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DEEP LEARNING DIFFUSION BY SEARCH TREND: A COUNTRY-LEVEL ANALYSIS

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ABSTRACT

Purpose: The theory of diffusion of innovation is the theoretical lens discussed in this research to analyze the diffusion of the deep learning theme in the BRICS and OECD countries. As little has been developed to understand country-level analysis and a theme such as innovation, this research sought to fill this gap.

Originality/Value: This research demonstrates how it is possible to use Search Trends to analyze the diffusion of a thematic, enabling the extension of the diffusion of innovation theory beyond the sale of products.

Methods: Google Trends was used for data collection and to provide up-to-date information, and two different statistical models were used: clustering to identify patterns in the first analysis, and the Bass diffusion model, aiming at comparing countries considering the curve peak, the innovation coefficient, and the imitation coefficient.

Results: The findings of this research identified that China has the highest innovation coefficient among the members of the BRICS and Japan among the members of the OECD.

Conclusions: This study brought both a theoretical contribution, allowing the expansion of the diffusion of innovations that use a theme as an object of innovation, as well as a practical implication, enabling research in an accessible and democratic way.

Keywords: Deep learning. Innovation diffusion. Search trend. Country-level analysis. BRICS. Google trends

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DIFUSÃO DO *DEEP LEARNING* ATRAVÉS DO *SEARCH TRENDS*: UMA ANÁLISE EM NÍVEL DE PAÍS

RESUMO

Objetivo: A teoria da difusão da inovação é a lente teórica discutida nesta pesquisa para analisar a difusão do tema *deep learning* nos países BRICS e OCDE. Como pouco foi desenvolvido para compreender a análise em nível de país e um tema como a própria inovação, esta pesquisa buscou preencher essa lacuna.

Originalidade/Valor: Esta pesquisa demonstra como é possível utilizar o *Search Trends* para analisar a difusão de uma temática, possibilitando a extensão da teoria da difusão da inovação para além da venda de produtos.

Métodos: O Google Trends foi usado para coletar dados e fornecer informações atualizadas e dois modelos estatísticos diferentes foram utilizados: *clustering* para identificar padrões na primeira análise, e o modelo de difusão de Bass, visando comparar países considerando o pico da curva, o coeficiente de inovação, e o coeficiente de imitação.

Resultados: Os achados desta pesquisa identificaram que a China é o país com maior coeficiente de inovação entre os membros do BRICS, e o Japão entre os membros da OCDE.

Conclusões: Este estudo trouxe tanto uma contribuição teórica, permitindo a ampliação da difusão de inovações que utilizam um tema como objeto de inovação, quanto uma implicação prática, possibilitando pesquisas de forma acessível e democrática.

Palavras-chave: Deep learning. Difusão de inovação. Search trend. Análise em nível de país. BRICS. Google trends

INTRODUCTION

Innovation diffusion modeling has become the fourth topic with the largest number of published articles between 1997-2016 in 11 journals from the academic study field of Technology and Innovation Management (TIM) (Lee & Kang, 2018). This topic is being used to analyze a multi-generational product diffusion considering the effect of customers' forward-looking behavior (Shi et al., 2014), the relationship between 'technology diffusion' and 'material diffusion' (Cheng, 2012), consumer behaviors, and the effects of a generation-specific price (Tsai, 2013), consumer groups as late-adopters (Jahanmir & Lages, 2016), and also regarding social network effects on diffusion (Hu, 2013).

The theoretical lens of Innovation Diffusion Theory (IDT) (Rogers, 2003) is also identified in academic literature in some works that used country-level analysis, for example, regarding new product diffusion considering macro-environmental variables (Talukdar et al., 2002) or about the influence of culture on diffusion (Desmarchelier & Fang, 2016; Takieddine & Sun, 2015).

This research uses the country-level as the unit of analysis, selecting a total of 42 countries to be studied – 37 OECD members (Organisation for Economic Co-operation and Development, 2020; The World Bank Group, 2020a), and 5 BRICS constituent countries (Ministry of Foreign Affairs - Brazil, 2020; South Africa Government, 2020), as detailed in Table 1.

Table 1 Groupings and names of the countries that were covered in this research

Group Names	Total of Nations	Names of all Countries	Reference
BRICS	5	Brazil, Russia, India, China, South Africa	(Ministry of Foreign Affairs - Brazil, 2020; South Africa Government, 2020)
OECD	37	Australia, Austria, Belgium, Canada, Chile, Colombia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States	(Organisation for Economic Co-operation and Development, 2020; The World Bank Group, 2020a)

Note: OECD = Organisation for Economic Co-operation and Development; BRICS = Acronym for Brazil, Russia, India, China, and South Africa.

Although the literature identifies in the works of Rogers (1976) and the authors Mahajan and Muller (Mahajan & Muller, 1994) the intrinsic aspect that the diffusion model can be used for both products, ideas, and technology, the development of the studies in this research paradigm was mainly paved by the diffusion of products/services (Im et al., 2007; Lassar et al., 2005), little has been developed to advance the theory of diffusion of innovations specifically using a thematic as the own innovation.

To fill this gap and expand the understanding of the diffusion of innovation studies, the authors chose the thematic of Deep Learning (DL) in the country-level context to address the following research question: How to analyze the diffusion of the Deep Learning thematic in the BRICS and OECD nations?

Bass Diffusion Model (BDM) (Bass, 1969) has been analyzed and adopted until today for diffusion analysis because it has good adherence to technological diffusion (Cheng, 2012;

Naseri & Elliott, 2013) and has been applied with some variations (Michalakelis et al., 2010) to understand how diffusion processes occur. With IDT and BDM together, it is possible to identify the diffusion comparatively of innovators and imitators, understanding and analyzing this behavior based on the country-level.

DL was the thematic chosen to be used in this work because new technologies can create opportunities, such as new business solutions and business models, reform of the public sector, renewable energy sources, intelligent transport, and the increased need for security as the quality of life improves for new economies (Lacasa et al., 2019; World Economic Forum, 2019), or enhance the competitiveness of already developed economies (Kong et al., 2017).

Google Trends (GT) (Google, 2020c) was set for the analysis of social behavior because it provides access to the amount of research on different terms over time, which allows the mapping of the human mind, analyzing Google users' behavior (Omar et al., 2017), in observing the diffusion of a thematic. This non-traditional data source (Dos Santos, 2018) has been used for more than ten years (Jun et al., 2018) to provide up-to-date information, showing how often a term is searched for relative to the total search volume in the specific region (Blazquez & Domenech, 2018; Jun et al., 2018).

Finally, data from the Global Innovation Index (GII) - a study from the collaboration of Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO) that inform a ranking about more innovative countries (Cornell University; INSEAD; WIPO, 2019b), was also used as an additional measurement for the countries included in this study.

LITERATURE REVIEW

IDT and BDM

According to Innovation Diffusion Theory (IDT) (Rogers, 2003), diffusion is a process in which: (1) an innovation, (2) is communicated through certain channels, (3) over time, and (4) among the members of a social system. Such theoretical concepts pointed out can be explained shortly: (1) Innovation can be an idea, practice, or object that is perceived as new; (2) Communication can be defined as the process in which individuals create and share information, with diffusion being a specific type of communication focused on new ideas; (3) Time can be understood as essential in the diffusion process and, although not so widely considered in other behavioral research, the adoption process cannot occur without contemplating elapsed time; and (4) Social System is also relevant to understanding diffusion and can be defined as a set of units interacting with a common goal.

Since 1970, research has focused on updating current models to increase forecast accuracy by incorporating greater flexibility (Peres et al., 2010). The diffusion of an innovation is a complex process involving several individual decisions and components of both hypotheses. Several writers have created more flexible adoption models that utilize various sorts of heterogeneity to increase the accuracy of forecasts (Meade & Islam, 2006).

To provide a coherent view of the fundamental theoretical principles and recent trends in the innovation adoption literature, van Oorschot (2018) conducted a literature review that led to the conclusion that innovation adoption is built on four theoretical pillars: institutional theory, theory of rational action, theory of determinants of adoption, and theory of diffusion. This final pillar claims that the evolution of the IDT discipline has centered on publications that address modeling diffusion processes, the spread of innovations in heterogeneous, international transmission models, and the transmission of subsequent generations of technology.

The process of new product and service diffusion has become increasingly complicated and varied, involving many factors ranging from word-of-mouth communication to online social networks and social signals. Given this context, research strives to comprehend the impact of trends by adapting its description and modeling of these impacts (Peres et al., 2010).

A mathematical diffusion model developed by Frank Bass (Bass, 1969), known as Bass Diffusion Model (BDM), was initially applied in studies to forecast product sales in marketing (Bass, 2004; Meade & Islam, 2006; Peres et al., 2010), to identify two different consumer groups: innovators - who intrinsically through information from communication for adoption, and imitators - who, by social pressures, are more susceptible to the influence of other consumers who have already adopted an innovation.

Although in the classic work of Mahajan and Muller (1994), the concept of the diffusion of new ideas and technologies in addition to products is present, the studies that followed did not adopt such premises and focused their main research specifically on products. One of the possible explanations for the most research interests using data sources based on product sales could be because this type of data was more accessible for collection and analysis.

A study identified in the literature that explores this versatility (focusing on data sources that are not sales data) is from Cheng (2012), which uses BDM to explore the relationship between technology diffusion and new materials. The author used citations of patents and sales, respectively, to conclude that it is possible to use BDM for analysis and that the diffusion of technology positively affects the diffusion of materials.

In a study that also used BDM in its design (Shi et al., 2014), among their findings was identified that the diffusion process of technological products of multi-generational consumption (video game consoles, computers, tablets, media players, smartphones) is changeable often by adapting the market, due to changes in the strategies adopted by the manufacturers. Following this same path, the study of Jun, Yoo, and Choi (2018) identified that the diffusion procedure for products is constantly observed in the conventional approach following their life cycles, also seen in the manufacturers' perspective. These same authors also reiterate the possibility of observing the diffusion process from the consumers' perspective.

According to the authors Meade and Islam (2006), due to the increasing availability of cross-sectional data and time series that characterize consumers, there are areas for future research in forecasting the diffusion of innovation where once there were few data. Also, the use of unstructured data was seen as a challenge in the diffusion of innovation study field to expand the dissemination of research (Peres et al., 2010).

Based on the considerations of these studies, there is a new research front to be widely studied, both in academia and the market. This article contributes to the IDT body of knowledge with a new line of research. Now, the perception of the diffusion of innovation can be based on a theme or an idea and seen from the perspective of individuals - free of interests, without bias, using popular internet search tools - instead of using time series related to sales of products or services obtained from a company, as traditionally occurs in research already published in this area.

Deep Learning

Artificial Intelligence (AI) has impacted economies and sectors, creating opportunities and challenges. Therefore, the involvement of governments, companies, academics, and civil society organizations interested in exploring its potential benefits is considered an important strategic asset for countries (World Economic Forum, 2019).

Deep Learning (DL) is a machine learning technique (a subset of the AI field) that uses multiple processing layers to process raw data, learn and classify or detect patterns (LeCun, 2018; LeCun et al., 2015), an extension of research in the field of artificial neural networks (ANNs) (Chen & Lin, 2014). DL is a topic that has received significant attention in recent years, with various studies exploring its potential applications and impact on different fields (Jordan & Mitchell, 2015). It allows computational models with multiple processing layers to learn data representations with multiple levels of abstraction. It has led to major advancements in speech recognition, visual object recognition, and drug discovery. The technology uses the backpropagation algorithm to train machine models and refine their internal parameters for optimal performance. Convolutional nets have been particularly useful in image and video processing, while recurrent nets have effectively handled sequential data such as text and speech (LeCun et al., 2015).

The use of DL has also shown potential for improving healthcare systems, particularly in medical diagnosis and treatment (Gulshan et al., 2016). For example, the technology has demonstrated promising results in diagnosing various diseases, such as cancer. According to Esteva et al. (2017), DL may be able to classify skin lesions with performance on par with dermatologists-after being trained on numerous clinical photos of various skin conditions; the algorithm was tested on two distinct types of skin cancer cases. In all instances, the algorithm outperformed specialists, proving that artificial intelligence can classify skin cancer with proficiency on par with dermatologists.

In addition, DL has been used to predict patient outcomes, identify disease risk factors, and improve treatment planning. For example, in a recent article, Hannun et al. (2019) show that DL can help accurately classify a wide range of arrhythmias from single-channel electrocardiograms, which can reduce interpretation errors and improve the efficiency of diagnosis by specialists.

DL has also been used to improve transportation systems, particularly in developing autonomous vehicles (AVs) (Bojarski et al., 2016). Modern types of AV employ autonomous driving systems using "end-to-end" technology, which uses a camera to map images to drive orders directly. This system can drive on heavily trafficked local streets and highways without relying on lane markings or other specific visual cues. It learns to detect road features needed for navigation, using only human steering commands as a training signal. Unlike the traditional approach, in which the problem is divided into stages, the "end-to-end" system optimizes all processes simultaneously, which leads to better performance and smaller systems. The technology has been used to improve AV perception, prediction, and decision-making, significantly improving AV safety and performance (Geiger et al., 2012).

DL has shown significant potential for improving various fields and industries, demonstrating its importance as a strategic asset for countries and organizations. As a result, its applications are expected to grow and expand, significantly improving various domains. However, challenges remain in ensuring DL's ethical and responsible use and addressing concerns regarding data privacy, bias, and discrimination (Burrell, 2016).

Emerging technologies can be used as early-stage technologies with rapid growth and potential for socioeconomic (Rotolo et al., 2015) and scientific impact (Kwon et al., 2019). The massive use of search engines on the internet by many people allows for obtaining data from these "digital footprints", which can be modeled in generating forecasts (Brynjolfsson et al., 2016).

In this way, studies on innovation diffusion can help to understand how countries are positioning themselves for this emerging technology by looking at the spread of DL thematic interest at the country level. This research used Google Trends (GT) as a proxy to extract data of interest from the DL thematic in the countries covered by the study.

Google Trends

Further study is required to address the issue of using data from different sources, such as social networks and web search engines, according to studies on the diffusion of innovation (Peres et al., 2010). Much data is generated through people's interactions with technology on digital platforms such as Internet search engines, Twitter, Facebook, and others. Google Trends (GT) (Google, 2020c), as a source of open data, has attracted academic attention, allowing the identification of possible market potential calibrated with the own interactions of users/individuals (Chumnumpan & Shi, 2019).

New data sources resulting from human interactions on the internet have been subject to exploitation by researchers (Schaer et al., 2019), and the web search trend analysis is being used in several areas of human and social sciences, such as: in economics, to predict economic activity (Choi & Varian, 2012), unemployment rates (Askitas & Zimmermann, 2015), and financial markets (Perlin et al., 2016); in politics, to predict referendum results (Mavragani & Tsagarakis, 2016), and even in marketing, to predict consumer behavior (Goel et al., 2010) and the behavior of the diffusion of products in the market (Chumnumpan & Shi, 2019).

Choi & Varian (2012) are the pioneers of using search trends data in social science. The researchers noted that the availability of real-time data on economic activity in various industries is a necessity for governments and businesses alike. Government agencies often release indicators of economic activity in various sectors, but these data are usually delayed for several weeks and are often revised a few months later. The article examines how Google query indexes can be correlated with various economic indicators, demonstrating how they can be useful for short-term economic forecasting, especially regarding consumer purchases and "nowcasting".

Another article exploring the use of search trends in social science is Askitas & Zimmermann (2015), which analyzes the potential of using internet data, especially concerning human resources issues especially as it can be applied to a wide variety of human resource issues, including predicting unemployment, detecting health problems, documenting matching processes, and measuring complex processes. Still, in social behavior, Goel et al. (2010) present studies that show that search trends can predict future behavior in the movie box office, video game sales, and music ranking on the Billboard Hot 100. The results indicate that search analysis can be highly predictive and improve the performance of models existing in other data sources.

Exploring the behavior of a population, Mavragani & Tsagarakis (2016) analyzed the feasibility of using Google Trends data to predict the results of the 2015 Greek referendum. The term "NO" was clearly higher and statistically significant, allowing a valid approximation of the result. Along the same lines, Chumnumpan & Shi (2019) analyzed the behavior of a population regarding adopting new products. The study is based on the iPhone and iPad cases, and the results indicate that the GT model has a better curve fit than the previous models. Although the new model and Google Trends performed differently regarding real-time prediction, both produced more accurate results than the previous diffusion models.

Finally, in a different area, Perlin et al. (2016) addressed in their research the relationship between Google searches related to finance and aspects of the stock market in four English-speaking countries. Words were identified whose search frequency is associated with changes in the dependent variables, including "stocks", whose search is related to an increase in volatility and a decrease in index returns.

The authors Schaer, Kourentzes, and Fildes (2019) identified that the GT is adopted in most studies that use search engine traffic, to the detriment of a few studies that explored the forecasting skills of popular social media platforms, such as Instagram, Snapchat, Pinterest, LinkedIn, and YouTube. In a study by Jun, Yoo, and Choi (2018), who reviewed the last decade in the development of articles that used GT, identified the expansion of research areas that used this source, with its popularization of use, and with the advantage of being accessible and free, updated and focused on the researcher's objective. The contribution of the study of Jun, Sung, and Park (2017) pointed out that the potential for using search traffic (i.e., search trends) brings a new perspective to generate forecasts by analogies. The authors clarified that the trend identified in this traffic might suggest in advance the possible adoption of the innovation that was the focus of the study.

Diffusion across countries

As an emerging technology in the digital economy, DL can enable new business models, capture value, and generate profit for organizations (Teece, 2018), contributing to developing countries.

The innovation diffusion literature brings studies using as a context the analysis of different countries (Desmarchelier & Fang, 2016; Takieddine & Sun, 2015; Talukdar et al., 2002). The study by Talukdar et al. (2002) was the first to analyze macroenvironmental variables at the country level using the Bass diffusion model. The results show that developing countries have about a third of the market potential of developed countries and take longer to reach maximum sales. The survey also investigated the impact of macroenvironmental variables such as culture, economics, and social and political factors on penetration potential and speed, providing useful information for companies to assess international markets.

Culture is a critical factor shaping technology adoption and diffusion across different countries. Hofstede's (2001) cultural dimensions theory is a widely used framework for understanding cultural differences across countries. Several studies have used this framework to investigate the adoption and diffusion of technology across different countries. For instance, Takieddine and Sun (2015) found that national culture was a significant moderator in the diffusion of internet banking in Europe. Countries with higher levels of individualism and lower levels of uncertainty avoidance showed a greater adoption of internet banking. Similarly, Desmarchelier and Fang (2016), that investigated the role of national culture in shaping innovation diffusion patterns in different markets, also found significance in the influence of culture on diffusion rates.

Economic factors are also critical for the adoption and diffusion of DL technology. Countries with higher income levels, education, and infrastructure are more likely to adopt and diffuse DL technology, according to Talukdar et al. (2002). Moreover, the availability of skilled human resources is essential for adopting and diffusing DL technology. Countries with higher education and skills development levels have a greater ability to adopt and diffuse DL technology.

Social factors, including social norms, trust, and social networks, are crucial for adopting and diffusing DL technology. Social norms and values can impact the adoption and diffusion of DL technology by shaping people's attitudes and perceptions toward it (Rogers, 2003). Trust is another critical factor influencing DL technology adoption and diffusion. Trust in technology can affect its adoption and diffusion (Gefen et al., 2003). Social networks also play a crucial role in shaping technology adoption and diffusion. Social networks can facilitate the spreading information and knowledge about DL technology, leading to greater adoption and diffusion (Valente, 1996).

Political factors such as regulations, policies, and government support are also important for the adoption and diffusion of DL technology. Policies and regulations can promote or hinder the adoption and diffusion of technology (Freeman & Soete, 2009). For example, policies that promote investment in education and research can enhance the adoption and diffusion of DL technology. Government support for technology adoption and diffusion can also play a crucial role in its uptake. Governments can provide funding and incentives for businesses to adopt and diffuse DL technology.

Several researchers reiterate the need to develop new studies for the diffusion of innovation with a cross-countries approach (Chumnumpan & Shi, 2019; Jun et al., 2017; Peres et al., 2010). However, obtaining data for cross-country studies can be challenging due to differences in how governments measure and report data across different countries. GT data is one method that has been used to analyze the adoption and diffusion of technology across different countries (Jun et al., 2017). GT data can provide insights into the relative popularity of DL technology across different countries, allowing for cross-country comparisons.

Obtaining data for comparative analysis between countries is restricted by the different ways of measuring and providing reliable information by the countries' governments, which practically is summarized as integrating social and economic data to the detriment of other research objects (i.e., deep Learning).

This study compared the weighted interest of individuals in the theme of DL, at the country level (OECD and BRICS), with the data coming from the GT, which are not absolute. However, this comparison is possible with the use and analysis of the BDM. This research presents a new method of communication from the user instead of the traditional forms currently known, resulting in the collection and analysis of a sequence of temporal data.

METHOD

This study extends the concept of innovation by using the diffusion of the Deep Learning thematic as its focus, as Straub (2009) noted that innovation could refer to something abstract, like an idea. The study considers people's interest in the thematic as the weighted interest of people by the thematic of DL instead of their actual adoption. The study modifies how the communication process is perceived and constructed, using web search engine data instead of proprietary data on consumption or adoption.

Fig. 1 was created to illustrate the detailed step-by-step method used in this research, which involved accomplishing four main steps: (a) collecting data, (b) compiling the dataset, (c) preparing the data, and (d) conducting statistical modeling.

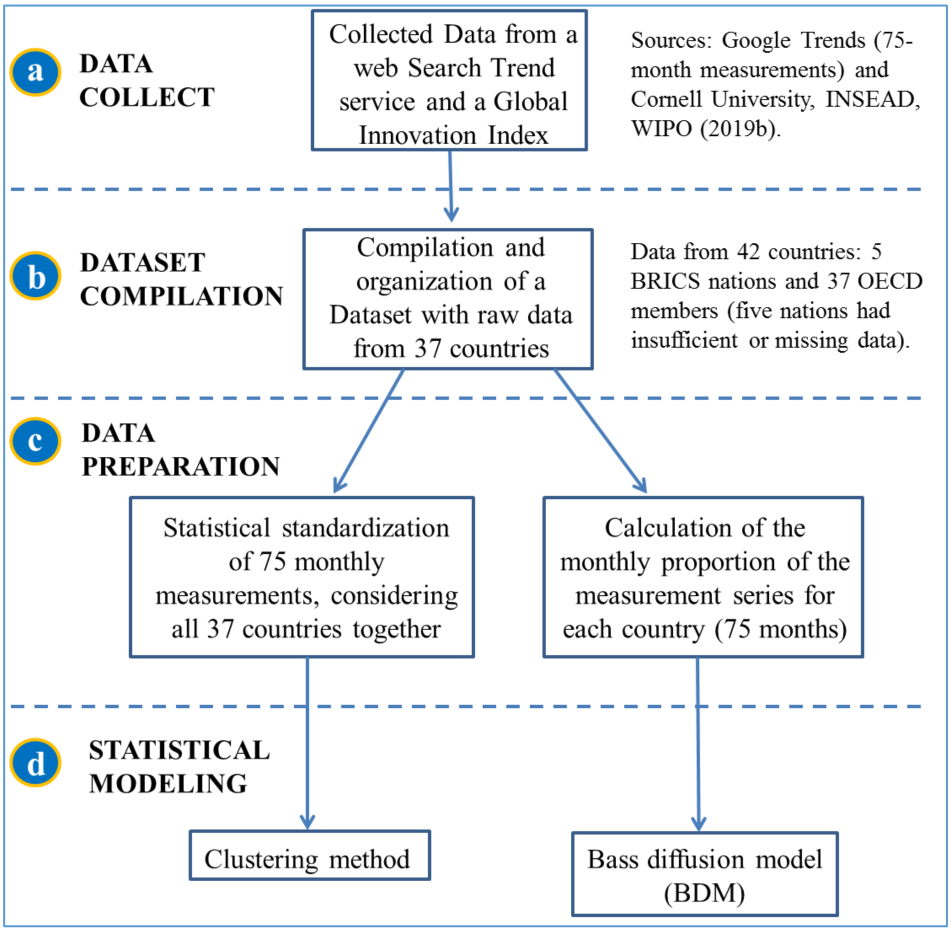


Fig. 1. The four main steps followed in the method of this research

(a.) Data Collect

To examine the diffusion pattern across countries, a total of 42 countries were analyzed, including the 37 member countries of the OECD and five member countries of BRICS. Therefore, the unit of analysis in this study was each country.

The first step was to collect data from two sources: firstly, from a web search trend service (Google, 2020c), which was chosen the search term "deep learning" on GT in a specific time interval, i.e., from January 2014 to March 2020, a total of 75-month measurements for each country with the same selection criteria; secondly, from the Global Innovation Index (GII), an index resulting from the collaboration of Cornell University, INSEAD and the World

Intellectual Property Organization (WIPO) (2019a, 2019b) - a secondary data source available for consultation on each country's innovation index/score.

The specific choice of GT by the researchers was due to be the most used search engine in the world (Brynjolfsson et al., 2016) and allow the criterion of query search could have the occurrence in the vast majority of countries (Choi & Varian, 2012).

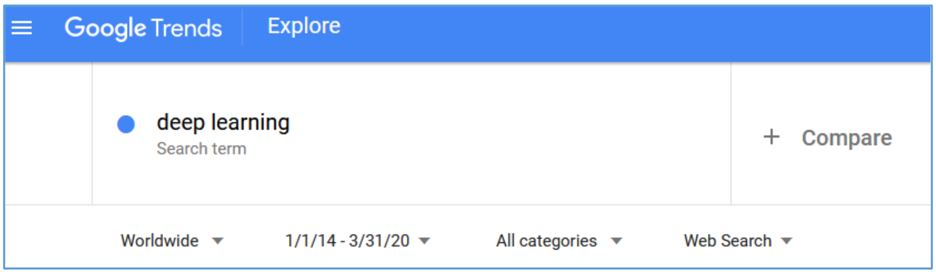


Fig. 2. Google Trends (GT) input options with filter interface

It proceeded with a sequence of five configurations in the GT interface (Google, 2020d) as informed in Fig. 2: 1) the search term (or keywords) in the query search was chosen as "Deep Learning"; 2) the geographical filter, indicated as "Worldwide" in Fig. 3, was modified specifically with the name of each of the 42 countries chosen for the study; 3) the date range of the search, was from 01/01/2014 to 03/31/2020; 4) the categories like "All categories" and finally, 5) search type like "Web Search". Using these criteria to analyze 42 countries, the Czech Republic and Iceland were withdrawn because there were no relevant "deep learning" searches on GT to show the results.

(b.) Dataset Compilation

The second step was compiling and organizing a dataset with raw data from 40 countries left, with 5 BRICS nations and 35 OECD members. The data are generated individually by country, monthly, and relative to the degree of interest. These data are adjusted by GT in two ways: (i) first, the search is relativized by the total number of searches for other subjects, considering the amount of data in a given interval of time, and (ii) after that, the GT normalizes with the time specified in the selection, setting the point of most interest in time as 100 and updating the rest of the time points according to this parameter. Fig. 3 shows an example of data extraction, considering BRICS nations.

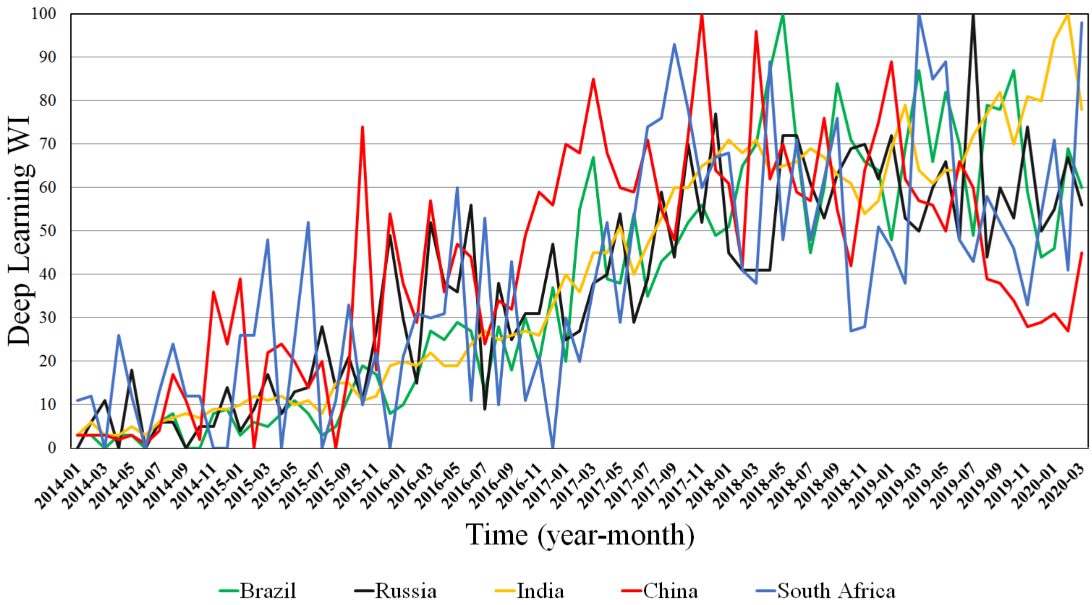


Fig. 3. Example of data extraction about Deep Learning search interest in BRICS nations from January 2014 to March 2020.

Notes: WI = Weighted Interest for a specific country's population, is a measure in percentage value (%). This percentage value changes each time the initial and final intervals of data extraction are modified, as these data are weighted, ranging from 0 (minimum value) to 100 (maximum value).

Due to a feature of the GT data generation system, there are situations in which it considers some data with a value "<1". So, the authors decided to replace "<1" values with "0" to be imported and processed into data analysis tools. After that, Latvia, Luxembourg, and Slovakia, three OECD members, were removed from the dataset for having more than thirty missing data in their extracted data series.

After data extraction and compilation, five nations were withdrawn from the study - two nations (Czech Republic and Iceland) had insufficient data relevance, and three other nations (Latvia, Luxembourg, and Slovakia) had excessive missing data, then totalizing 37 countries in the final compilation of the research dataset.

(c.) Data Preparation

As a third step, from the dataset compiled for the research, it was necessary to perform two adjustments to the data format due to the request of each technique to be used in the statistical analysis step – the following step (d.) of this method.

To prepare the data for the execution of the cluster analysis (first adjustment), and to avoid the imprecise comparison between all countries (Kupfer & Zorn, 2019), it was performed statistical standardization of the dataset when viewed in an integrated way for the 75 monthly measurements from all 37 countries together, with the subtraction of the mean and division by the standard deviation.

To prepare the data for the analysis of the Bass model (second adjustment) for each country, individually, the data series obtained from GT (the 75 monthly measurements) - are not absolute values because they are normalized concerning the maximum volume of the series, which is 100 - were converted proportionally, using the specific series for each country, dividing the monthly value by the total sum of this same series. So, with the calculated proportional monthly value, this new series obtained now has a sum of values equal to 1 for each of the 37 countries.

(d.) Statistical modeling

The fourth and last step of the method was statistical modeling. Two different models of analysis were necessary to understand how similarities and differences in the diffusion processes of the *deep Learning* thematic in the BRICS and OECD countries

The first statistical model used was the clustering method to identify similarities between countries (pairwise distances between data items) and to find groups. In the execution of the *hierarchical cluster analysis* procedure using *Orange Data Mining* software (Demšar et al., 2013; Godec et al., 2019), the *ward* linkage method was chosen (Ward, 1963), with the *manhattan* normalized distance metric.

The second statistical model used was the *Bass diffusion model* (Bass, 1969) to identify the comparison between all countries, considering three measurements: the diffusion peak, the innovation coefficient (p), and the imitation coefficient (q). From formulation created by Bass to use diffusion series with accumulated data, as shown in Eq.(1):

$$S(t) = K\frac{1-e^{-(p+q)t}}{1+\ (q/p)e^{-(p+q)t}} \qquad (1)$$

Where the function S(t) represents the total accumulated individuals who have already adopted/accepted an innovation (in this research, the interest in a thematic or idea), at time *t*; *p* is the innovation coefficient (individual's intrinsic tendency to adopt the innovation), *q* is the coefficient of imitation (contagion force by social pressures), and K is the carrying capacity (maximum size of the target population that can be achieved), other mathematical transformations were carried out.

As the study interest was in the variation (rate) of the diffusion of *Deep Learning* thematic to be analyzed in different countries, it was possible to adopt the maximum value of K = 1 and to use the differentiation of the Eq.(1) mentioned, to generate the non-cumulative distribution, resulting in Eq.(2), given by the following equation:

$$\frac{dS(t)}{dt} = \frac{p(p+q)^2 e^{-(p+q)t}}{(p+qe^{-(p+q)t})^2} \quad (2)$$

Besides the Eq.(2), which is also detailed discussed in innovation diffusion literature (Mahajan, Muller, & Bass, 1990; Mahajan, Muller, & Srivastava, 1990), it is possible to calculate the non-cumulative adopter distribution peak at time T*, by Eq.(3), that occurs when:

$$T^* = peak = -\frac{1}{(p+q)}\ln(p/q) \quad (3)$$

In this study, the statistical results of the three coefficients estimated by the Bass model (p, q, peak, and their significance levels) were obtained using Nonlinear Least Squares (NLS) procedure (Meade & Islam, 2006) with the R software (R Core Team, 2020). In addition, the R software was used to generate the countries' diffusion curves and the variables' correlation diagrams. In contrast, the dendrogram, the geographic maps, and the dispersion diagrams were generated with the *Orange Data Mining* (Demšar et al., 2013) software.

Also, GII score data from the Global Innovation Index (GII) (Cornell University; INSEAD; WIPO, 2019a) was used, which measures the level of innovation in the countries.

RESULTS AND DISCUSSION

Based on the execution of the *hierarchical clustering* procedure, the corresponding clustering was constructed and then visualized in a dendrogram, as shown in Fig. 4.

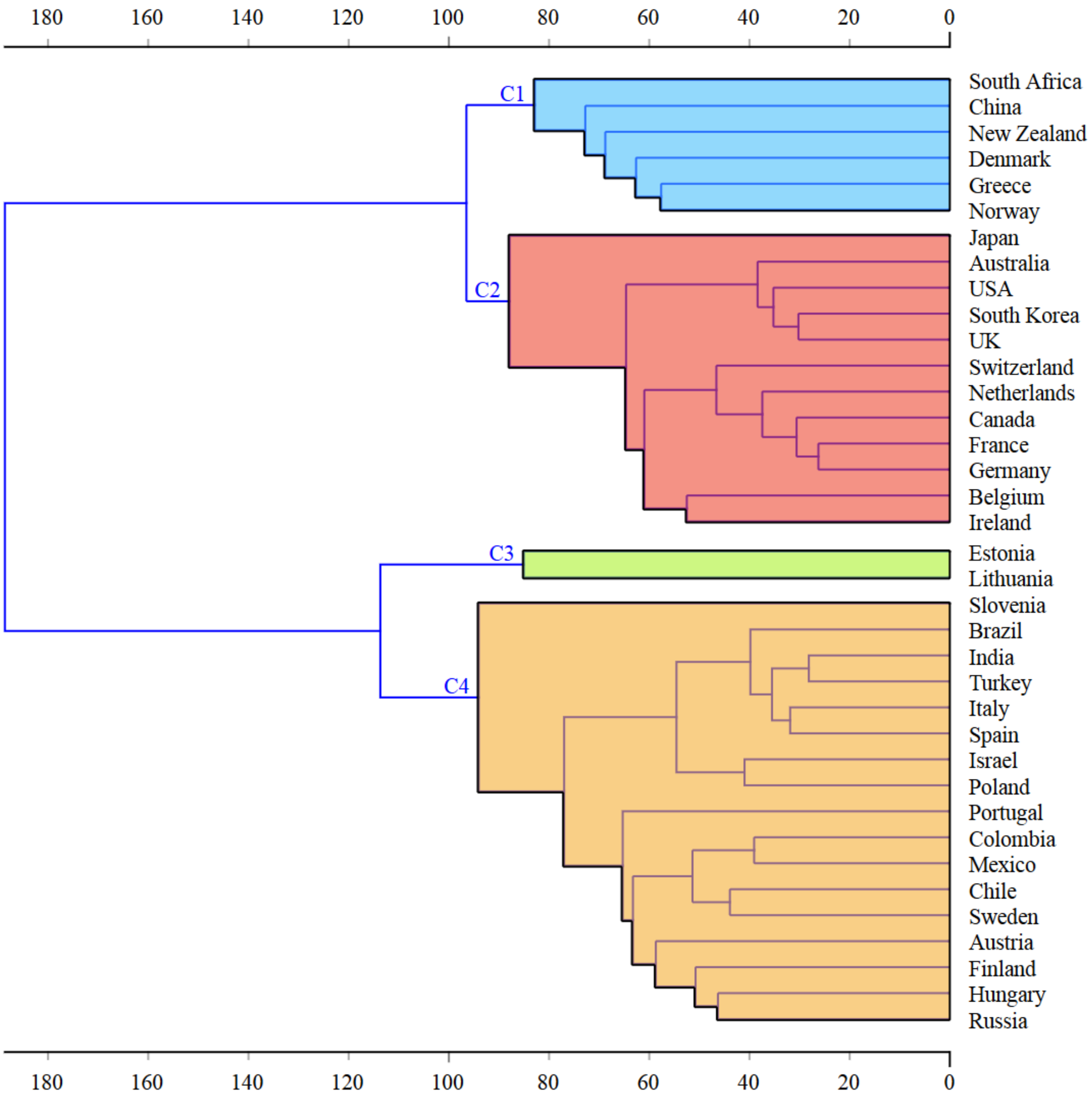


Fig. 4. Dendrogram of four clusters (C1, C2, C3, and C4) obtained with the research data
Note: Based on the Deep Learning thematic search interest (BRICS and OECD members), from January 2014 to March 2020, N=37 (except for countries Czech Republic, Iceland, Latvia, Luxembourg, and Slovakia).

Fig. 4 shows that cluster 1 (C1, six countries) is formed by two BRICS countries, South Africa and China, and by the other four countries (New Zealand, Norway, Denmark, and Greece). In cluster 2 (C2, 12 countries) are grouped the main economies of the OECD, the United States (USA), United Kingdom (UK), France, Germany, and Japan, and seven other countries. Cluster 3 (C3, two countries) is formed only by Estonia and Lithuania. Finally, the other three BRICS countries (Brazil, India, and Russia) appeared in cluster 4 (C4, 17 countries) and other countries in Latin America and Europe.

Another intuitive way of presenting the cluster analysis results [with the visualization of the country groupings] is by displaying the world geopolitical map, as shown in Fig. 5.

Fig. 5. Geopolitical world map showing clustered groupings and detailed outline of the European continent.

As seen in Fig. 5, cluster 1 (C1) is the most geographically dispersed, with nations spread across four continents (Europe, Africa, Asia, and Oceania), with no apparent connection. In cluster 2 (C2), 58.3% comprises seven European countries (Belgium, France, Germany, Ireland, Netherlands, Switzerland, and the United Kingdom). The remainder (41.7%) comprises five countries (Australia, Canada, Japan, South Korea, and the United States) bordering the Pacific

Ocean. In cluster 3 (C3), formed only by Estonia and Lithuania, both countries are considered Baltic states. Finally, cluster 4 (C4) consists of three BRICS member countries (Brazil, India, and Russia), three other Latin American countries (Chile, Colombia, and Mexico), and eleven other countries (Austria, Finland, Hungary, Israel, Italy, Poland, Portugal, Slovenia, Spain, Sweden, and Turkey), mostly European countries. By integrating the results of the statistical models used in this research and the data from the GII score, it was possible to elaborate on Table 2.

Table 2. List of countries and their specific characteristics resulting from this research

id	country	cluster	GII_score	p_Bass	q_Bass	peak (time)
1	Australia	C2	50.3	0.0008986	0.0826810	54.1
2	Austria	C4	50.9	0.0007827**	0.0817768	56.3
3	Belgium	C2	50.2	0.0007117	0.0877859	54.4
4	Brazil	C4	33.8	0.0003064	0.1006571	57.4
5	Canada	C2	53.9	0.0006889	0.0882885	54.5
6	Chile	C4	36.6	0.0003180**	0.0999629	57.3
7	China	C1	54.8	0.0014849	0.0825330	47.8
8	Colombia	C4	33.0	0.0001833**	0.1031665	61.3
9	Denmark	C1	58.4	0.0010194	0.0789050	54.4
10	Estonia	C3	50.0	0.0016489*	0.0659346	54.6
11	Finland	C4	59.8	0.0011022	0.0775769	54.1
12	France	C2	54.2	0.0005789	0.0887267	56.3
13	Germany	C2	58.2	0.0005634	0.0900551	56.0
14	Greece	C1	38.9	0.0011845	0.0740519	55.0
15	Hungary	C4	44.5	0.0008394	0.0803998	56.2
16	India	C4	36.6	0.0003946	0.0921502	58.9
17	Ireland	C2	56.1	0.0010376	0.0830967	52.1
18	Israel	C4	57.4	0.0007706	0.0862402	54.2
19	Italy	C4	46.3	0.0005416	0.0893864	56.8
20	Japan	C2	54.7	0.0023159	0.0705841	46.9
21	Lithuania	C3	41.5	0.0012107*	0.0749115	54.2
22	Mexico	C4	36.1	0.0004502	0.0902426	58.4
23	Netherlands	C2	61.4	0.0008115	0.0837711	54.8
24	NewZealand	C1	49.6	0.0012386	0.0750143	53.8
25	Norway	C1	51.9	0.0010240	0.0786206	54.5
26	Poland	C4	41.3	0.0005797	0.0895694	55.9
27	Portugal	C4	44.6	0.0002965	0.0991460	58.4
28	Russia	C4	37.6	0.0007570	0.0831109	56.0
29	Slovenia	C4	45.3	0.0012885*	0.0692714	56.5
30	South Africa	C1	34.0	0.0009356**	0.0807443	54.6
31	South Korea	C2	56.6	0.0012622	0.0750161	53.6
32	Spain	C4	47.9	0.0006182	0.0887010	55.6
33	Sweden	C4	63.7	0.0009354	0.0845617	52.7
34	Switzerland	C2	67.2	0.0007094	0.0862221	55.2
35	Turkey	C4	36.9	0.0002226	0.1017565	60.1
36	United Kingdom	C2	61.3	0.0009662	0.0804839	54.3
37	USA	C2	61.7	0.0009835	0.0824653	53.1

Source: Elaborated by the authors based on research data
Notes: 'no marks' $p<0.001$, '**' $p<0.01$, '*' $p<0.05$, '.' $p<0.10$, ns = not significant; Statistical significance was estimated using R software (R Core Team, 2020).

Table 2 summarizes the information from the *hierarchical cluster analysis* (C1, C2, C3, and C4), the *GII score* (level of innovation), the *Bass diffusion model* - p_Bass (coefficient of innovation), q_Bass (coefficient of imitation), and peak (country diffusion peak) with the statistical significance of each coefficient, for each of the 37 study countries.

The five nations identified with the largest innovation coefficients (p_Bass), significant at p<0.001, were: Japan, China, South Korea, New Zealand, and Greece, located into cluster C1 or cluster C2, and the five nations identified with the lowest p_Bass, also significant at p<0.001, were respectively: Turkey, Portugal, Brazil, India, Mexico - all of them located in cluster C4.

On the other hand, the five countries with the highest imitation coefficient (q_Bass) identified in the study were Turkey, Brazil, Portugal, India, and Mexico, all belonging to cluster C4. The five countries with the lowest p_Bass were Japan (C2), Greece (C1), New Zealand (C1), South Korea (C2), and Finland (C4).

To further explore the numeric variables of the study (GII score, p_Bass, q_Bass, and peak), a correlation table between the variables was presented in Fig. 6.

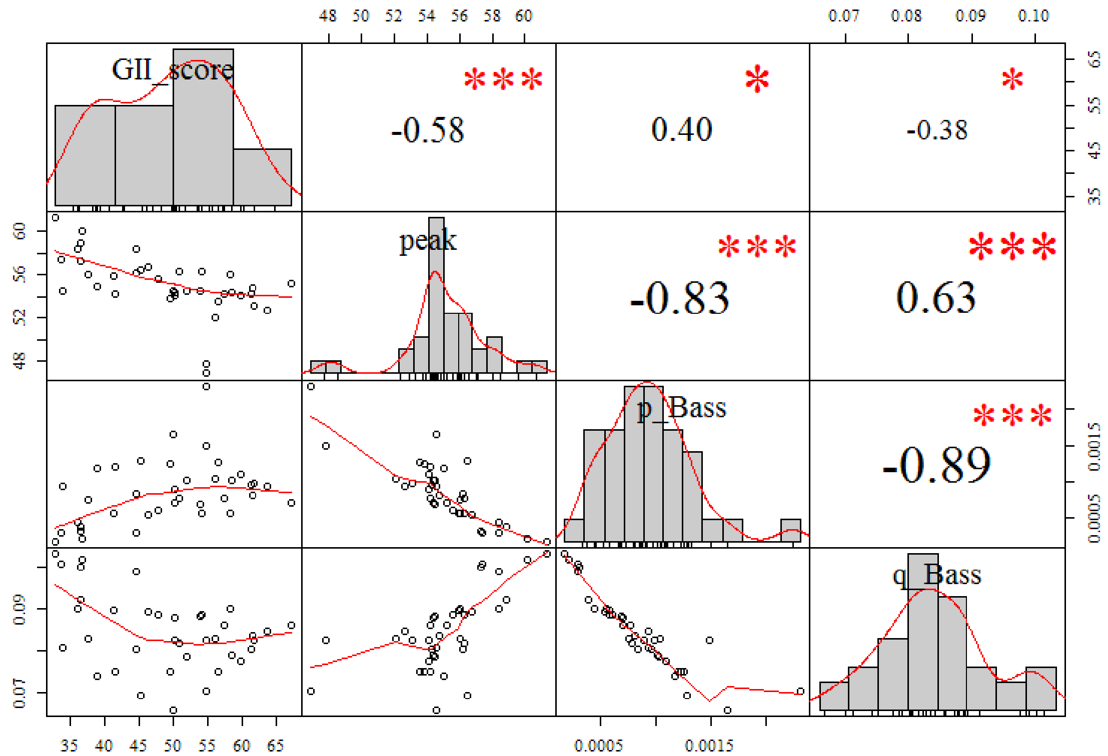


Fig. 6. Correlation between the GII_score, the coefficient of innovation (p_Bass), the coefficient of imitation (q_Bass), and the Bass model curve peak

Fig. 6 shows that all relationships between variables are statistically significant. The variable GII_score has a weak correlation to the variables p_Bass (0.40) and q_Bass (-0.38) and a negative and moderate correlation with the variable peak (-0.58), which may suggest that the more grows the GII_score, the peak value of diffusion decreases, i.e., the time due to the diffusion curve reaches its peak is lower. The other associations between the variables peak and p_Bass (-0.83) and q_Bass and p_Bass (-0.89), both strong and negative, are confirmed by theoretical concepts.

One way to identify the results of the BDM in this study and graphically visualize the diffusion curve of the DL thematic interest from countries can be represented by Fig. 7.

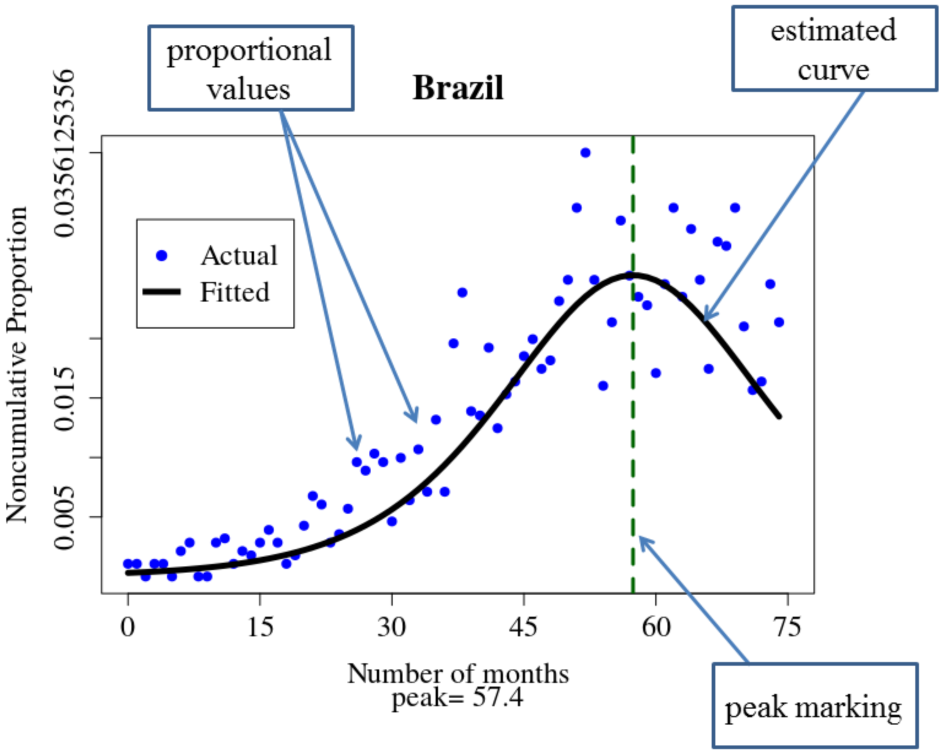


Fig. 7. Example of the real data and its fit with the Bass model diffusion curve

Fig. 7 shows an example of the real data and its fit of the diffusion curve after using the BDM to Brazil, a BRIC nation. In this example, the points displayed in blue represent the history of real data (actual), measured monthly, identified by non-cumulative *proportional values* (y-axis) series. The *bold black line represents the estimated curve (fitted) generated by the model (Bell curve)*. The green dotted line indicates the *peak marking* of the curve, with the measurement value of the x-axis (number of months) being the time elapsed in the diffusion process (57.4), represented by the measurement of the respective month.

This visual exploration, exemplified by Fig.7, was carried out in the following section, bringing a comparative analysis between the five BRICS countries and the five largest economies of the OECD.

Despite the results obtained by the cluster analysis, which allowed to group of the major OECD economies in cluster 2 (C2, United States, United Kingdom, France, Germany, Japan, and other seven countries), as well as the BRICS member countries appeared in cluster 1 (C1, China and South Africa, plus other four countries). Cluster 4 (C4, Brazil, Russia, and India, plus 14 other countries), by the researchers' choice, the following analyzes and discussions were intensified in the findings of BDM.

From the initial month measured by this research (January / 2014), and as shown in Table 2, the values of the diffusion peaks of each country varied from 46.9 months (November / 2017), the lowest value, associated with Japan, up to 61.3 months (February / 2019), the highest value, associated with Colombia.

For comparative analysis between the five BRICS member countries (Brazil, Russia, India, China, and South Africa), where China and India represent the second and fifth economies in the world, respectively, the researchers chose the five OECD member countries representing, in order, the largest economies in this bloc (USA, Japan, Germany, United Kingdom, France (The World Bank Group, 2020b).

One way to compare and analyze the diffusion of innovation across countries is to use the variation of the peak of the diffusion curve, which commonly follows a bell-shaped curve (Geroski, 2000), and graphically in this case (Fig. 9 and Fig. 10), shows on the Y-axis (ranging from 0 to 1) the non-cumulative proportion of interest in the DL thematic of the population of a certain country versus the time spent in this diffusion, measured on the X-axis (ranging from 0 = January / 2014 to 74 = March / 2020, a total of 75 measurements) for the number of months in the evaluated period.

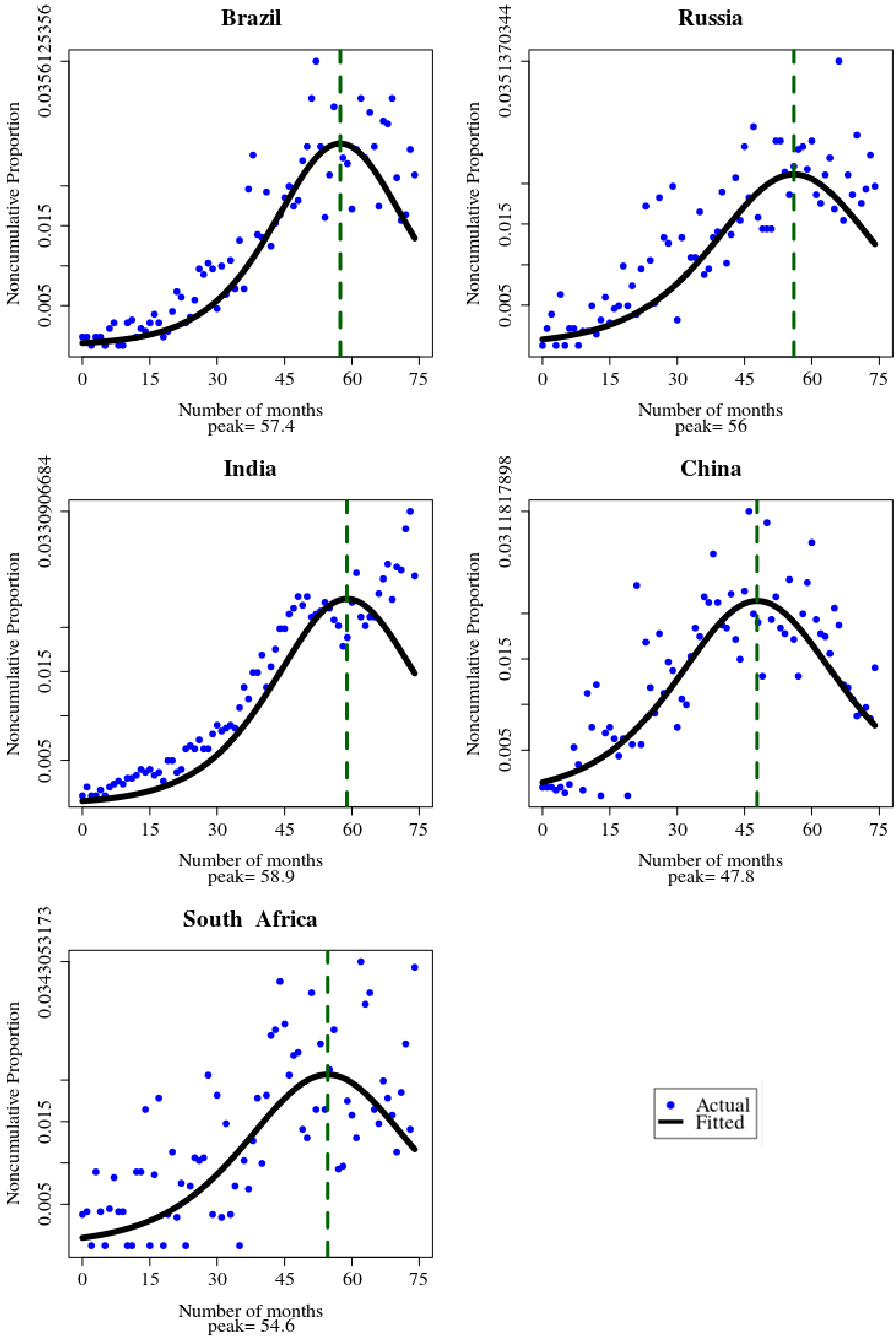


Fig. 8. Diffusion bell-shape curve to the BRICS members – Brazil, Russia, India, China, and South Africa (Ministry of Foreign Affairs - Brazil, 2020; South Africa Government, 2020)

Notes: Actual data (blue points) - obtained from GT, fitted data (a black bell-shaped curve), and diffusion peak (green dotted line) - obtained from BDM.

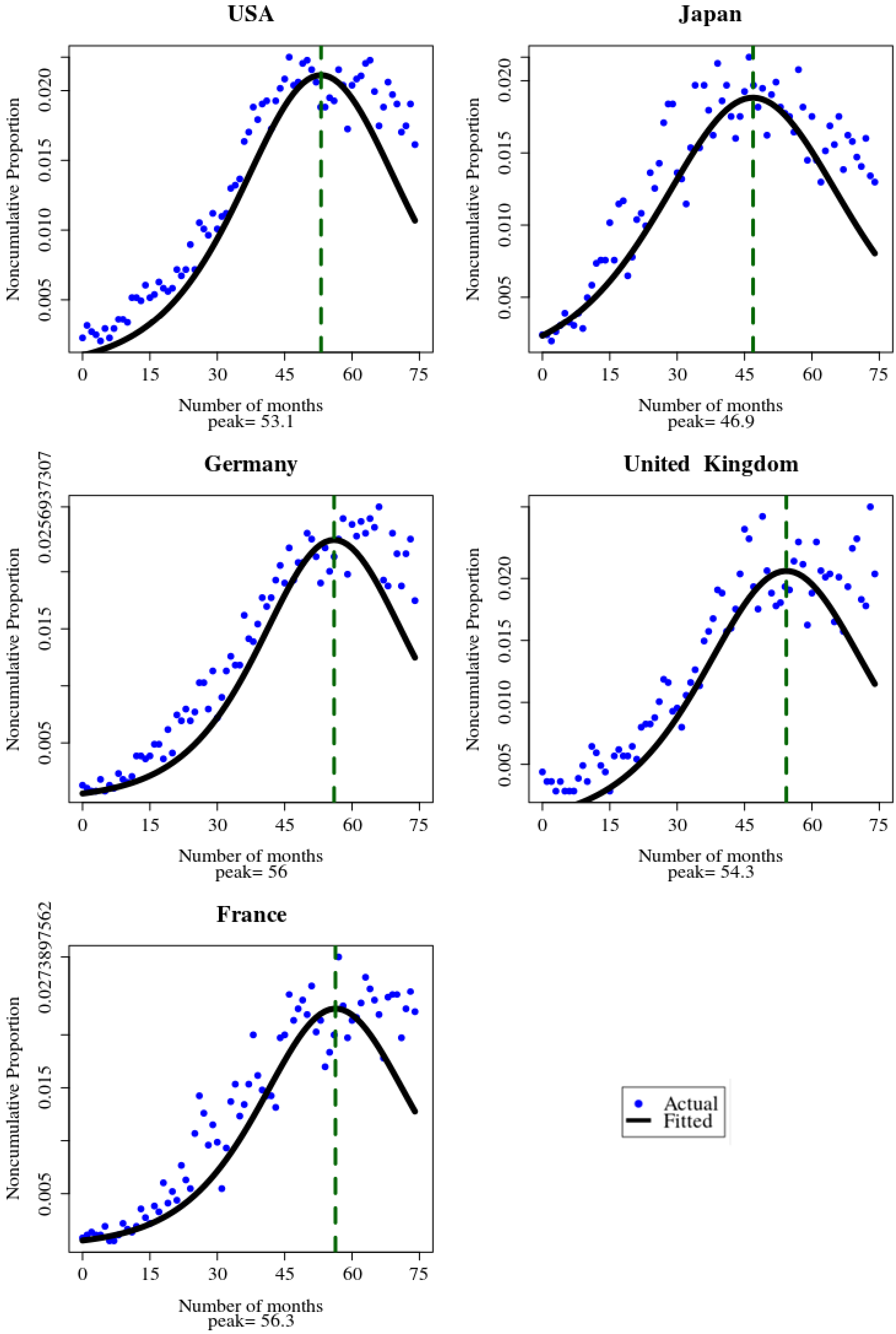


Fig. 9. Diffusion bell-shape curve to the five largest economies of the OECD members – USA, Japan, Germany, United Kingdom, and France (The World Bank Group, 2020b)
Notes: Actual data (blue points) - obtained from GT, fitted data (a black bell-shaped curve), and diffusion peak (green dotted line) - obtained from BDM.

Fig. 8 and Fig. 9 show, respectively, the diffusion bell-shape curve to the BRICS members – Brazil, Russia, India, China, and South Africa (Ministry of Foreign Affairs - Brazil, 2020; South Africa Government, 2020), and to the five largest economies of the OECD members – USA, Japan, Germany, United Kingdom, France (The World Bank Group, 2020b). The lower the peaks, the faster the speed of the country in which the DL thematic is disseminated.

It was identified that the lowest peak in the BRICS member countries was China (47.8), and for the OECD member countries, the lowest peak was Japan (46.9). This demonstrates that in these two countries, the diffusion of innovation as measured by the DL thematic was faster than the others, reaching its peak in December / 2017 and November / 2017, respectively.

As for the other countries of each block, the peaks in BRICS (i.e., respectively in the countries South Africa, Russia, Brazil, and India), ranging from 54.6 (July / 2018) to 58.9 (November / 2018) - at least seven months after the peak of diffusion occurred in China. In the five largest OECD economies, the peaks range from 53.1 (June / 2018) to 56.3 (September / 2018), in order, in the countries the USA, United Kingdom, Germany, and France, and, in the same way, the diffusion occurred in these other OECD countries, at least seven months after the peak of diffusion in Japan.

As it is a transversal subject with applications and impact on different fields (Jordan & Mitchell, 2015), o DL is considered a valuable strategic asset for nations (World Economic Forum, 2019). When observing a comparison of the average between the variation of the diffusion peaks of the DL thematic among these five countries of the two blocks (i.e., BRICS and OECD), this study demonstrated that the five BRICS experience a slower DL interest rate, on average 2.9% more to be achieved (54.9 against 53.3 months) compared to the five largest OECD economies. This finding differs from the study of Talukdar et al. (2002), which also used BDM in its analyzes, where it was identified that in developing countries, the peak sales of a set of products takes an average of 17.9% more to be achieved (19.25 against 16.33 years) when compared to developed countries. Regarding the quality adjustment of the BDM (actual data versus fitted data), it was identified in Fig.8 that among the BRICS members, India obtained the best fit in the diffusion curve. The USA and Germany also had the best adjustments among the five OECD countries evaluated in Fig. 9.

According to a study by Desmarchelier and Fang (2016), the increase in connectivity in a globalized world, intensified by new technologies, can accelerate diffusion rates in all markets. This result was corroborated by this research when the average peak of the diffusion of the DL thematic in the BRICS was 54.9 months, and 53.3 months in the five largest economies of the OECD, presenting a difference of only 1.6 months between these countries.

With the results presented in Table 2, the scatterplots (a) and (b) of Fig. 10 were created, with the innovation coefficients (p_Bass) on the horizontal axis and the imitation coefficients (q_Bass) on the vertical axis.

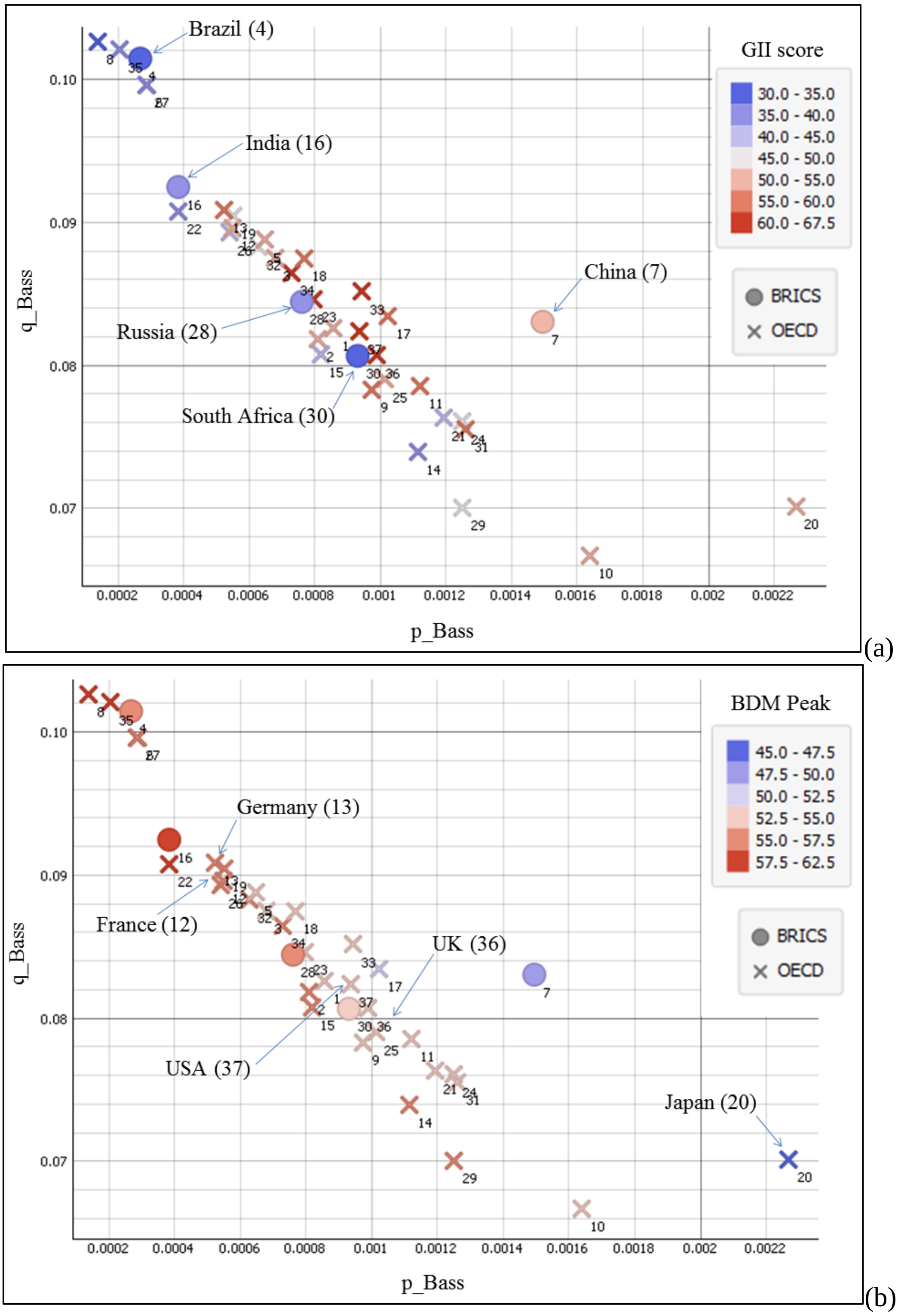


Fig. 10. Relationship between the coefficients of innovation (p_Bass) and imitation (q_Bass) **Notes**: two types of marks - circle to BRICS or cross to OECD nations; two different variables (GII score and BDM Peak) to scatterplot color legends (a) GII score and (a) BDM Peak; the country names and id number (obtained from Table 2) were highlighted by the arrows.

In Fig. 10, the colors used in the legends of each scatterplot allowed us to compare two types of continuous numerical measurements, with graph (a) highlighting the *GII score* and graph (b) the BDM Peak.

In the scatterplot (a), the arrows highlight the positions of the countries belonging to the BRICS, with the GII *score* ranging from 33.8 (Brazil) to 54.8 (China). The lowest identified value of the innovation coefficient (p_Bass) of all BRICS countries is Brazil (0.0003064, $p<0.001$), and the highest is China (0.0014849, $p<0.001$). Excluding China, the *GII score* of other BRICS countries is less than at least 28 OECD countries, corresponding to 87.5% of the OECD countries assessed in the study (28/32).

In the scatterplot (b), the arrows highlight the positions of the countries that integrate the five largest economies of the OECD (USA, Japan, Germany, United Kingdom, France), with the measurement of the BDM Peak of these countries ranging from 46.9 (Japan) to 56.3 (France). The lowest identified value of the innovation coefficient (p_Bass) between these five OECD countries is Germany (0.0005634, $p<0.001$), and the highest is Japan (0.0023159, $p<0.001$). Similarly, when excluding China, the BDM Peak of 15 OECD countries (46.9% of the 32 OECD countries in this study), compared to South Africa - the second-best placed among the BRICS, with a value of 54.6, is inferior to the other BRICS countries.

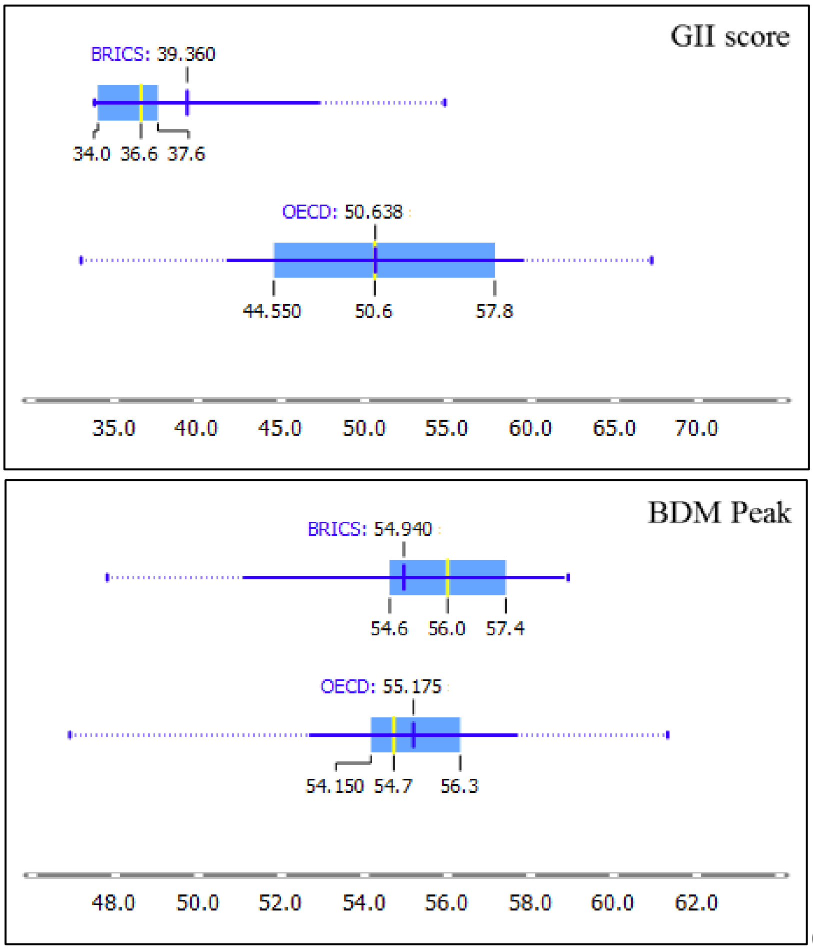
When observed by the imitation coefficient (q_Bass), among all 37 countries in this study (5 BRICS and 32 OECD), five countries were identified as the most imitators, in this order: Colombia (0.1031665, $p<0.01$), Turkey (0.1017565, $p<0.001$), Brazil (0.1006571, $p<0.001$), Chile (0.0999629, $p<0.01$), and Portugal (0.099146, $p<0.001$). Four of these countries (Colombia, Turkey, Brazil, and Chile) have a very low *GII score*, ranging from 33 to 36.9, among the lowest identified in the study, while Portugal has a *GII score* value of 44.6.

As the *GII score* measures the level of innovation in a country, in these five countries observed in the upper left positions of the graph in Fig. 10 (a), when aspects of the theoretical bodies of IDT and BDM are also integrated, it is possible to state that the higher the value of q_Bass, the more slowly the process of diffusion of innovation occurs, and thus, characterizing the country as less innovative.

Among the BRICS, Brazil was considered the least innovative country in the diffusion process of the DL thematic, and Colombia was the least innovative among OECD countries.

It was identified that among all the countries in the study, Japan (p_Bass = 0.0023159, $p<0.001$) and China (p_Bass = 0.0014849, $p<0.001$), had the lowest BDM Peaks, respectively 46.9 and 47.8. In this sense, by observing the theoretical aspects and the rightmost positions of the graph in Fig. 11 (b), it can be considered that the countries that have the fastest diffusion process on the DL thematic are the most innovative.

It was identified by Fig.12, by the two Boxplot charts, the comparison of the measurements of the *GII score* (an innovation indicator), external to the research, with the measurements of the BDM Peak (Bass diffusion model curve peak).



(c)
(d)

Fig. 11. Comparative Boxplots between *GII score* and BDM Peak measurements
Notes: the yellow mark indicates the median of the distributions; (c) *GII score* measure – in the BRICS ranging from 33.8 to 54.8, and for OECD countries ranging from 33 to 67.2; (d) BDM Peak measure – in the BRICS ranging from 47.8 to 58.9, and for OECD countries ranging from 46.9 to 61.3;

Fig.11 (c), when observed by the *GII score*, which in this study ranged from 33 (Colombia) to 67.2 (Switzerland), characterized as a clear indicator that follows a complex methodology when excluding Colombia (33) and China (54.8), the other BRICS countries, that is, Brazil (33.8), South Africa (34), India (36.6), and Russia (37.6), when compared to OECD countries, are less dispersed and worst ranked in the ordered list of the 37 countries included in the study.

In contrast, by Fig.11 (d), when observed by the BDM Peak measuring, which in this study ranged from 46.9 (Japan) to 61.3 (Colombia), characterized as an accessible, up-to-date, and specifically targeted measurement, no discrepant statistical differences were found between the dispersions of the countries in the two blocs (BRICS and OECD), with the approximation of the mean values between the BRICS (54.9) and OECD (55.2), and also the median between the BRICS (56) and OECD (54.7).

While the GII score is a complete indicator, which considers several characteristics of countries, both social and economic, the BDM Peak in this study only measures users' interest in a given thematic.

Although previous studies, such as Talukdar's (2002), show that developing countries take longer to reach peak sales. In the measurement of the BDM Peak of DL, it is possible to notice little difference in the comparison between BRICS and OECD because the interest in a thematic does not imply the adoption or acquisition of any product or service, disregarding the purchasing power of a population, and resulting in a more genuine interpretation of the interest of a country's population.

Another form to visualize the location of all countries analyzed in this study, in the world geopolitical map, based on the measurement of the BDM Peak of the diffusion curve for each of these, is shown in Fig.12.

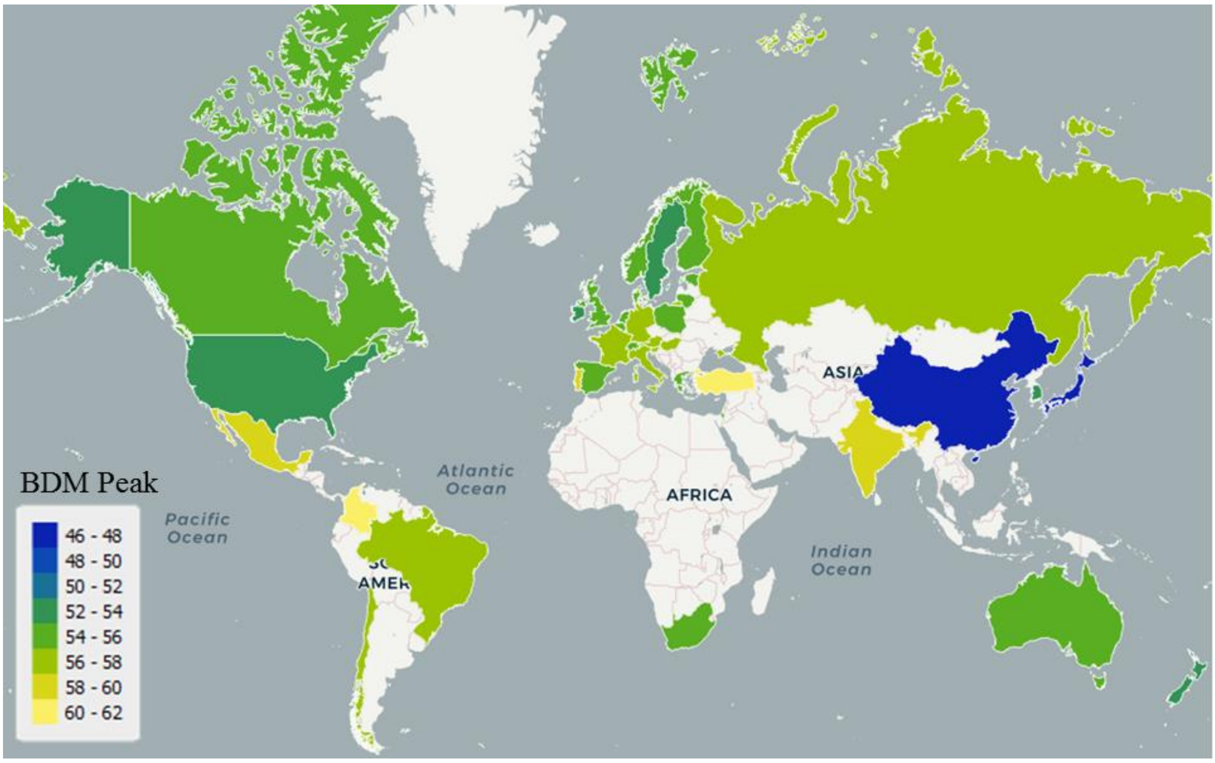


Fig. 12. Geopolitical world map showing BDM peak intervals to BRICS and OECD nations studied in this research

By Fig.12, the only two countries in dark blue are Japan (at the peak time of 46.9 months, i.e., November / 2017), belonging to the group of the five largest OECD economies, and China (at the time of 47.8, i.e., December / 2017) as a member of the BRICS.

Despite the study by Desmarchelier and Fang (2016), which identified that countries culturally "close" to Anglo-Saxon cultures are the most likely to experience fast diffusion processes, while Latin Americans are slow, this study demonstrated that countries with Anglo-Saxon cultures (Ireland, USA, New Zealand, Australia, United Kingdom, Canada, South Africa) had the average BDM Peak in 53.8 months, while countries of Latin American cultures (Chile, Brazil, Colombia) had the average of BDM in 58.7 Peak, being found only a small difference between them (4.3%).

The finding presented in this study is noteworthy as it aligns with the results of prior research conducted by Takieddine and Sun (2015), which demonstrated the importance of national culture as a significant moderator in the diffusion process. This fact highlights the significance of cultural context in shaping the diffusion of innovation and further strengthens the argument that adopting new ideas, practices, and technologies is contingent upon the cultural values, beliefs, and norms of the society in which they are being introduced. The implications of these findings suggest that a deeper understanding of cultural context is necessary for the successful implementation of innovation and that policymakers and practitioners must consider these factors in their decision-making processes.

Theoretical contributions

This research brought three theoretical contributions to Innovation Diffusion Theory (IDT) studies. The *first* theoretical contribution was using a thematic as an innovative object of analysis of the IDT instead of considering the diffusion process of a product, technology, or service. The thematic allows us to conduct numerous analyses of the diffusion of concepts and ideas when using actual data in sales or adoption is impossible.

Few studies identified in the literature have used other information besides sales data as a proxy, such as patents (Cheng, 2012), programming language within source codes font (Papagiannidis et al., 2015), and the adoption of ethical behaviors (Ganglmair-Wooliscroft & Wooliscroft, 2016). They brought alternative forms for the analysis of the diffusion process, but these works used ad hoc data, making these studies little applied to other contexts.

The contribution of this work, which focused on the diffusion of a thematic such as the *innovation* or the new innovative object, incorporated into the theoretical body of the IDT an important and versatile way of carrying out new analyzes for diffusion processes in different contexts.

The *second* theoretical contribution of this work is the expansion of understanding of what the theory considers as a social system of mutual attraction through the use of interest of a population in a particular thematic, not necessarily this population considered a member of a social system of adopters or buyers of any product or service.

In this study, it was used the weighted interest of thematic of DL by the inhabitants of each of the studied nations, members of the BRICS or OECD, considered by theory, the *members of the social system*, those people who were interested in the thematic of DL, rather than, similarly, having adopted or bought some product, service or technology.

Finally, as a *third* theoretical contribution, this research identified a new way of how communication works or is seen implicitly, without direct dependence on other known communication sources (mass media and social pressure) by modifying the way the *communication process* is perceived and constructed, with the own interactions from users/individuals and their 'digital footprints' (Blazquez & Domenech, 2018), i.e., the weighted interest of people in each country, OECD and BRICS, using a web search engine which also has trend analysis feature, as one way or proxy for the existence of this diffusion process.

In a complementary way, when using the time series of different nations (BRICS and OECD) obtained through a web search engine trend with open access instead of a proprietary data series on the consumption or actual adoption of products, technology, or services, it demonstrates the intrinsic or spontaneous interest of people when searching in a web search engine like Google (Google, 2020b), that also generates the relative weighting of these searches as Google Trends (GT) (Google, 2020a), i.e., the own concept of a population's weighted interest.

Methodological contribution

As a complementary contribution to the study of innovation diffusion modeling, this research brought a significant methodological contribution to this field by detailing the step by step of methodological procedure followed, starting with the obtaining of raw data, such as time series, coming from a search engine for free and open use (Google Trends), followed by the standardization of data that would allow it to be clustered among the nations studied (members of the BRICS and OECD), and additionally using Bass's first derivative equation, which results in the identification of a Bell curve (non-cumulative proportions) instead of an S-curve (accumulated values), by using percentage measurements, to the detriment of subtotaled (summed) measurements, commonly used in other studies already known in the literature.

Although the GT does not report absolute data, it was possible to analyze the weighted data of interest from a population on specific thematic (not tangible) and their variation over time and also to demonstrate how the data from the search trend fits well with Bass's mathematical model, making it possible to accurately calculate comparable coefficients, i.e., the innovation (p) and imitation (q) coefficients, allowing to understand the diffusion of 37 countries analyzed.

This aspect also allows the comparison of countries considering only the people interested in the researched thematic, presenting a more realistic perspective of how that innovation was spread over time. Other researchers will be able to investigate something that has not even been adopted yet, as a way of interest for the possible adoption [of the innovation] (Jun et al., 2017, 2018) or identify possible market potential calibrated with their interactions of users/individuals (Chumnumpan & Shi, 2019), such as an "anticipated" and "exploratory" diffusion process, obtained from spontaneous manifestations by people, in an accessible and democratic way.

Practical contribution

Analyzes extracted from "digital footprints" identified that the procedure for diffusing an innovation can be driven by the perception of individuals (i.e., the population of a country) when interacting spontaneously with digital tools on the internet (i.e., web search), with externalization interest about a thematic, idea or new knowledge.

Thus, from the perspective of individuals rather than organizations, which usually use sales data series for their products or services, BDM analysis can no longer be used based only on these series provided by organizations. With the use of this artifice, companies will be able to predict the population's interest in a specific innovation and build their country-level positioning process for their products, services, strategy development, etc., according to the elapsed time identified at the peak of the diffusion curve of those countries selected by the company.

While the traditional approach (i.e., use of time series of goods and services) has focused on the life cycle of a product or service, and the evaluation of this process seen from the perspective of organizations (Jun et al., 2018), the practical contribution of this study reinforces that the process of diffusion of a thematic can be seen from the perspective of the individuals in a population of a country.

Due to constant market changes, the drivers of diffusion have also been constantly changing, and in turn, influencing new products in the current market (Shi et al., 2014). Following this path, this study also brought another practical contribution which reflects in the identification of the acceleration of diffusion when analyzing the peaks of the innovation diffusion curves of different countries and comparing them to an external indicator (i.e., GII score) generated annually and used by governments to compare their developments.

In a world with a growing demand for the practical utility of academic work (Crane et al., 2016), this research identified that while the *GII score* integrates important indicators with coverage for several countries, its elaboration follows a broad and complex methodology on the other hand, BDM Peak analyzes bring advantages of immediacy when allowing the realization in the desired time, up-to-date and directed to a thematic, idea or knowledge, technology of interest to researchers, whether individuals, organizations, societies or governments.

STUDY LIMITATIONS AND FUTURE STUDIES

This research has identified limitations in obtaining and compiling data from the GT, on the DL thematic, from 42 countries originally belonging to the study (5 members of the BRICS and 37 members of the OECD).

In the data collection stage, two nations, the Czech Republic and Iceland, due to the low interest in the thematic in these countries, did not generate sufficient data availability during the study period. In the dataset compilation stage of the raw data from three other countries, Latvia, Luxembourg, and Slovakia, an excess of null values or missing data were identified in the time series. Thus, the researchers chose to remove these five countries from the research, remaining with a total of 37 countries in the study.

To motivate future studies and encourage new questions (Linton, 2016), the researchers suggest three new paths to follow: 1) explore and consolidate the methodology that has been described in detail in this study, using other thematics and research problems, freely chosen by fellow scholars; 2) isolate the effect of a population's purchasing power, considering similar interest levels on a given thematic, compared to certain sales series (or adoption) of products or services acquired (or adopted) by that population; 3) generate theoretical contribution and theoretical development for IDT considering causal approaches depending on the diffusion process according to the economic stage of a population, which is located in different geographical regions, in groups of nations, or some cities of the world.

CONCLUSION

This study analyzed the diffusion of the thematic of Deep Learning from member nations of the BRICS and OECD, using data obtained from Google Trends and the Global Innovation Index, with the support of the theoretical framework of the Innovation Diffusion Theory and the Bass Diffusion Model.

Considering the peak of the diffusion of innovation through the Bell curves of each nation, no discrepant statistical differences were identified between the dispersions of the two groups of countries (BRICS and OECD), which may mean a more genuine interpretation of the interest in the population of a country in a thematic, not implying the adoption or acquisition of any product or service.

This study brought to the academic community in the study field of the Innovation Diffusion Theory theoretical, methodological, and practical contributions, which allowed to extend of new understandings for works on the diffusion of innovations that use a thematic as the object of innovation and the data series of the diffusion process as the weighted interest of a given population in a country.

As implications of this study, organizations now have access to a methodological procedure to generate the prediction of the interest of innovation according to a specific population, enabling the development of business strategies more adherent to the market reality. Governments will also be able to use this study to identify, in comparing results between nations. These perceptions promote adopting actions to stimulate the development of their global competitiveness.

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