yamamoto, 2012). Entrepreneurs often operate in large markets far from their headquarters; thus, easy access to potential regional markets is critical for startups.

3. Research design

3.1 Necessary condition analysis

The NCA is an approach introduced by Dul (2016a, 2016b) that provides information about the necessity of an input for a certain desirable output. A necessary condition is a key driver of an output: without a certain condition, the output will not be achieved. This concept imposes only a necessary condition, thus differing from fuzzy-set qualitative comparative analysis (fsQCA) (Ragin, 1987; Ragin, 1989; Rihoux & Ragin, 2009), which deals with sufficient conditions [2]. For example, without certain input variables (e.g. RD) reaching an output variable will not be possible (e.g. a filled/granted patent), and this cannot be compensated by other critical factors. However, the presence of a necessary condition does not guarantee the outcome (this is the case of a sufficient condition). Figure 1 shows the main concepts and rationale of a necessary condition.

The NCA assumes that an X (input) condition constrains a Y (output) result by tracing a line on top of a set of values plotted on a scatter plot X vs Y graph (Figure 1). This ceiling line can be produced by two methods: ceiling regression-free disposal hull (CR-FDH) line



Bottleneck results, CE-FDH

Y (output)	X (input)
1	NN
2	1.2
3	2.8
4	3.8
5	3.9
6	5.4
7	5.5
8	6.6
9	6.6
10	6.6

Source: Elaborated by the authors based on Richter *et al*. (2020, p. 2,246)

Figure 1. Exemplification of NCA rationale

(orange); ceiling envelopment-free disposal hull (CE-FDH) line (red). The area above this ceiling line – top left corner on Figure 1 – is named empty space, which suggests that high output levels (Y) cannot be achieved by low input levels (X). Computing the proportion of empty space size in relation to the total space (TS) gives us the effect size (*d*) statistic, a measure of necessity. Therefore, the greater the ES, the greater the restriction imposed by X to Y (Dul, 2020). To trace the ceiling line, we selected the CE-FDH, a method recommended when the sample is composed of a limited number of outputs. Figure 1 shows that the benefit of using this technique (CE-FDH) is its 100% accuracy, that is, no observations are within the empty space.

Additionally, we choose to apply NCA to investigate necessity conditions, as important theoretical and empirical evidence shows that NCA leads to better and robust results than fsQCA, concerning necessity analysis. In short, the evidence claims that:

- NCA can make a statement "in degree," whereas fsQCA can make only "in kind" statements.
- fsQCA uses Boolean logic to set the pertinence of a condition to a given result, and doing that, the resultant analysis is sensitive to some extent to the calibration procedures (logistic or standardized algorithm) and chosen threshold parameters (raw or proportional reduction in inconsistency (PRI) make the results sensitive).
- fsQCa can produce more false negative/positive (Baumgartner, 2015, 2022; Dul, 2016a, 2016b; Patala et al., 2021; Vis & Dul, 2018).

Finally, the NCA also displays a result named bottleneck (right side of Figure 1). The researcher can choose between percentage or original values of variables and then inform the exact value that X bounds Y (yellow lines). In this illustration, since the scale is from 0 to 10, we can easily interpret interchangeably that, if we intent obtain an output of Y = 7 (70%), we need at least an input of X = 5.5 (55%); otherwise, the output will be impossible. Obviously, if this condition was satisfied it still configures a nonsufficient condition to the output (Y) happening, but it is certain that, if not a certain amount of X, then not at all a certain amount of Y. This is a strong appealing to policy marking analysis and formulation as the bottleneck results provide an "in kind" qualitative evidence (that X is necessary for Y) and, most important, an "in degree" quantitative extrapolation states that at least a minimum amount of X is a necessary condition to make achieving a given level Y of output possible.

3.2 Data and sample

The IESE Business School of Navarra points out startups based on advanced materials, artificial intelligence, biotechnology, blockchain, drones and robotics and quantum computing as the main sectors of deep-tech ventures (Siota & Prats, 2021). In addition to these sectors, Start-up Genome (2020) also includes AgTech and Big Data business as a category of deep technologies.

To collect data on deep-tech entrepreneurship we used the Crunchbase database. Based on IESE business school (Siota & Prats, 2021) and Start-up Genome (2020) studies on deep technology sectors, we collected data directly from the search engine of Crunchbase website (see www.crunchbase.com/discover/organization.companies) and the sectors (they used the word industry) taxonomy used by them is as follows:

> Advanced materials, AgTech, Artificial intelligence (artificial intelligence, intelligent systems, machine learning, natural language processing, and predictive analytics), Big Data, Biotechnology (bioinformatics, biometrics, biopharma, biotechnology, genetics, life science, neuroscience, and quantified self), Blockchain, Drones and robotics (drone management, drones, and robotics), and Quantum computing (Crunchbase, 2021, website).

We have defined the five-year period to ensure that we only select companies that are similar in terms of their growth stage. The period delimitation is also relevant for allowing us to select only innovative start-ups.

To test whether a resource provided by an EE is a necessary condition for deep-tech entrepreneurship, we collected data from the Global Innovation Index (GII). We selected 15 variables (Table 1) that represent innovation inputs provided by EE at country-level (Cornell University, INSEAD, & WIPO, 2020). Using GII indicators is also interesting, since it is a longitudinal and systematic study of the factors that affect innovation in different countries. It is an internationally harmonized and comparable data source that focuses on both innovation inputs and outputs. Our sample corresponds to data from 132 countries participating in the GII 2021 report [3].

To run the NCA we normalized the data from 0 to 1, although it is not needed for NCA purposes. We applied the max-mix method ($[Max - value\ observed]/[Max - Min]$). Outliers' values were identified and replaced by the interquartile interval method, an approach used in EEs composite indices such as the Global Entrepreneurship Index (Ács et al., 2019) and the European Innovation Scoreboard 2022 (Hollanders et al., 2022). Appendix 1 brings the descriptive statistics for all variables in raw (original) data as well normalized.

4. Findings and discussions

4.1 Necessary analysis

Figure 2 allows a visual inspection of the eight scatter plots whose conditions have proven to be necessary for deep-tech entrepreneurship [4]. The scatter plots are the graphic solution of NCA necessary analysis results. Usually, the abscissa axis (X) represents the conditions variable ("condition" and not "independent" according to developers' syntax), i.e. variables that measure the EEs' conditions, whereas the ordinate axis (Y) represents the deep-tech startup variable, the outcome. The countries (observations) are represented by the blue dots.

The effect size (*d*), a criterion to infer if a condition is or isn't a necessary one, is computed by the ratio between the "empty space" (upper left corner above the ceiling line, the red line in Figure 2) and the "total space." Thus, the larger the empty space, the more an EEs condition

Type, variable, code and brief description	Source
Outcome	
Deep-tech startup, DTS	Crunchbase
Number of active deep tech-based companies founded between 2016–2021	
Conditions	
Institutions	Global Innovation Index
Political environment, PE	
It measures the countries' political stability, the quality of public services and the capacity to implement public policies	
Regulatory environment, RE	
It measures the ability of governments to implement policies and regulations that promote private-sector development	
Business environment, BE	
It captures the procedures, time and cost required to start a business	
Human capital and research	
Education, E	
It measures the quality of secondary education by the total government spending on education, average spending per student, PISA performance and the pupil–teacher ratio	
Tertiary education, TE	
It captures the quality of and access to higher education through the proportion of tertiary education enrollment, and the proportion of graduates in science and engineering	
Research and development, RD	
It measures the number of full-time researchers involved in R&D activities. The total domestic R&D expenditure (% GDP) and largest companies' expenditure on R&D in a country	
Infrastructure	
Information and communication technologies, ICT	
It measures the access and use of ICTs by both the population and governments	
General infrastructure, GI	
It measures energy production, logistics performance, and gross capital formation (as % GDP)	
Ecological sustainability, ES	
It measures how close countries are to meeting environmental policy goals	
Market sophistication	
Credit, C	
It captures the ease of getting credit, as well as the proportion of microfinance loans and credit available to the private sector	
Investment, I	
It measures the regulation and extent of the financial market	
Trade, diversification and market size, TDMS	
Originally named "Trade, Diversification, and Market Scale", it measures domestic industry diversification and internal market size	
Business sophistication	
Knowledge workers, KW	
It captures the proportion of employment in knowledge-intensive services and business expenditures on R&D	
Innovation linkages, IL	
It measures business-university cooperation, the level of diffusion and development of clusters, foreign-funded R&D expenditures, the number of joint ventures and strategic alliances, as well as the number of patents filed	
Knowledge absorption, KA	
It measures knowledge absorption, considering intellectual property charges, imports of high technology, flows of foreign direct investment and the number of full-time researchers in the business sector	

Notes: GII is available at: www.globalinnovationindex.org/Home; Crunchbase is available at: www.crunchbase.com/
Sources: Based on Global Innovation Index – GII (Cornell University, INSEAD & WIPO 2020) and Crunchbase, Elaborated by the authors

Table 1. Entrepreneurial ecosystesms variables and definitions

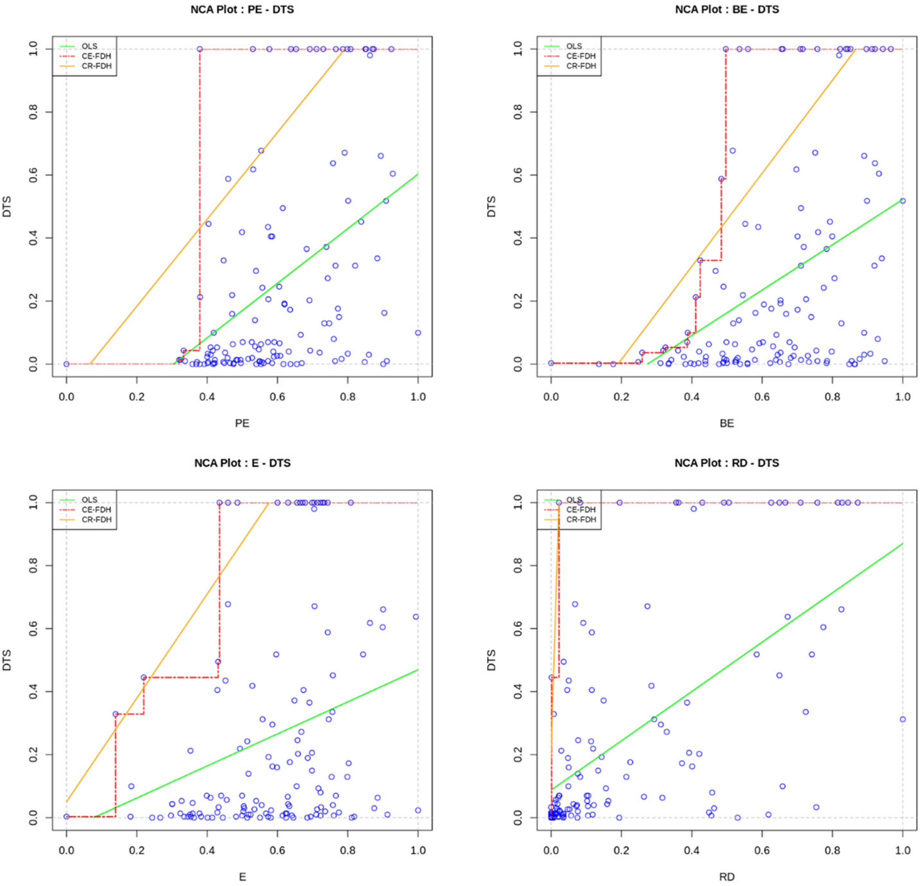


Figure 2.
Scatter plot between each condition (X) vs outcome (Y)

(*continued*)

constrains the outcome. Additionally, to the visual inspection, the specialized literature recommends using two criteria to consider a condition as necessary: effect size (*d*) and a *p*-value [5], although the threshold is up to the researcher's judgment. We selected the necessary conditions that meet at least medium effect size (*d*) and a *p*-value statistically significant at least 5% level, shown in Table 2. The shaded cells are the ultimate necessary conditions.

Thus, the political, regulatory and business environment (PE, RE and BE) are pointed out by the EE literature as moderating (in NCA terminology, an allegation assumption about sufficiency) factors of entrepreneurship (Sendra-Pons, Comeig, & Mas-Tur, 2022). Our results of the multivariate NCA indicate that the two institutional conditions (PE and BE) are necessary conditions for deep-tech entrepreneurship.

Our results agree with the study of Torres and Godinho (2021), which analyzed data from 27 EU member states, with the former member UK, and applied fsQCA and NCA to discover single necessary conditions (NCA was able, whereas fsQCA was not), finding that "Formal

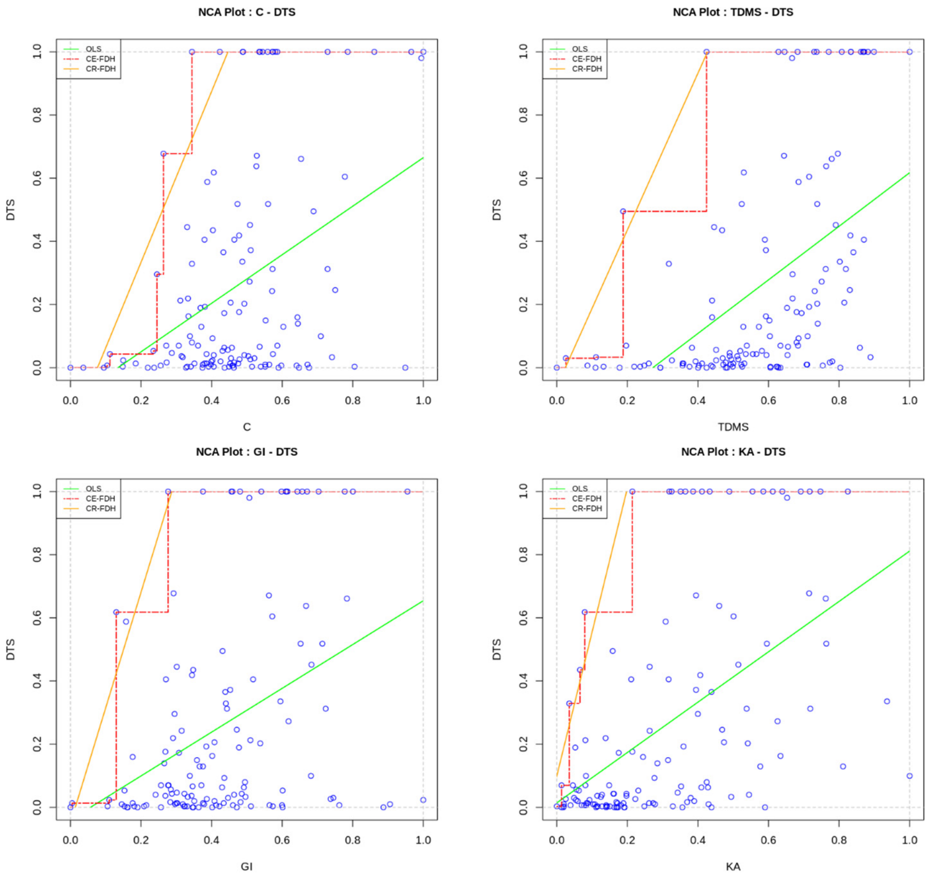


Figure 2.

Source: Elaborated by the authors

institutions, regulations and taxation" (Table 3 at p. 38) are necessary conditions for what the authors called digitally enabled unicorns and new business creation. Regarding the regulatory environment (RE), the results showed a nonsignificant value; therefore, it cannot be a necessary condition for deep-tech entrepreneurship.

Regarding the dimension entitled "Human capital and research," two conditions also attended to our criteria threshold, showing a large (Education – E) and medium (Research and development – RD) effect size and being both statistically significant. Tertiary education (TE), despite showing a small effect size, had a nonsignificant p-value. Therefore, it is not a necessary condition for deep-tech entrepreneurship.

Not surprisingly, the RD variable – which measures the number of full-time researchers, average expenditures of the three largest companies in RD, and quality of universities and research institutes – showed both effect size and significant p-value. Studies on EE (Jafari-Sadeghi et al., 2021; Tavassoli et al., 2021) show that researchers influence entrepreneurship, as well as RD expenditures and the quality of universities. Thus, our results agree with the EE literature.

Table 2.
Results of multivariate necessary condition analysis and permutation test (*p*-value)

Dimensions	Variables	Effect size (*d*)	*p*-value
Institutions	PE Political environment	0.377^{l}	0.028**
	RE Regulatory environment	0.219^{m}	0.081^{ns}
	BE Business environment	0.458^{l}	0.000***
Human capital and research	E Education (secondary)	0.312^{l}	0.019**
	TE Tertiary education	0.076^{s}	0.095^{ns}
	RD Research and development	0.013^{m}	0.000***
Infrastructure	ICT Information and communication technology	0.109^{m}	0.139^{ns}
	GI General infrastructure	0.184^{m}	0.019**
	ES Ecological sustainability	0.047^{s}	0.152^{ns}
Market sophistication	C Credit	0.278^{m}	0.001***
	I Investment	0.127^{m}	0.270^{ns}
	TDMS Trade, diversification and market size	0.302^{l}	0.004***
Business sophistication	KW Knowledge workers	0.093^{s}	0.068^{ns}
	IL Innovation linkages	0.119^{m}	0.054^{ns}
	KA Knowledge absorption	0.113^{m}	0.000***

Notes: ns = not significant, Effect size (*d*): small = $(0 < d < 0.1)$; medium = $(0.1 \leq d < 0.3)$; large = $(0.3 \leq d < 0.5)$; very large = $(d \geq 0.5)$, *p*-value: ** = significant at 5% $(p < 0.05)$; *** = significant at 1% $(p < 0.01)$; ns = nonsignificant. Shaded cells are the ultimate necessary conditions to be used in the next step
Source: Elaborated by authors

Table 3.
Bottleneck analysis

. . .different desired levels (%) of outcome (DTS) **Y =** deep-tech startup	Required minimum levels of the necessary condition (%) for . . . Institutions PE	Institutions BE	Human capital and research E	Human capital and research RD	Infrastructure GI	Market sophistication C	Market sophistication TDMS	Business sophistication KA
0	NN	NN	NN	NN	NN	NN	NN	NN
10	37.9	41.1	13.9	0.1	13.0	24.5	18.8	3.5
20	37.9	41.1	13.9	0.1	13.0	24.5	18.8	3.5
30	37.9	42.4	13.9	0.1	13.0	26.3	18.8	3.5
40	37.9	48.4	21.9	0.1	13.0	26.3	18.8	6.6
50	37.9	48.4	43.5	2.2	13.0	26.3	42.5	7.9
60	37.9	49.7	43.5	2.2	13.0	26.3	42.5	7.9
70	37.9	49.7	43.5	2.2	27.7	34.4	42.5	21.4
80	37.9	49.7	43.5	2.2	27.7	34.4	42.5	21.4
90	37.9	49.7	43.5	2.2	27.7	34.4	42.5	21.4
100	37.9	49.7	43.5	2.2	27.7	34.4	42.5	21.4

Note: NN = not necessary
Source: Elaborated by the authors

The next dimension – infrastructure – showed all conditions with effect sizes greater than zero. Although ecological sustainability (ES) and ICT are pointed out in the literature as enabling factors and a spaces of opportunity for creating new ventures (Tavassoli et al., 2021; Tiba et al., 2021), our results showed a nonsignificance statistical *p*-value which discarded them. Consequently, only general infrastructure (GI) is a necessary condition for deep-tech entrepreneurship. This condition also finds support in the literature on EE (Jafari-Sadeghi et al., 2021; Audretsch, Heger, & Veith, 2015) as a condition that facilitates access to markets.

Regarding the market sophistication dimension, the investment (I) showed a nonsignificant p-value, even though the literature indicates that it (Gigler, 2018; Spigel & Vinodrai, 2020), mainly in the form of venture capital, is important for entrepreneurship. On the other hand, credit (C) can be considered necessary for deep-tech entrepreneurship. Access to credit, particularly in the form of finance and loans – as measured by GII – for early stages deep-tech startups sounds plausible instead of investments series A, B and C rounds – as measured by GII – for a more incumbent startup (Gompers et al., 2020).

Our results indicate the remaining market sophistication condition, named trade, diversification and market size (TDMS) is a necessary condition for deep-tech startups. Indeed, market size is a crucial factor with our results agreeing with previous studies (Ali, Kelley, & Levie, 2020; Tavassoli et al., 2021).

Finally, the last dimension – business sophistication – showed that only knowledge absorption (KA) had both significant effect size and p-value over the threshold. Although knowledge workers (KW) and innovation linkages (IL) have effect sizes greater than zero, their p-values are slightly higher than 5% (0.68 and 0.54, respectively). Knowledge absorption (KA) finds support both in seminal (Kim, 1997) and more recent literature, such as the study of Khan and Tao (2022) that used the same data source as we did – the GII – and encountered evidence of positive correlation between knowledge absorption and innovation performance of manufacture firms.

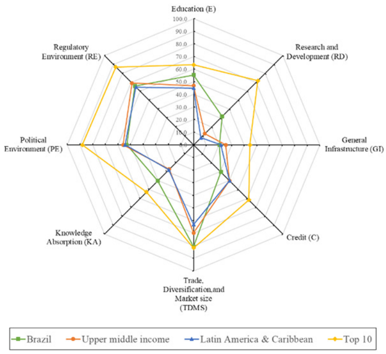
4.2 Bottleneck analysis

After the NCA's necessity analysis, we performed the bottleneck analysis. Here lies the most important power advantage of this technique, which, to the best of our knowledge, no other technique provides: it "[. . .] precisely identifies what level of X is necessary for what level of Y" (Vis & Dul, 2018, p. 882) or "[. . .] shows which level of the condition is a bottleneck for a given desired level of the outcome" (Dul, 2020, p. 1518). In Table 3, the first column shows the possible and/or wished levels of outcome (Y = DTS = deep-tech startup) on a scale from 0 to 100% and the remaining columns (from 2 to 9) show the levels of necessity for each condition to obtain a certain desired level of output.

Our results show that even to low DTS levels (Y = 10%) all eight conditions are necessary. However, the level of necessity varies for each condition. To focus our analysis, Figure 4 shows the GII 2021 results of Brazil. On the left side is a radar graph with a benchmarking of Brazil (green line) against: all upper-middle (34) income countries (orange line); all Latin America & Caribbean (18) countries (blue line); and top 10 best performance countries (yellow line).

From a key performance indicators (KPI) evaluation Brazil ranks 11th among the 34 upper middle income and 4th among 18 Latinamerican & Caribbean economies. These results are not surprising since our national system of innovation and entrepreneurship ecosystem is one of the most mature in the region (Alves et al., 2021; Dionisio et al., 2021; Fischer et al., 2022). However, it can improve as shows the radar graph in the left side of Figure 4. Brazil has the strongest positions only in four conditions compared with its counterpart region (E, RD, TDMS and KA) and income group economies (RE, E, RD, TDMS and KA). Obviously, compared with the top 10 performing economies in the GII, Brazil has a long way to go.

From an NCA that aims to support policy, prioritizing the conditions where Brazil has its weakest performance on GII (shaded in gray at the right side of Figure 3), i.e. general infrastructure (GI: 20.5), credit (C: 30.5), and research and development (RD: 31.9), is advisable. This focus is plausible and desirable since the government, specially the Federal Government, struggles due to the expenditure cap (from the Portuguese, "teto de gastos") on the public budget.



X (conditions)		Score
Institutions		
PE	Political Environment	53.0
BE	Business Environment	65.9
Human Capital and Research		
E	Education (secondary)	55.4
RD	Research and Development	31.9
Infrastructure		
GI	General Infrastructure	20.5
Market Sophistication		
C	Credit	30.5
TDMS	Trade, Diversification, and Market Size	80.8
Business Sophistication		
KA	Knowledge Absorption	40.4
Y (outcome), deep-tech startup		527

Notes: GII is available at: www.globalinnovationindex.org/Home, Crunchbase is available at: www.crunchbase.com/, World Bank available at: http://data.worldbank.org/about/country-and-lending-groups, According to the World Bank (July 2020) classification: Upper-middle: China, Bulgaria, Malaysia, Turkey, Thailand, Russia, Montenegro, Serbia, Mexico, Costa Rica, Brazil, North Macedonia, Iran, South Africa, Belarus, Georgia, Colombia, Armenia, Peru, Argentina, Jamaica, Bosnia and Herzegovina, Kazakhstan, Azerbaijan, Jordan, Albania, Indonesia, Paraguay, Ecuador, Lebanon, Dominican Republic, Namibia, Guatemala and Botswana; Latin America & Caribbean: Chile, Mexico, Costa Rica, Brazil, Uruguay, Colombia, Peru, Argentina, Jamaica, Panama, Paraguay, Ecuador, Dominican Republic, El Salvador, Trinidad and Tobago, Guatemala, Bolivia and Honduras; Top 10: Switzerland, Sweden, USA, UK, South Korea, The Netherlands, Finland, Singapore, Denmark and Germany
Sources: Based on Global Innovation Index – GII (Cornell University, INSEAD & WIPO 2020) and Crunchbase; Elaborated by the authors

Figure 3.
Brazilian conditions and outcome

Table 3 shows that these conditions needed to be at least 27.7%, 34.4% and 2.2%, respectively, for Brazil could be able to reach the outcome of high deep-tech startups ($Y \geq 80\%$), measured here in numbers of firms. Thus, as Table 3 is expressed in percentage, we get the minimum necessary scores of 18.6, 30.3 and 2.0 for GI, C and RD, respectively. This is obtained by multiplying each requirement level from Table 3 by the maximum value in the sample (it is the value normalized as 1, for instance: $GI = 27.7\% \times 67.3 = 18.6$; $C = 34.4\% \times 88.0 = 30.3$; $RD = 2.2\% \times 89.8 = 2.0$.

Brazil is very close to this threshold in GI (20.5 against the minimum of 18.6) and C (30.5 against the minimum of 30.3). Thus, attention is needed to improve to overcome the fragilities of these conditions. Therefore, for the Brazilian EE to have the possibility of originating deep-tech ventures, allocating efforts – in terms of strategic national programs and goals – to overcome the fragilities of these two necessary conditions (GI and C) is necessary.

Note again the concept of necessary conditions, i.e. “If these conditions are not in place (at the right level), the outcome will not occur.” and “Other conditions cannot compensate for their absence” (Dul, 2016a, 2016b, p. 1522).

Therefore, it does not matter how many and whatever the mix of configurations that the policymakers want to implement, the necessary conditions must be present in these minimum requirements to assure the possibility of realization of the outcome. However, although they are necessary and cannot be replaced by other necessary conditions, the presence of these conditions does not guarantee that the output will occur. In short, if these conditions are not present, the EE capacity to generate deep-tech entrepreneurship is guaranteed to fail.

5. Final remarks

This research aimed to assess the level of necessary conditions of EEs for deep-technology entrepreneurship. Entrepreneurship is the result not only of attitudes of potential entrepreneurs but of the context in which these individuals are inserted, i.e. the quality of environmental factors, which are called the "entrepreneurial ecosystem" (Stam, 2015). The EE is composed of a set of interconnected actors that offer a variety of resources that affect entrepreneurial activity, such as human capital, financing, and infrastructure. The market size can also boost or inhibit entrepreneurship. Therefore, the quality of an EE is defined by its capability to provide resources to stimulate entrepreneurial activity (Ács, Autio, & Szerb, 2014).

To investigate this, we applied a recent technique called necessary conditions analysis (Dul, 2016a, 2016b; Dul, 2020) to uncover the necessary conditions from an initial set of fifteen conditions recognized as critical to EEs by literature (Audretsch & Belitski, 2017; Roundy et al., 2018; Stam, 2015; Stam & van de Ven, 2021). As sustained by a growing number of social scientists, many social phenomena are classified as complex ones, and thus lack a single variable that could explain the causal relations between antecedents and consequences, therefore the concept of equifinality (different mix of conditions that leads to a similar outcomes) re-emerges nowadays with strong appealing (Alves et al., 2019; Muñoz et al., 2020; Spigel, 2017; Vedula & Fitza, 2019).

Both core analyses provided by this study identified eight single necessary conditions (PE, BE, E, RD, GI, C, TDMS and KA) for deep-tech entrepreneurship, underpinning the level of necessity of each one of them, considering the desired level of outcome. Mainly, for the Brazilian case, the general infrastructure (GI), credit (C) and RD are those that policymakers must focus on as they are at the edge of the minimum requirement level of necessity. Also, conditions such as political and business environments (PE and RE) also must be maintained as, although Brazil surpasses these minimum requirements, they are not low, and any carelessness can cause the country to fail to reach them.

This research has relevant implications for academics and policymakers. From an academic point of view, our results contribute to previous studies on causal relationships between EEs' resources and entrepreneurial activity. As far as policy implications are concerned, our results fuel the debate about the resources needed in EEs. The results of bottleneck analysis can guide the formulation of policies to support deep-tech entrepreneurship, as they allow identifying priority areas for resource allocation.

In the NCA's bottleneck analysis, policymakers need not focus on the weakest elements of an EE, but rather allocate resources to strengthen the conditions that lead to an increase in the deep-tech entrepreneurial output levels. Despite this, policymakers cannot neglect the other elements of the ecosystem, even if these show low levels of need. For even if the requirement for these components is minimal to generate a result, they must be present at some level for the result to occur. In this sense, policymakers must ensure that these conditions are present and maintain their level of performance for deep technology entrepreneurial activity to take place.

This study is limited to assessing only whether an EE's resource is a necessary condition to boost entrepreneurship. Future studies could apply the s alongside the NCA to determine the sufficient conditions for deep-tech entrepreneurship and complement the debate about equifinality. As this is a study on the conditions of the EEs portraying data from 2021, periodic studies are also necessary to identify whether the need for each condition has changed.

Notes

1. It can be mathematically formalized in many ways, and two are recurrent in literature: if $Y = 1$, *then* $X = 1$ or if *not X, then not Y*. The latter usually applies the symbol "$\sim$" as negation, so if $\sim X$, *then* $\sim Y$. Note that when $X = 1$, then $Y = 1$ or $Y = 0$.
2. Sufficient conditions, likewise, can be mathematically formalized in many ways, two are recurrent in literature: if $X = 1$, *then* $Y = 1$ or if *not Y, then not X*. The latter usually applies the symbol "$\sim$" as negation, so if $\sim Y$, *then* $\sim X$. Note that when $X = 0$, then $Y = 1$ or $Y = 0$.
3. The data set collected and prepared by the authors is available at: https://doi.org/10.25824/redu/NBRF7U.
4. Appendix 2 shows the other seven scatter plots from nonselected conditions.
5. The p-value was calculated according to the recommendations from blueprint reports and manuals of NCA, running a bootstrap procedure with 10,000 permutations (Dul, 2016a, 2016b). We used the NCA R package (Dul, 2022) and the Colab© notebook environment to run the analysis. The entire code is available at: <https://colab.research.google.com/drive/1D5THHL8ysk9uhwI-FJGuoLe14TTnyPG7?usp=sharing>.

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Appendix 1

Raw data	Code	SD	Minimum	Mean	Maximum
Outcome					
Deep-tech startup	DTS	103.5	0.0	77.3	301.0
Conditions					
Institutions					
Political environment	PE	17.5	0.00	60.0	100.0
Regulatory environment	RE	18.0	17.4	64.6	99.1
Business environment	BE	12.3	31.3	70.2	93.1
Human capital and research					
Education	E	15.3	0.00	48.0	82.5
Tertiary education	TE	15.8	0.00	30.2	63.4
Research and development	RD	23.7	1.60	19.4	89.8
Infrastructure					
Information and communication technologies	ICT	19.9	21.3	63.4	94.8
General infrastructure	GI	12.5	2.60	30.2	67.3
Ecological sustainability	ES	12.6	12.7	30.8	60.4
Market sophistication					
Credit	C	15.9	0.30	41.4	88.0
Investment	I	16.9	4.00	34.4	88.4
Trade, diversification and market size	TDMS	14.7	26.7	67.0	96.9
Business sophistication					
Knowledge workers	KW	18.2	3.3	34.1	44.7
Innovation linkages	IL	15.3	1.20	25.8	82.1
Knowledge absorption	KA	13.5	11.4	29.4	70.7
Normalized data					
Outcome					
Deep-tech startup	DTS	0.34	0	0.26	1
Conditions					
Institutions					
Political environment	PE	0.17	0	0.60	1
Regulatory environment	RE	0.22	0	0.58	1
Business environment	BE	0.20	0	0.63	1
Human capital and research					
Education	E	0.18	0	0.58	1
Tertiary education	TE	0.25	0	0.48	1
Research and development	RD	0.26	0	0.22	1
Infrastructure					
Information and communication technologies	ICT	0.27	0	0.57	1
General infrastructure	GI	0.19	0	0.43	1
Ecological sustainability	ES	0.26	0	0.38	1
Market sophistication					
Credit	C	0.18	0	0.47	1
Investment	I	0.20	0	0.36	1
Trade, diversification and market size	TDMS	0.21	0	0.57	1
Business sophistication					
Knowledge workers	KW	0.24	0	0.41	1
Innovation linkages	IL	0.19	0	0.30	1
Knowledge absorption	KA	0.23	0	0.30	1

Note: SD = standard deviation
Source: Elaborated by the authors

Table A1. Descriptive statistics for the selected variables

Appendix 2

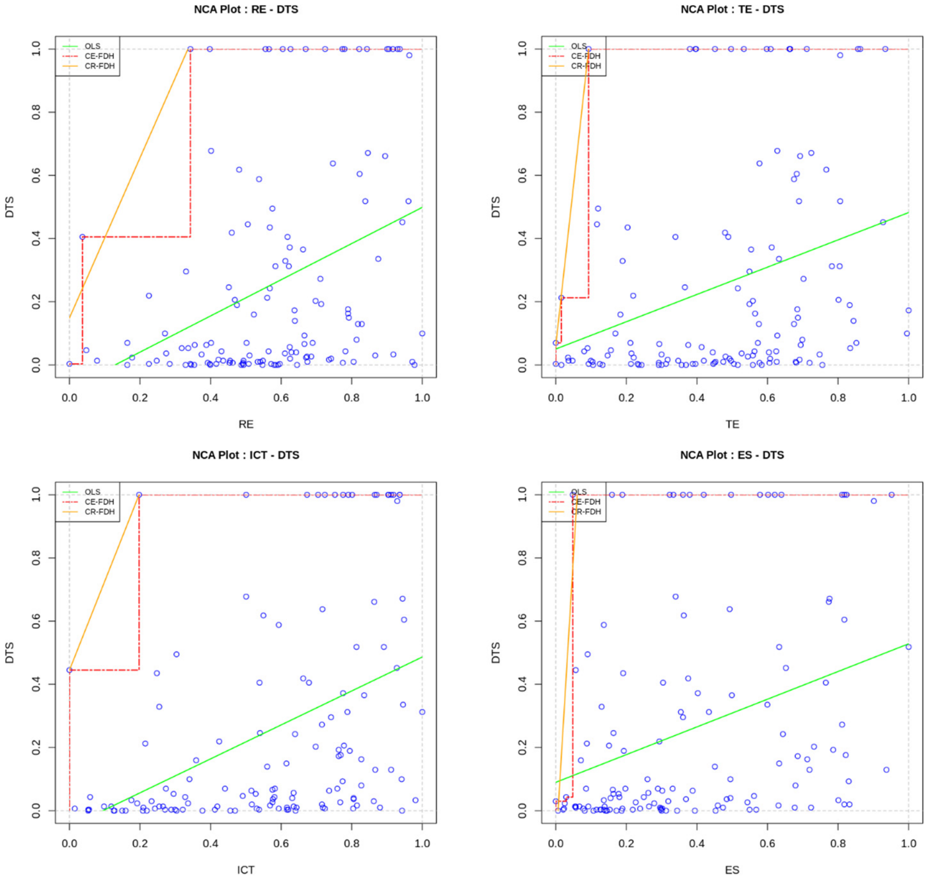

Figure A1.
Scatter plot of nonselected conditions

(*continued*)

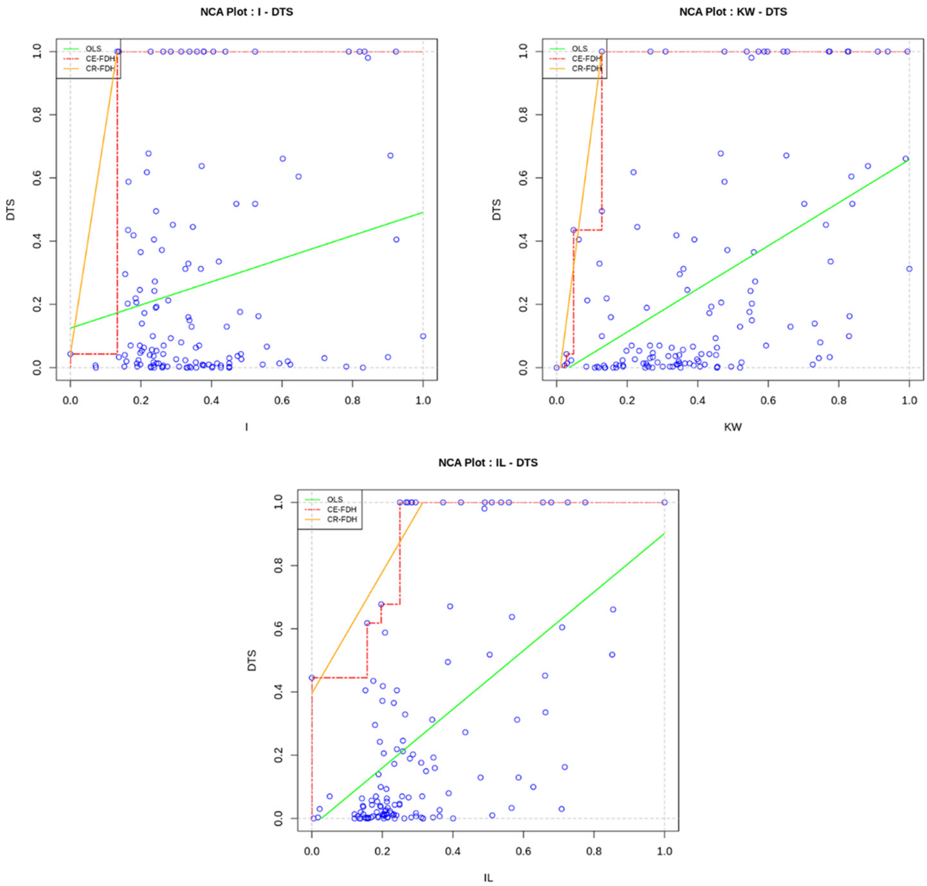

Figure A1.

Source: Elaborated by the authors

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