Individual Master's Thesis

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Collaborative Invention and Knowledge Diffusion: Evidence from Co-patents of Artificial Intelligence in Europe

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Abstract

Scholars consider artificial intelligence (AI) a general purpose technology that enables regions to diversify into new economic activities and facilitates green transition. Limited literature investigates how AI knowledge diffuses spatially. Investigating collaborative inventions of AI in European regions, this research examines how collaborative knowledge regarding AI technology development and technology application diffuses between and within regions during 2011-2020. Researchers adopt a logit regression method to estimate effects on collaboration formation of AI development. Results indicate that interregional collaborations of co-inventors between NUTS 2 regions are positively related to the establishment of collaborative ties for AI development. As for AI application, researchers adopt a Zero-inflated Negative Binomial regression method, and results suggest that not only intra-regional but also interregional collaborations across neighbouring regions increase the intensity of co-innovations of AI application. Our results contribute to diffusion theories suggested by Rogers and Hägerstrand by taking into consideration the nature of exchanged knowledge (i.e. AI development and AI application) in the diffusion process. Thus, innovation policies may consider the spatial dimension of policy schemes that target the development and application of AI technologies.

Keywords: Collaborative Innovation; Geographical Proximity; Technology Diffusion; AI Patents; European Regions

JEL Classification O33

1 Introduction

Artificial intelligence (AI) has been one of the most important fields for innovation. AI, as General Purpose Technologies (GPTs), has been developing for a long period of time and applied in various industries such as education, energy, health services, etc. (Petralia 2020). Because of these features, AI is necessary for Europe's 'twin transition' including regional diversification and green transition (Janssen and Abbasiharofteh 2022). However, European countries are greatly lagging behind other developed counterparts (e.g. the U.S. and Japan) in AI patents, even though the number of global AI patents skyrocketed in the last few decades (Iori et al. 2021; Dernis et al. 2021). To this end, a programme named Horizon Europe is initiated in Europe to support socially and technologically positive influences of AI development and applications (European Commission, n.d.). This programme aims to build trustworthy AI prioritising social benefits and to improve European regions' competitiveness.

Many existing studies find that collaborative ties among inventors foster innovation by combining various knowledge together (Abbasiharofteh and Broekel 2021). To date there has been a lack of empirical studies investigating how AI knowledge diffuses spatially for innovation. This research aims to fill this research gap about how the establishment of interregional and intra-regional collaborations influence AI knowledge diffusion between co-inventors across regions. There are two types of AI knowledge, for instance, AI technology development based on the Science-Technology-Innovation (STI) mode and AI technology application in the Doing, Using and Interacting (DUI) mode (Alhusen and Bennat 2021). This research examines the question of how two types of AI knowledge diffuse through collaborative innovation networks across regions. We analyse 1,221 NUTS-2-region pairs with AI collaborations by adopting a logit regression method for AI development collaborations and a Zero-inflated Negative Binomial regression method for AI application. Results indicate that interregional collaborations support the formation of AI development relations, while both intra- and inter-regional collaborations between neighbouring regions increase the intensity of AI application co-innovations. These findings contribute to diffusion theories of Rogers (1962) as well as Hägerstrand (1968) and suggestions for regional innovation policies.

This research is structured as follows. Section 2 discusses two main diffusion theories suggested by Rogers (1962) and Hägerstrand (1968). In addition, this section builds on the extant literature on the innovation modes (Janssen and Abbasiharofteh 2022) to reconcile the two theories in one theoretical framework. Section 3 introduces research processes such as data preparation, data cleaning, construction of variables and regression methods. Section 4 presents regression results. Section 5 discusses the contributions to knowledge diffusion theories, suggests recommendations for innovation policies and concludes the paper.

2 Spatial and relational dimensions of knowledge diffusion

2.1 Geographical and social proximity

Geographical and social proximity between inventors determine local knowledge diffusion. Social proximity indicates that individuals are closely connected because of the same enterprise or similar cultural backgrounds (Boschma 2005; Agrawal et al. 2008; Johansson and Karlsson 2019). Rogers (1962) illuminates that various individuals absorb knowledge from their peers through local communication channels. These local channels greatly influence the rate of adoption of innovations, including interpersonal networks. Interpersonal diffusion networks connecting mostly geographically close individuals promote knowledge spillovers directly or indirectly (Rogers 1962). These individuals who are spatially and socially close to each other are more likely to be integrated within the diffusion networks, compared with other weakly linked pairs of distant counterparts. In this diffusion theory (Rogers 1962), geographical proximities and social connectivity are critical for the establishment of diffusion networks among inventors.

Social proximity between inventors facilitates the adoption of technologies across space. Hägerstrand (1968) investigates the unevenly distributed adoption of innovation to answer research questions: *"Where are adopters of original innovation located?"* and *"Why do adopters locate in specific areas?"*. Similar to Roger's theory, Hägerstrand mentions that private information obtained from face-to-face conversations between inventors contributes to the adoption of new technologies. For instance, size and colocation of farms influence spatial distribution of adopters using agricultural innovation. Differently, migration of inventors and Information and Communication Technology infrastructure greatly facilitate the diffusion of innovative knowledge across space rather than only locally. In this case, the adoption is subject to a distance decay that the frequency of migration and telephone calls between inventors in different areas decreases as their geographical distances increase. Hägerstrand (1968) investigates neighbourhood effects of innovation diffusion between socially close inventors, whereas Rogers (1962) examines face-to-face interactions between spatially close individuals diffusing tacit knowledge. There is no agreement of which proximity dominates knowledge diffusion.

Complex knowledge production, on the one hand, requires vertical integration among local innovative actors, for instance, communications and computer software in large cities (Balland et al. 2019, 2020; Haller and Rigby 2020). However, these studies conceal influences of interregional networks. On the other hand, inter-regional collaborations stimulate innovative activities by spreading codified knowledge (Lundvall 2016). Reconciling this argument, Lengyel et al. (2020) find that knowledge of original innovation transfers to distant areas at the beginning based on hierarchical diffusion, and subsequently diffuses locally by contagious diffusion over the life-cycle of this innovative technology. Nevertheless, limited research investigates how the nature of exchanged knowledge interacts with the knowledge diffuses within and between regions.

2.2 The nature of knowledge and its diffusion

Knowledge pieces of patents are different in nature. Basic research of General Purpose Technologies (GPTs) is conducted based on Science-Technology-Innovation (STI) mode for technology development. Innovation happens in this mode through co-innovation networks among public research institutes and enterprises in different regions (Lundvall and Rikap 2022). Taking advantage of the basic research, private sectors seek opportunities to implement these innovative technologies in products and local markets based on the Learning-by-Doing, -Using and -Interacting (DUI) mode (Mazzucato 2014; Lundvall 2016). Technology development is achieved based on the STI mode by facilitating the diffusion of scientific knowledge, whilst inventors encourage technology application by transferring tacit knowledge in the DUI mode (Alhusen et al. 2021). More particularly, artificial intelligence (AI) technologies as a type of GPTs are strongly complementary to novel technologies for development, and applied in a wide range of products (Petralia 2020), for instance, AI based on local ICT knowledge bases (Xiao and Boschma 2021).

Channels determine how knowledge is diffused spatially. global pipelines across clusters intensify interactions between local innovative actors and distant inventors by transmitting codified knowledge, and local buzz facilitates knowledge diffusion regarding emerging technologies among local inventors (Bathelt et al. 2004). The combination of the STI mode with distant diffusion and the DUI mode with local diffusion promotes technological progress, for instance, technology development and technology application (Alhusen and Bennat 2021). In brief, global pipelines, which are consistent with the diffusion theory of Hägerstrand (1968), support technology development in the STI mode, and local buzz, which aligns with the theory of Rogers (1962), facilitates technology applications in the DUI mode (Bathelt et al. 2004).

2.3 Technology development

Collaborations between inventors within regions stimulate the knowledge production of technology development. On the one hand, inventors with shorter geographical distances tend to spread more technological knowledge, whilst spatial and social proximity have negative interaction effects on knowledge spillovers (Agrawal et al. 2008). Maggioni et al. (2007) find that geographical spillovers exert greater effects on collaborative patenting activities than social networks between distant innovative centres. Lundvall (2016) mentions that spatially distant inventors may have difficulties in decoding technological knowledge without face-to-face contact. Zhou et al. (2017) find that spatial proximity significantly facilitates knowledge transfer within less developed regions in China in ICT industries, but insignificantly within developed regions.

Balland et al. (2020) conclude that the concentration and diffusion of technological knowledge are supported by economic and knowledge foundations of large cities but not well through ICT infrastructure. Scientific knowledge with a longer existence in patents has a higher level of concentration in large cities/technopoles. Technopolis refers to a new type of agglomeration where local R&D innovations are connected with ‘excellent’ universities closely (Lundvall 2016). For instance, AI patenting activities of Chinese or American tech-giants tend to be concentrated in global technopoles and apply for new patents (Lundvall and Rikap 2022).

Hypothesis 1: Intra-regional collaborations encourage knowledge diffusion of technology development

On the other hand, networks connecting innovative actors contribute to knowledge spillovers across space (Kilkenny 2015), whilst employees concentrated within developed areas are more productive by learning with each other (Roca and Puga 2017). Kilkenny (2015) mentions that inventors in large cities tend to share knowledge with distant researchers by maintaining their social connections with previous enterprises. Van der Wouden and Rigby (2019) illuminate that innovative actors in specialised areas are more sensitive to cognitive distance rather than geographical distance when co-innovating with partners in other urban areas. Studies find that knowledge networks have been intensified by global pipelines as digital technologies make it more effective to collaborate and exchange innovative knowledge remotely (Bathelt et al. 2004; Paunov et al. 2019).

Hypothesis 2: Interregional collaborations facilitate knowledge diffusion of technology development

2.4 Technology application

Tacit knowledge is another source of learning in the DUI mode, which requires face-to-face interactions between innovative actors. These actors concentrate in large cities to share talent pools, sufficient knowledge bases and economic infrastructure (Zheng 1998; Wheeler 2003; Brakman et al. 2019). For instance, Wang and Bu (2010) conclude that ICT services grow intensively in developed regions in China by adopting the methods of global and local spatial autocorrelation. Paunov et al. (2019) mention that ICT patents not only concentrate in developed cities in OECD economies, but also increase the concentration of total patenting activities in these top cities. This contribution is attributed to the benefit generated by ICT patents in large cities, for instance, wide application of ICT technologies in various industries.

Kaplinsky and Kraemer-Mbula (2022) illustrate that the adoption of emerging ICT in Africa improves innovative potentials of local informal sectors in geographical centres. Local organisations are more likely to establish codes of conduct and mutual trust, which promotes experience-based knowledge diffusion between suppliers and customers (Lundvall 2016). Without face-to-face contact, it is difficult for suppliers to fully understand and utilise new technologies from scientific collaboration (Haus-Reve et al. 2019). More particularly, Ter Wal (2013) finds that more collaborations within a cluster increasingly facilitate coherent local networks which foster more intensive patenting activities in each five-year time period.

Hypothesis 3: Intra-regional collaborations facilitate knowledge diffusion of technology application.

Some emerging technologies may be transferred inter-regionally. Although AI professionals proactively adopt AI technologies in local sectors, some of them absorb AI knowledge between distant areas in codified forms based on the global pipelines (Yu, Liang and Xue 2021). Some IT companies establish R&D departments in global technopoles to co-innovate with international organisations via their corporate networks (Lundvall and Rikap 2022). These R&D enterprises licence state-of-the-art technologies back to their home country and local market based on organisational proximity. Organisational proximity refers to relationships between agents or enterprises based on market rules, formal and contractual agreements (Lagendijk and Lorentzen 2007). De Noni, Orsi and Belussi (2018) find that collaborative innovation between developed regions with sufficient knowledge bases and lagging-behind NUTS 2 regions contributes to higher innovation performances of these less developed regions by analysing co-patents from the OECD REGPAT database. However, according to diffusion models of Hägerstrand (1968), the proportion of adoptions decreases dramatically as spatial distances from innovation centres increase because information of complex knowledge greatly loses over distance (Haggett and Cliff 2005; Balland et al. 2020). A theoretical framework is created based on four hypotheses (see Table 1).

Hypothesis 4: Distant interregional collaborations restrain knowledge diffusion of technology application.

Table 1 Theoretical Framework of Collaborations and Knowledge Diffusions

	Technology development	Technology application
Intra-regional collaborations	YES (Hypothesis 1)	YES (Hypothesis 3)
Interregional collaborations	YES (Hypothesis 2)	NO (Hypothesis 4)

Source: Own elaborations

3 Collaborative invention between/within European regions

This section consists of three parts such as data, construction of variables and methods. Figure 1 below illustrates the empirical setting.

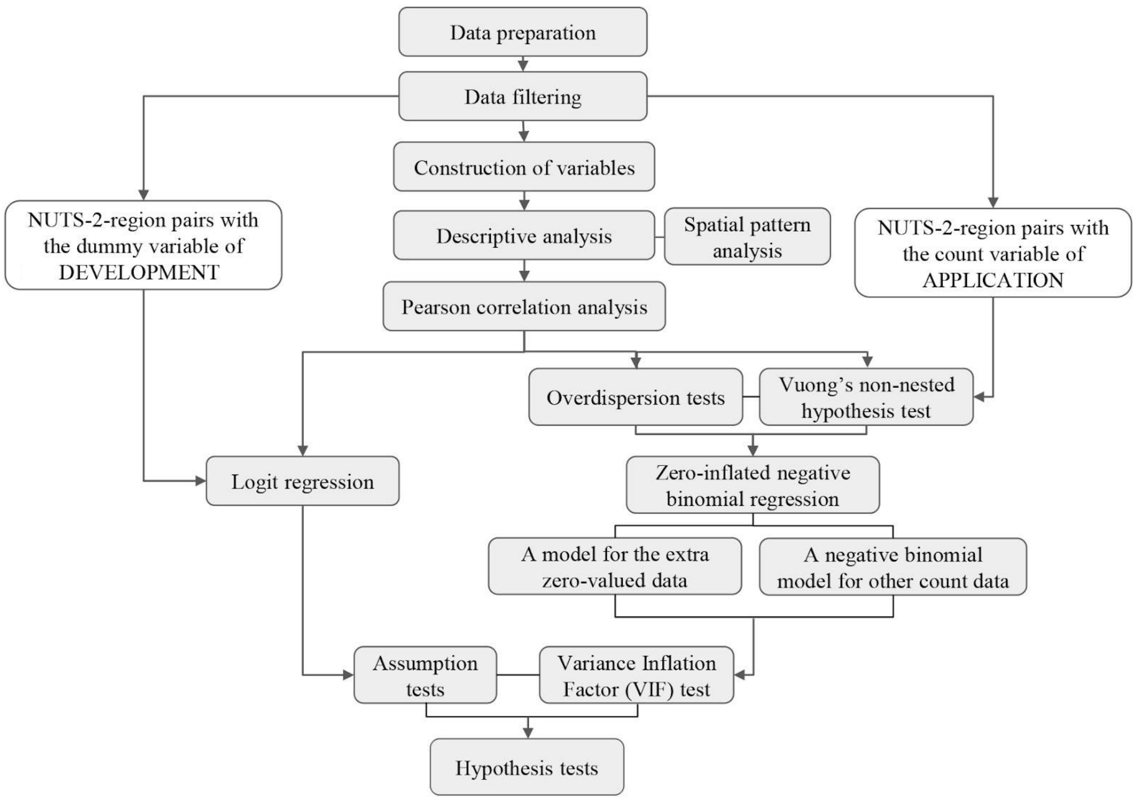


Fig. 1 A Flowchart of Research Design
Source: Own elaborations

3.1 Data preparation

3.1.1 Collaborative patents

This research analyses collaborative innovation of AI patents (thereafter, AI co-patents) from the OECD REGPAT database (version: 2022)[2]. Based on the AI co-patents, the researcher aims to investigate effects of types of collaborations on the nature of knowledge diffusion (i.e. AI technology development and AI application). The OECD REGPAT database includes patents granted by the EPO and the Patent Cooperation Treaty (PCT). This research retrieves patents in countries of Europe (including EU27, UK, Norway and Switzerland) from not only the EPO but also PCT in order for sufficient observations for regression analyses.

[2] The OECD REGPAT database (version: 2022): https://www.oecd.org/sti/intellectual-property-statistics-and-analysis.htm. Accessed 1 April 2022

This patent data has more completed addresses than that of patents from the Worldwide Patent Statistical Database (PATSTAT), the United States Patent and Trademark Office (USPTO) and World Intellectual Property Organisation (WIPO), for instance, NUTS region codes (Maraut et al. 2008). This data includes information of EPO application number, NUTS 2 and 3 level code, region's share, inventor's share, EPO filing year, CPC codes. There are no ethical issues about data privacy because everyone can download this secondary data (i.e. Patents) from the OECD REGPAT database.

3.1.2 Socio-economic factors

Regional socio-economic data (e.g. GDP, Population and R&D employment) between 2001-2015 are downloaded from Eurostat [3] and complemented by the data from the OECD [4]. Regional GDP per capita is computed by dividing GDP per year by total population in each year and taking the average for each region.

Additionally, data missing not at random (e.g. GDP, population and the number of R&D employees) in some NUTS 2 regions is treated differently, for example, by imputation and carrying over values in previous years. As for the missing data of UKI1 (Inner London) and UKI2 (Outer London), each is replaced by a half of corresponding data of UKI (i.e. NUTS 1 region) from the OECD. Missing data of Switzerland (e.g. R&D employees in CH01, CH02, …, and CH07) are complemented by data from the World Bank[5]. We take one seventh of the national average for every NUTS 2 region in Switzerland.

3.2 Data filtering

3.2.1 Cooperative Patent Classification (CPC) codes

The entire process of filtering data is shown in Figure 2 below. The researcher derives AI-related CPC codes from WIPO PATENTSCOPE Artificial Intelligence Index (n.d.)[6]. Next, AI patents are filtered out among the retrieved patents from the REGPAT database (version: 2022) by matching technology codes of patents with the AI-related CPC codes in R software. These filtered AI patents are categorised as AI technology development (thereafter, AI TD) if their CPC codes are all AI-related, whilst those with both AI-related and -unrelated CPC codes are classified as AI technology applications (thereafter, AI TA).

However, some CPC codes for several AI technologies are lost, for instance, machine learning and natural language processing. Thus, to cover a wider range of AI-related patents, the researcher adds all CPC codes at the 4-digit level under G16 (i.e., Information and Communication Technology, specially adapted for specific application fields). In this way, more ICT(/AI)-related

[3] Eurostat data:
https://ec.europa.eu/eurostat/web/regions/data/database?p_p_id=NavTreeportletprod_WAR_NavTreeportletprod_INSTANCE_BQqmHeCfV1BE&p_p_lifecycle=0&p_p_state=normal&p_p_mode=view. Accessed 15 April 2022

[4] OECD data: https://www.oecd.org/regional/regional-statistics/. Accessed 15 April 2022

[5] Researchers in R&D (per million people):
https://data.worldbank.org/indicator/SP.POP.SCIE.RD.P6?end=2015&start=2001. Accessed 15 April 2022

[6] PATENTSCOPE Artificial Intelligence Index:
https://www.wipo.int/tech_trends/en/artificial_intelligence/patentscope.html. Accessed 1 April 2022

patents are filtered out and classified as AI TA, while other AI patents with only AI-related CPC codes are categorised as AI TD. Additionally, two maps are created in ArcGIS to illustrate spatial patterns of co-inventors regarding AI TD and AI TA across NUTS 2 regions.

3.2.2 Country codes

The researcher further filters these AI patents as within- or outside-Europe according to country codes. Next, the researcher selects AI patents with at least two inventors of which one is located in one of 30 countries in Europe (inc. UK, Norway and Switzerland); inventors from other countries are excluded from the data set. Among these AI patents, some with only one inventor in Europe are excluded from the data frame because this research investigates collaborative innovation between two inventors both located in NUTS 2 regions (thereafter, NUTS-2-region pairs) in the 30 European countries. In this way, AI co-patents with at least two inventors in Europe are selected, and the quality of each AI co-patent is assumed to be similar.

3.2.3 NUTS 2 region codes

The spatial unit of this research is NUTS 2 regions because this unit is neither too large nor small. NUTS 2 regions, which are different from NUTS 1 and 3 regions, do not include national boundaries and do not include spatial units within cities. NUTS 2 region codes are extracted from information of AI co-patents. The researcher excludes repeated region codes of each AI co-patent and calculates the sum of the number of region codes for each co-patent. In this way, AI co-patents with more than 1 region code are classified as interregional collaborations, whilst the other with only one region code is defined as intra-regional collaborations.

NUTS-2-region pairs are created according to combinations of every two NUTS 2 regions for each AI co-patents. These pairs represent bilateral collaborations between/within NUTS regions in which AI inventors collaborate and diffuse knowledge. Put it differently, we allocate the intelligent property of co-inventors to NUTS 2 regions to analyse knowledge diffusion across regions (Boschma et al. 2015). Then, the researcher calculates the sum of each NUTS-2–region pair based on all AI co-patents and obtains observations of analysis as the final dataset. These NUTS-2-region pairs are used to conduct regression analyses of tie formation of AI TD and AI TA co-innovation on inter-/ intra-regional collaborations. Regression results justify proposed hypotheses and answer research questions. R codes for data filtering and regression analysis are available from the corresponding researcher on reasonable request.

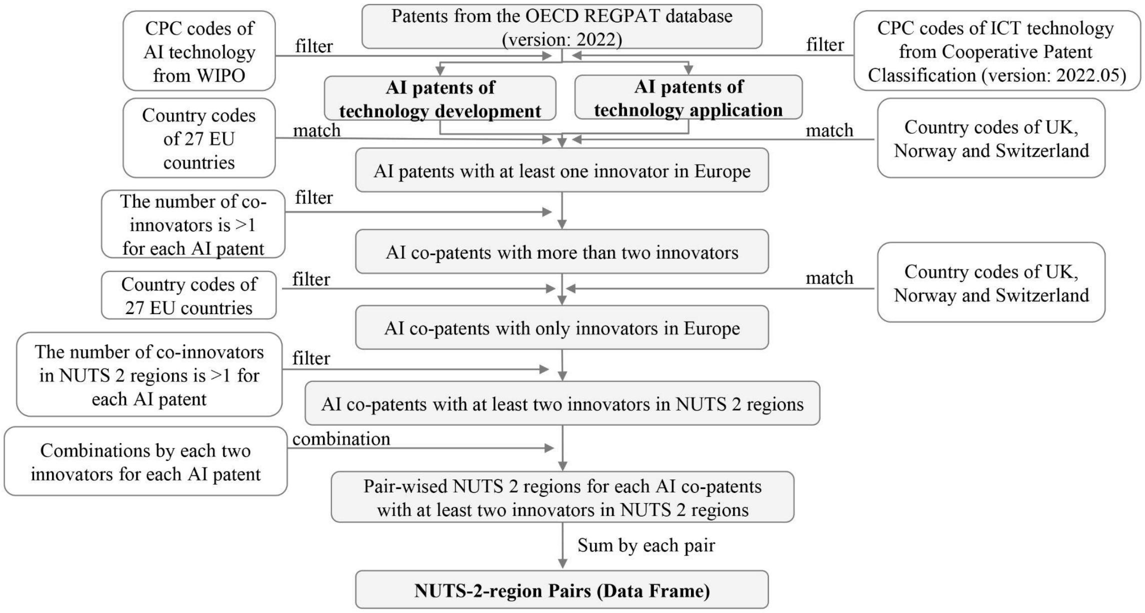


Fig. 2 A Flowchart of Data filtering
Source: Own elaborations

3.3 Construction of variables

3.3.1 Dependent variables

One dependent variable: $DEVELOPMENT$ is a dummy variable of whether each NUTS-2-region pair with AI co-patents has AI development collaborations or not between 2011-2020. The reason why we use a dummy variable rather than a count one is that the number of region-pairs with AI development co-patents is low and can only perform regression of its discrete variable. As shown in Table 2 of descriptive analysis[7], there are 1,221 observations (i.e. NUTS-2-region pairs), but many observations have the value of 0 for two dependent variables: $DEVELOPMENT$ and $APPLICATION$ (i.e. 1202 pairs (98.44%) and 229 pairs (18.76%) with 0 values, respectively). Another dependent variable: $APPLICATION$ is the count variable of the frequency of AI application collaborations in each NUTS-2-region pair with AI co-patents during 2011-2020.

Some studies choose a five-year time window because patents are granted by EPO/PCT several years after co-inventors collaborate and apply for patents (Ter Wal 2013; Menzel et al. 2017). However, we choose a ten-year period between 2011-2020 to acquire more AI co-patents for regression analysis. In this ten-year period, the number of observations is larger in a group of analysis than that in preceding and shorter time-windows. At last, the researchers conduct robustness tests after regression analysis by changing the time window of dependent variables to a shorter period: 2011-2015 (Fleming et al. 2007; Janssen and Abbasiharofteh 2022).

[7] Descriptive statistics: The researchers use the stargazer R package from Hlavac & Marek (2022) to conduct descriptive analysis.

$$DEVELOPMENT_{p,t} = \{0, 1\} \quad (1)$$

$$APPLICATION_{p,t} = N_p \quad (2)$$

where 1 of $DEVELOPMENT_{p,t}$ refers to the formation of AI TD collaboration ties in each NUTS-2-region pair (p) from 2011 to 2020, whilst 0 is the opposite; N_p is the total number of the formation of AI TA collaborative relations for each pair (p) in the same time period.

Table 2 Descriptive analysis

Statistic	N	Mean	St. Dev.	Min	Max
DEVELOPMENT	1,221	0.02	0.1	0	1
APPLICATION	1,221	52.4	574.2	0	19,306
InterRegpc	1,221	0.7	1.0	0.0	5.2
IntraRegpc	1,221	0.3	1.1	0.0	7.7
DISTANCES	1,221	0.3	0.4	0	1
POP	1,221	27.9	0.9	24.5	31.1
GDPpc	1,221	20.8	0.5	16.7	23.1
RnDpc	1,221	4.5	1.5	-2.5	7.1
POP_dif	1,221	11.9	4.2	0.0	15.4
GDPpc_dif	1,221	7.9	2.9	0.0	11.4
POP_1_sq	1,221	193.9	17.2	149.8	241.1
POP_2_sq	1,221	196.4	17.5	149.8	241.1
POP1_X_POP2	1,221	194.8	12.8	149.8	241.1
COMPONENT	1,221	0.90	0.30	0	1

Source: Own elaborations

3.3.2 Independent variables

This research examines the effects of interregional and intraregional collaborations on collaborative innovation of AI TD and AI TA. The formation of patent collaborations between or within NUTS 2 regions act as a proxy of knowledge diffusion; this variable is better than patent citations in terms of avoiding the selection and information bias (Jaffe 2000, 2019; Henderson et al. 2005). There are many relevant studies about collaborative innovation. For instance, De Noni et al. (2017) mention that innovative collaborations between NUTS 2 regions contribute to knowledge creation and diffusion. Santoalha (2019) investigates the effects of collaborative innovations within and between regions on technological diversification at the NUTS 2 region level based on co-patents from the REGPAT database.

We use $InterRegpc_{p,t-1}$ and $IntraRegpc_{p,t-1}$ as two independent variables in the time period between 2001-2010 (i.e. t-1). The reason why the researchers choose a previous time window is that inventors tend to maintain previous collaborations diffusing knowledge (Santoalha 2019), and this data avoids endogeneity issues between dependent and independent variables in the same period. These two variables are adjusted by the population of NUTS-2-region pairs to circumvent the multicollinearity issue with the control variable of population (POP) (see equation (9)).

$$InterRegpc_{p,t-1} = log(\frac{e_{i,t-1}}{Pop_{i,t-1}} * \frac{e_{j,t-1}}{Pop_{j,t-1}} + 1) \tag{3}$$

$$IntraRegpc_{p,t-1} = log((\frac{e_{ii,t-1}}{Pop_{i,t-1}})^2 + 1) \tag{4}$$

where $e_{i,t-1}$ or $e_{j,t-1}$ is the number of interregional collaborations in which co-inventors in the NUTS 2 region (i or j) involve during the time period of (t-1) (i.e. 2001-2010); $e_{ii,t-1}$ refers to the number of intra-regional collaborations within region (i) in (t-1); $Pop_{i,t-1}$ or $Pop_{j,t-1}$ is the average population of the NUTS 2 region (i or j) between 2001-2010.

Except for the independent variables of $InterRegpc_{p,t-1}$ and $IntraRegpc_{p,t-1}$, there is another explanatory factor: $DISTANCES$ which investigates the effect of Euclidian distance between the centroids of NUTS 2 regions in which inventors are located on the creation of AI TD and AI TA co-innovation (Mitze and Strotebeck 2019; Lengyel et al. 2020). This variable refers to whether the distance (d_p) of each NUTS-2-region pair (p) is larger than that of the 75 quantile group among all observations.

$$DISTANCES = \{0, 1\} \tag{5}$$

where 1 of $DISTANCES$, which is larger than the 75 quantile group refers to distant knowledge diffusion, and 0 indicates local diffusion which is lower than the 75 quantile group.

3.3.3 Control variables

There are additional driving forces behind the formation of AI TD and AI TA collaborations, for instance, technological relatedness (Boschma et al. 2015), structural as well as socio-economic factors (Rodríguez-Pose et al. 2021) and network related variables (Abbasiharofteh et al. 2020). However, variables of technological relatedness are highly correlated with GDP and the number of inventors (Boschma et al. 2015). Thus, this research includes $GDPpc$, $GDPpc\_dif$, $RnDpc$, POP, POP_dif, POP_1_sq, POP_2_sq and $COMPONENT$ as control variables excluding technological relatedness. These control variables are all within the time period between 2001-

2010 (i.e. t-1) same as the independent variables (Santoalha 2019). Calculations of each variable are shown below.

The prosperousness of cities/regions support knowledge generation, for instance, GDP per capita (Balland et al. 2020). Rodríguez-Pose et al. (2021) mention that developed cities/regions with higher GDP per capita develop a more sophisticated innovation system for patenting activities than their lagging counterparts. In this innovation system, GDP per capita of regions and their difference in GDP per capita determine the extent to which knowledge diffuses across regions (Autant-Bernard, Fadairo and Massard 2013). In this research, $GDPpc_{p,t-1}$ and $GDPpc\_dif_{p,t-1}$ are included in regression models.

$$GDPpc_{p,t-1} = log(Gdp_{i,t-1} * Gdp_{j,t-1}) \tag{6}$$

$$GDPpc\_dif_{p,t-1} = log(|Gdp_{i,t-1} - Gdp_{j,t-1}| + 1) \tag{7}$$

where $Gdp_{i,t-1}$ or $Gdp_{j,t-1}$ indicate the average of GDP per capita of NUTS 2 regions (i or j) in the time period of (t-1);

Knowledge foundations of cities/regions exert effects on local diffusion of complex knowledge (Balland et al. 2020). On the one hand, human capital (e.g. Educated employees and specialised workers) diffuse tacit knowledge with each other to collaboratively innovate (Van der Wouden and Rigby 2019). On the other hand, lagging regions with less human capital or employees with lower education levels may have lower absorptive capacities to learn from inventors in other regions (Crescenzi 2021). Thus, a control variable of $RnDpc_{p,t-1}$ is included to control the effect of human capital. This variable refers to the magnitude of R&D personnel in each NUTS-2-region pair, which is adjusted by the total population of each region (i and i or j) for coping with the multicollinearity issue.

$$RnDpc_{p,t-1} = log[(\frac{RD_{i,t-1}}{Pop_{i,t-1}}) * (\frac{RD_{j,t-1}}{Pop_{j,t-1}})] \tag{8}$$

where $RD_{i,t-1}$ or $RD_{j,t-1}$indicates the average number of R&D employees in NUTS 2 regions (i or j) in the time period of t-1 (i.e. 2001-2010); $Pop_{i,t-1}$ or $Pop_{j,t-1}$ is the average population of the NUTS 2 region (i or j) in (t-1).

Population of regions determines the number of patent applications to some extent. Much research includes population as control variables to investigate effects on technological collaborations (Miguelez and Moreno 2013). This research includes not only total population of region-pairs (i.e., POP), but also their differences in population (POP_dif) and quadratic terms of population (POP_1_sq and POP_2_sq). The reason is that agglomeration and urbanisation economies impose effects on knowledge spillovers non-linearly (Roca and Puga 2017).

$$POP_{p,t-1} = log(Pop_{i,t-1} * Pop_{j,t-1}) \tag{9}$$

$$POP\_dif_{p,t-1} = log(|Pop_{i,t-1} - Pop_{j,t-1}| + 1) \tag{10}$$

$$POP\_1\_sq_{p,t-1} = [log(Pop_{i,t-1})]^2 \tag{11}$$

$$POP\_2\_sq_{p,t-1} = [log(Pop_{j,t-1})]^2 \tag{12}$$

where $Pop_{i,t-1}$ or $Pop_{j,t-1}$ similar with other control variables is described in 3.3.2.

Many existing studies in the field of regional innovation investigate effects of structural properties of co-innovation networks on the number of patents granted in regions (Abbasiharofteh et al. 2020). The largest component of knowledge networks, which intensify among connected clusters, impose detrimental effects on the spillovers of extensive and breakthrough knowledge (Lucena-Piquero and Vicente 2019). Thus, a control variable ($COMPONENT$) is included in regression models in this research. $COMPONENT$ is a dummy variable of whether each NUTS-2-region pair is within the largest component of their collaborative networks or not.

$$COMPONENT \in \{0, 1\} \tag{13}$$

where 1 indicates that NUTS-2-region pairs comprise the largest component of their co-innovation networks, whilst 0 refers to the opposite. The entire dataset analysed in this study is shared in the Figshare repository[8].

3.4 Methods

3.4.1 Pearson correlation

The researcher conducts Pearson Correlation Analysis of variables before choosing one of the regression methods with the best goodness of fit. Figure 3 illustrates correlations of coefficients between variables based on Pearson Correlation. There are significantly positive correlations between intra-regional and AI TD ($DEVELOPMENT$) as well as AI TA ($APPLICATION$) co-innovation, but interregional effects are insignificant. Spatial distance of each NUTS-2-region pair has insignificantly negative correlation both with AI TA and AI TD. Correlation coefficients between variables are also shown in the heatmap of Figure 11 in the Appendix A.

The dependent variable: $DEVELOPMENT$ complies with a Bernoulli Distribution. Thus, a logit regression method is appropriate for regression analysis of the binary variable: $DEVELOPMENT$. Another variable: $APPLICATION$ has a Negative Binomial Distribution, and the variance of this variable is larger than its mean. Therefore, a Zero-inflated Negative Binomial (ZINB) Regression method should be a suitable method for this variable (Greene 1994). However, we need to conduct further model tests in the next part to determine one of the most appropriate regression models.

[8] The Figshare repository: https://doi.org/10.6084/m9.figshare.20237541.v1. Generated on 6th July 2022

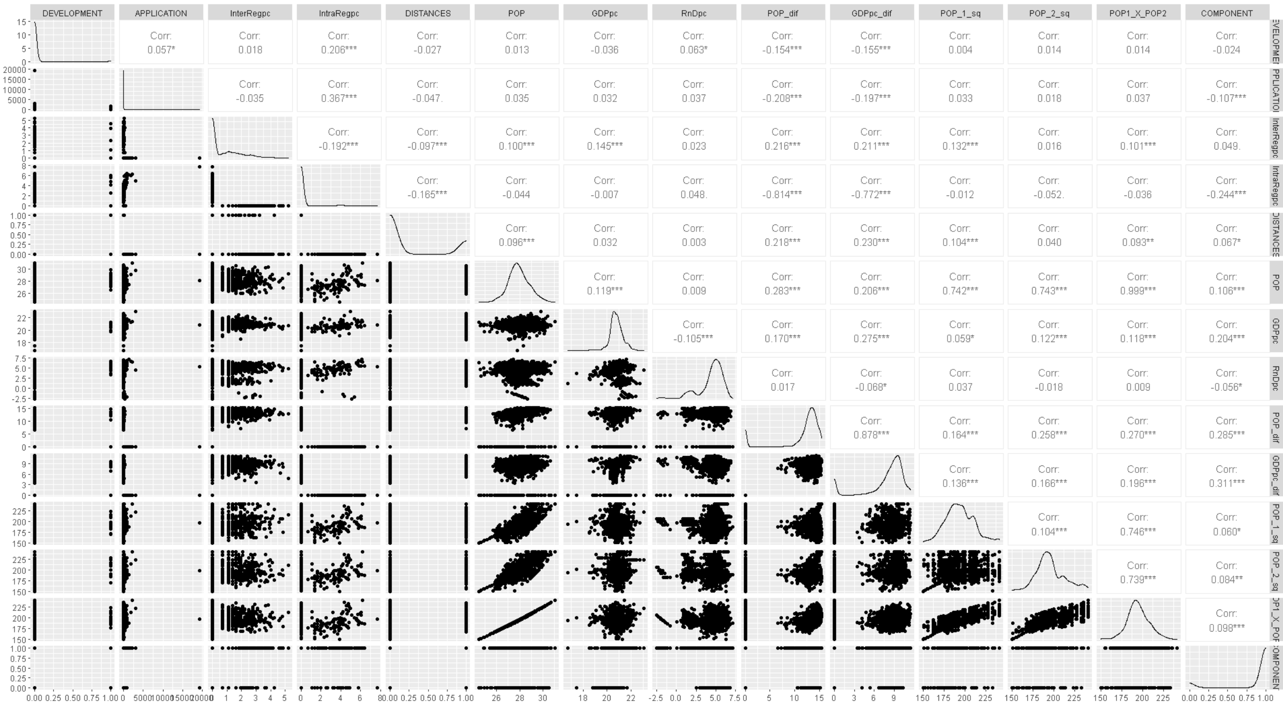


Fig. 3 A Cross Table of Correlations between variables
Source: Own elaborations

3.4.2 Regression models

The binary variable: $DEVELOPMENT$ is analysed by the logit model based on the maximum likelihood (see a baseline model in the equation (14)). The reason why the logit model is more appropriate is its interpretability of odds/probability and more accurate estimations than the Ordinary Least Square (OLS) method, except for the reason of limited observations (Von Hippel 2017).

There are several assumptions of the logit model as follows. There is linearity between the odds of $DEVELOPMENT$ and independent variables (e.g. $InterRegpc$ and $IntraRegpc$). Residuals of the logit regression are assumed to be logistically distributed and absent from multicollinearity, from influential observations, and from correlation between error terms and independent variables. In addition, the VIF test is conducted to examine the existence of the multicollinearity issue.

$$ln\left(\frac{P(DEVELOPMENT\ =\ 1)}{1-P(DEVELOPMENT\ =\ 1)}_{p,t}\right) = \beta_0 + \beta_1 IntraRegpc_{p,t-1} + \beta_2 InterRegpc_{p,t-1} + \beta_3 DISTANCES + \beta_4 Z_{p,t-1} + \varepsilon_{p,t-1} \tag{14}$$

where independent variables are $IntraRegpc_{p,t-1}$, $InterRegpc_{p,t-1}$ and $DISTANCES$; $Z_{p,t-1}$ denotes 8 control variables including $GDPpc_{p,t-1}$, $GDPpc\_dif_{p,t-1}$, $RnDpc_{p,t-1}$, $POP_{p,t-1}$, $POP\_dif_{p,t-1}$, $POP\_1\_sq_{p,t-1}$, $POP\_2\_sq_{p,t-1}$ and $COMPONENT$; $\varepsilon_{p,t-1}$ refers to a residual of a regression model; β_0 is a constant, β_1, β_2, β_3 and β_4 are coefficients.

As for the count variable: $APPLICATION$, the researcher uses a likelihood ratio test for overdispersion (namely, odTest)[9] in the count data and Vuong's non-nested hypothesis test (namely, vuong)[10] to choose one of the best regression methods. Results of this odTest determine whether we should choose a Poisson regression model or a Negative Binomial regression model. Results of the vuong test indicate that we should choose a Zero-inflated Poisson/Negative Binomial model or its ordinary counterpart.

Based on the testing results, we adopt the Zero-inflated Negative Binomial Regression (ZINB) model to regress the variable ($APPLICATION$) with extra zero-valued observations. This research follows the ZINB method of Bokányi et al. (2021). It is inappropriate to adopt an OLS model due to the negative binomial distribution of the count data (see Figure 3). This ZINB model consists of two models including a similar logit model for the zero part (thereafter, the Logit model) (see a baseline model in the equation (15a)) and a negative binomial regression model to regress the count part (see a baseline model in the equation (15b)) (Greene 1994). More particularly, this ZINB model separately examines effects on the establishment of AI TA collaborative relations of NUTS-2-region pairs without AI co-patents and on the intensity of AI TA co-innovations of region pairs with AI co-patents.

Estimated coefficients for the zero part should be multiplied with negative 1 (i.e. (-1)) for interpretations which are the opposite of that in a normal logit model. The reason is that this Logit model for the zero data examines the absence of AI TA collaborations. Additionally, the interpretation of the negative binomial model for the count data is similar to that of an OLS model. However, some control variables, for example, POP_1_sq and POP_2_sq, are excluded from the baseline model in the equation (15b) because of divergence of regression results.

There are some assumptions of this ZINB model. For instance, there is correlation between observations such as overdispersion, no multicollinearity issue among variables and no influential outliers. These assumptions should be tested after regression analysis by the VIF test.

$$ln(\frac{P(APPLICATION\ =\ 0)}{1-P(APPLICATION\ =\ 0)}_{p,t}) = \beta_0 + \beta_1 IntraRegpc_{p,t-1} + \beta_2 InterRegpc_{p,t-1} + \beta_3 DISTANCES + \beta_4 InterRegpc\_X\_DISTANCES\ + \beta_5 C_{p,t-1} + \varepsilon_{p,t-1} \tag{15a}$$

$$ln(APPLICATION_{p,t}) = \beta_0 + \beta_1 IntraRegpc_{p,t-1} + \beta_2 InterRegpc_{p,t-1} + \beta_3 DISTANCES + \beta_4 InterRegpc\_X\_DISTANCES\ + \beta_5 C_{p,t-1} + \varepsilon_{p,t-1} \tag{15b}$$

where $P(APPLICATION = 0)$ in the equation (15a) is for the extra zero part and $ln(APPLICATION)$ in the equation (15b) is for the count part; $InterRegpc\_X\_DISTANCES$ refers to the interaction effect of interregional collaboration and spatial distance of each region

[9] odTest: https://www.rdocumentation.org/packages/pscl/versions/1.5.5/topics/odTest. Accessed 15 May 2022
[10] vuong: https://www.rdocumentation.org/packages/pscl/versions/1.5.5/topics/vuong. Accessed 15 May 2022

pair on AI application collaborations; $C_{p,t-1}$ denotes 6 control variables including $GDPpc_{p,t-1}$, $GDPpc\_dif_{p,t-1}$, $RnDpc_{p,t-1}$, $POP_{p,t-1}$, $POP\_dif_{p,t-1}$ and $COMPONENT$.

4. Prediction of the nature of diffused knowledge

4.1 Patent analysis

4.1.1 Patents of artificial intelligence

Among the filtered AI patents, there are 28,775 inventors from all around the world regarding AI technology development (AI TD), and 252,138 inventors for AI technology applications (AI TA). For instance, a patent named Indication of Accuracy of Quantitative Analysis with the publication number of EP1593092 is categorised as AI TD with all AI-related CPC codes. This patent contributes to the evaluation of medical images by developing AI technologies. Another patent named Exchanging Data with a Mobile Communication Network with the publication number of EP3183894 is classified as AI TA with not only AI-related CPC codes but also other CPC codes. This patent improves the remote control of functions of machine type communication devices by using AI technologies in intelligent homes.

4.1.2 AI co-patents in Europe

There are 16,379 AI co-patents with at least two inventors in Europe, consisting of 11,177 intra-regional collaborations and 5,202 interregional collaborations between the NUTS 2 regions. Germany and Great Britain are two main countries greatly contributing to co-patenting activities of AI TD and TA among the 30 countries between 1982-2020 (see Figure 7 and 8 in the Appendix A). During this period, collaborative inventors increasingly created co-inventions for AI TA, whilst co-patents of AI TD in Europe increased and peaked in 2002 and fluctuated between 2002-2015 (see Figure 4 below; Figure 9 in the Appendix A). Both AI TD and TA co-patents decreased sharply between 2016-2020 because most patent applications are under verification. This fact is the reason why this research chooses a current 10-year time window for dependent variables.

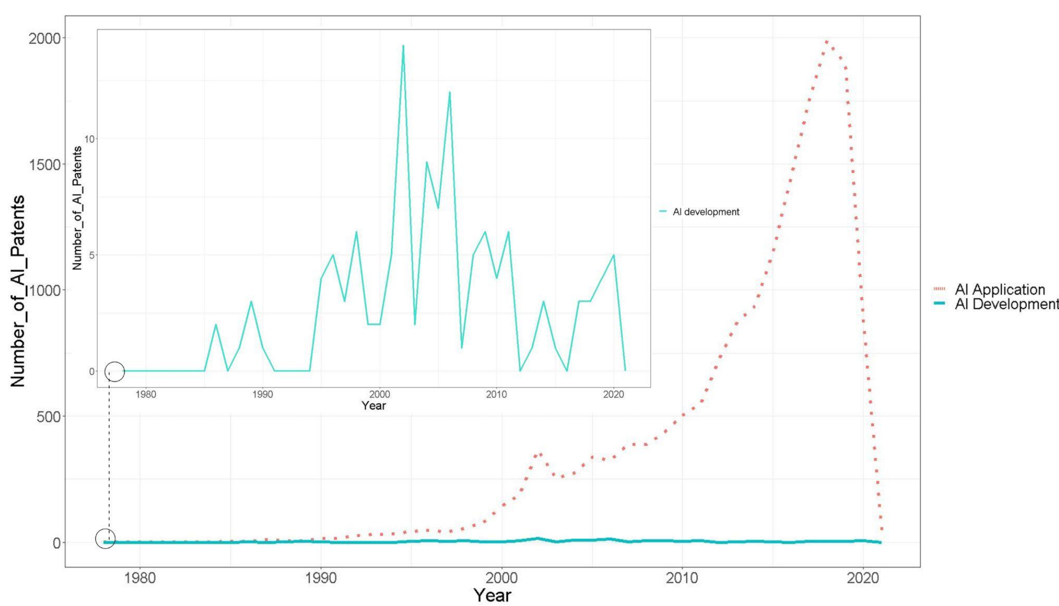
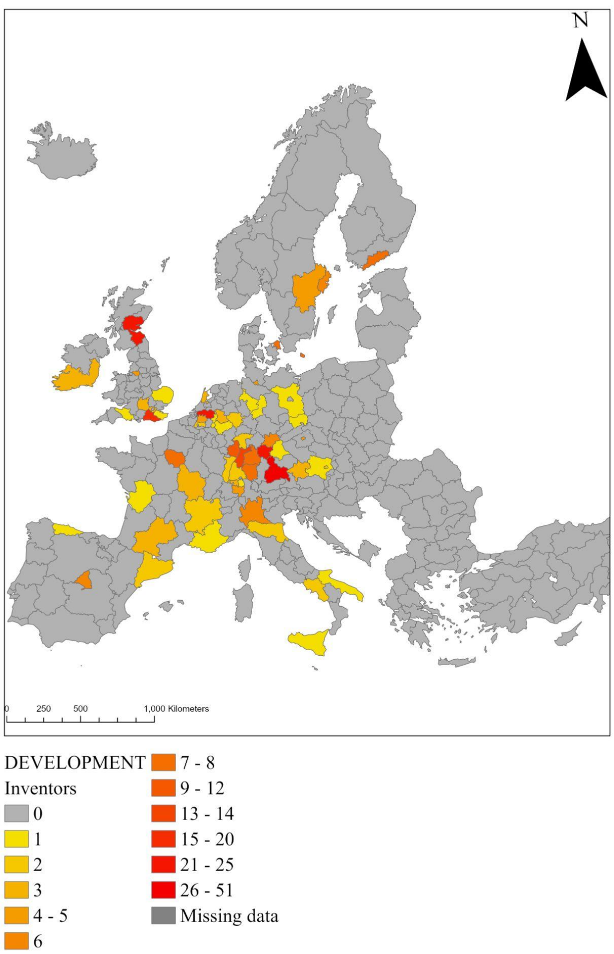


Fig. 4 The Number of AI Co-patents with At Least Two European inventors in Each Year by Knowledge Type, 1982-2020, NUTS 2 Region Level
Source: Own elaborations on the OECD REGPAT database (version: 2022)

These AI co-patents include 328 collaborative inventors in Europe for AI TD and 56,237 co-inventors for AI TA. There are 216 co-inventors cooperatively developing AI technology within NUTS 2 regions, whilst 112 co-inventors create co-innovations for AI TD interregionally. 36,275 co-inventors adopt AI technologies collaboratively within NUTS 2 regions, whilst 19,962 co-inventors located in different NUTS 2 regions collaborate to create AI application co-inventions.

4.1.3 Spatial distribution of AI co-inventors

Maps (Figure 5 and 6) illustrate where co-inventors with regards to AI TD and AI TA were located across NUTS 2 regions between 1982-2020. As for AI TD, co-inventors scatter across NUTS 2 regions, whilst as for AI TA, their co-patenting activities concentrate in specific regions, for instance, the south of the Netherlands and of Germany. More particularly, NL41 (Noord-Brabant) has the most frequent AI co-innovations (n = 12,446 in total), whilst FR10 (Île de France) ranks the second (n = 2,377).



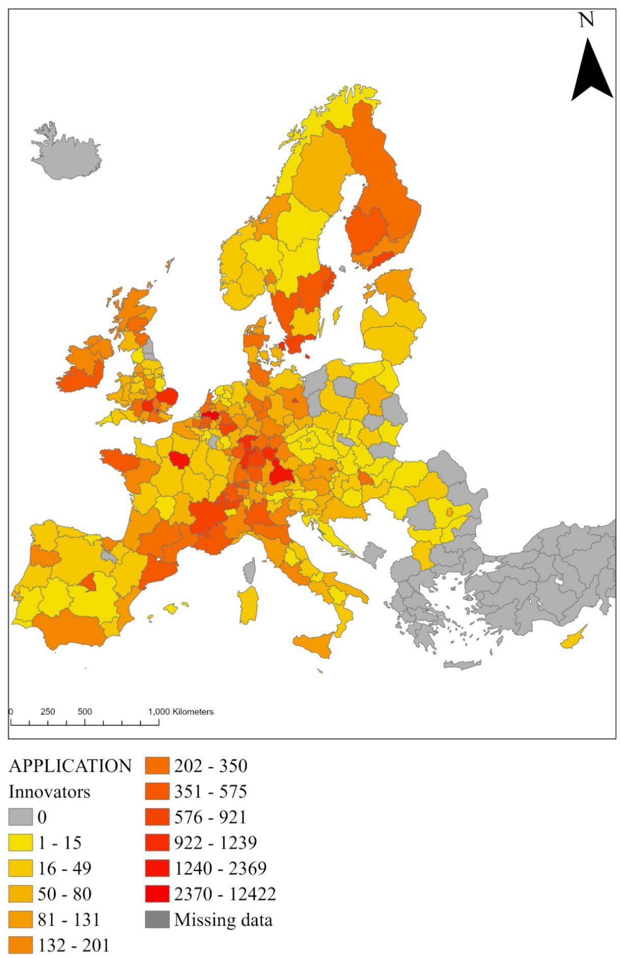


Fig. 5 The Number of Co-inventors for Technology Development of AI, NUTS 2 Region Level, 1982-2020

Fig. 6 The Number of Co- inventors for Technology Application of AI, NUTS 2 Region Level, 1982-2020

Source: Own elaborations on the OECD REGPAT database (version: 2022)

4.1.4 NUTS-2-region pairs

The researcher creates NUTS-2-region pairs by combinations of every two NUTS 2 regions in which AI co-inventors are located as pairs for each AI co-patents and summing each pair. Different region pairs have different frequencies of inter- and intra-regional collaborations between AI co-inventors. Co-inventors in the NUTS-2-region pair: Noord-Brabant—Noord-Brabant involved in the most co-patenting activities between 2001-2010 (2,161 intra-regional collaborations among which 28 for AI TD and 2,133 for AI TA).

4.1.5 Collaborative innovation networks

Based on these NUTS-2-regions pairs, the researchers create an AI innovation network which has a skewed degree distribution. This type of distribution indicates a large number of nodes with low node degrees and a few nodes with high degrees (see Figure 10 in the Appendix A). The mean distance of the entire network is approximately 2.58, diameter is 5 and the edge density is about 2.617.

Among these nodes, several vertices are hubs with the highest degrees and closeness values in terms of AI knowledge diffusion for AI TA and AI TD. More particularly, these knowledge hubs are Noord-Brabant, Île-de-France and Oberbayern with the degrees of 43499, 7226 and 6646, respectively, and with values of closeness of 0.002, 0.002 and 0.002. Several nodes (e.g. Oberbayern) create large components connecting different knowledge communities. For instance, NUTS-2-region pairs which are included in the largest components have a value of 1 for the control variable: $COMPONENT$.

4.2 Regression results

4.2.1 Technology development

The researcher chooses Model 10 as the best regression model of $DEVELOPMENT$ according to the VIF test and maximum likelihood. VIF values of each independent variable in this model with the highest maximum likelihood are smaller than 5. In this regression analysis, estimated coefficients of the variable: $InterRegpc_{p,t-1}$ are consistent in terms of signs and confidence levels among all models (see Table 3).

The sign of $InterRegpc$ is positive, and its confidence level is 99%. Its coefficient indicates that an 1 percent increase in the frequency of interregional collaborations between NUTS 2 regions in the previous period causes an increase in the odds of the formation of AI technology development (TD) collaborations with 0.916 percentage points in the current period, maintaining all the other variables constant. This result significantly supports Hypothesis 2 that innovative knowledge diffuses between regions based on global pipelines (Bathelt et al. 2004), which aligns with the Science-Technology-Innovation mode (Alhusen and Bennat 2021). In addition, the coefficient of $DISTANCES$ is insignificant. These findings support the conclusion of Van der Wouden and Rigby (2019) that cognitive distance rather than spatial distance is more likely to influence the establishment of collaborations between specialised inventors and their counterparts in other urban areas.

Assumption tests of residuals in the logit regression model are shown in Figure 12 in the Appendix A. These tests illustrate that residuals of Model 10 are independent, have a logistic distribution and are not related to independent variables. Thus, regression results are reliable.

Table 3 Regression Results of DEVELOPMENT

	Dependent variable: DEVELOPMENT (2011-2020)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IntraRegpc	0.55^{***}	0.66^{***}	0.68^{***}	0.68^{***}	0.72^{***}	0.66^{***}	0.46^{*}	0.44^{*}	0.40	0.41
	(0.10)	(0.12)	(0.13)	(0.13)	(0.13)	(0.14)	(0.26)	(0.26)	(0.26)	(0.27)
InterRegpc		0.50^{**}	0.52^{**}	0.52^{**}	0.60^{***}	0.55^{**}	0.60^{**}	0.60^{**}	0.65^{***}	0.65^{***}
		(0.22)	(0.23)	(0.23)	(0.23)	(0.23)	(0.24)	(0.24)	(0.25)	(0.25)
DISTANCES			0.30	0.30	0.34	0.26	0.43	0.50	0.64	0.63
			(0.69)	(0.70)	(0.70)	(0.71)	(0.74)	(0.75)	(0.76)	(0.76)
POP				-0.01	0.01	0.04	0.11	0.09	11.52	9.78
				(0.23)	(0.23)	(0.24)	(0.24)	(0.25)	(10.48)	(10.62)
GDPpc					-0.77^{**}	-1.08^{**}	-0.93^{*}	-0.90^{*}	-0.80	-0.87
					(0.39)	(0.49)	(0.51)	(0.52)	(0.52)	(0.53)
RnDpc						0.49	0.51^{*}	0.52^{*}	0.52^{*}	0.53^{*}
						(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
POP_dif							-0.08	0.001	-0.03	-0.03
							(0.10)	(0.16)	(0.16)	(0.16)
GDPpc_dif								-0.15	-0.15	-0.15
								(0.22)	(0.22)	(0.22)
POP_1_sq									-0.43	-0.36

									(0.38)	(0.38)
POP_2_sq									-0.38	-0.32
									(0.37)	(0.37)
COMPONENT										0.42
										(0.74)
Constant	-4.67***	-5.19***	-5.29***	-5.08	10.20	13.47	9.41	9.23	-153.85	-128.26
	(0.30)	(0.43)	(0.50)	(6.34)	(10.12)	(11.25)	(12.06)	(12.31)	(149.47)	(151.92)
Observations[a]	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221
Log Likelihood	-86.24	-84.01	-83.92	-83.92	-82.21	-80.36	-80.01	-79.79	-78.39	-78.22
Akaike Inf. Crit.	176.48	174.03	175.85	177.85	176.41	174.72	176.03	177.58	178.78	180.45

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: [a]The number of observations refers to the number of NUTS-2-region pairs;
t statistics in parentheses
Source: Own elaborations

4.2.2 Technology application

Results of the odTest shows that there exists overdispersion in the count variable ($APPLICATION$) (Chi-Square Test Statistic = 43010.4257, p-value = < 2.2e-16). Thus, the ZINB model outperforms the Zero-inflated Poisson model. In addition, the ZINB model has more significant explanatory power than the negative binomial model according to the result of the vuong test (p = 0.005 for the AIC-corrected value). Model 10 with the highest maximum likelihood (i.e. the best goodness of fit) is the best regression specialisation of the ZINB model.

As for the zero part, results of Model 10 indicate that the sign of $InterRegpc$ is positive at the 99 percent confidence level, but its coefficient should be interpreted in an opposite way different from a normal logit model (i.e. Multiplying coefficients with negative 1) (see Table 4). This coefficient means that the odds of the establishment of AI TA collaborations decrease with 0.804 percentage points in the current period significantly, maintaining all other variables constant, if the frequency of interregional collaborations between NUTS 2 regions increases with 1 percent in the previous period. More particularly, the coefficient of $InterRegpc\_X\_DISTANCES$ is significantly positive, which means that inter-regional collaborations with lower spatial distances are more likely to form the AI TA relations between NUTS 2 regions without AI co-patents. These results support Hypothesis 4, which is consistent with diffusion theories of Hagerstrand (1968) that distance decay exists as spatial distances between inventors and adopters increase.

As for the count data, results of the model (9) show that signs of $IntraRegpc$ and $InterRegpc$ are both positive, and their confidence levels are 99% (see Table 5). The coefficient of $IntraRegpc$ means that an 1 percent increase in the frequency of intra-regional collaborations increases the intensity of AI TA co-inventions with 0.47 percentage points in the next period, whilst keeping all other variables constant. This result supports Hypothesis 3 significantly and contributes to diffusion theories of Rogers (1962). The coefficient of $InterRegpc$ indicates that the intensity of AI technology application (TA) collaborations increases with 0.52 percentage points if the frequency of interregional collaborations in each NUTS-2-region pair increases with 1 percentage point, maintaining other variables unchanged.

In addition, the coefficient of $InterRegpc\_X\_DISTANCES$ is significantly negative at the 99 percent confidence level as for the NUTS-2-region pairs with AI co-patents. This result means that interregional collaborations between spatially closer NUTS 2 regions in which AI co-inventors are located encourage more AI TA co-innovations and vice versa, which supports Hypothesis 4 significantly. This finding contributes to theories of Hagerstrand (1968) and justifies local knowledge diffusion patterns of Balland et al. (2020) and Haller and Rigby (2020). However, it contradicts empirical evidence of Lengyel et al. (2020) that new technologies are adopted between large towns in early stages of the entire life cycle of technologies. Table 6 below shows results of two regression models with the highest maximum likelihood.

Table 4 Results of ZINB Regression of AI APPLICATION for the Zero Part

	Dependent variable: APPLICATION (2011-2020)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IntraRegpc	-2.28	-2.68	-2.69	-2.61	-2.83	-2.72	-2.79	-1.78	-1.82	-1.26
	(475.52)	(6.23)	(13.18)	(6.21)	(5.26)	(4.45)	(4.72)	(2.54)	(2.45)	(1.73)
InterRegpc		0.62^{***}	0.90^{***}	0.51^{***}	0.56^{***}	0.57^{***}	0.56^{***}	0.55^{***}	0.56^{***}	0.59^{***}
		(0.10)	(0.22)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)	(0.11)	(0.11)
DISTANCES			2.10^{**}	-0.11	-0.01	-0.11	-0.15	-0.19	-0.16	-0.37
			(1.05)	(0.55)	(0.54)	(0.51)	(0.51)	(0.46)	(0.48)	(0.50)
POP					-0.56^{***}	-0.48^{***}	-0.48^{***}	-0.48^{***}	-0.49^{***}	-0.73^{***}
					(0.19)	(0.18)	(0.18)	(0.18)	(0.18)	(0.21)

GDPpc						-0.28	-0.29	-0.26	-0.22	-0.32
						(0.28)	(0.28)	(0.29)	(0.31)	(0.34)
RnDpc							0.04	0.06	0.06	0.07
							(0.11)	(0.10)	(0.11)	(0.11)
POP_dif								0.07	0.08	0.06
								(0.09)	(0.10)	(0.11)
GDPpc_dif									-0.04	0.02
									(0.12)	(0.13)
COMPONENT										15.28
										(318.48)
InterRegpc: DISTANCES				0.85^{***}	0.97^{***}	0.95^{***}	0.93^{***}	0.97^{***}	0.97^{***}	1.19^{***}
				(0.30)	(0.29)	(0.29)	(0.29)	(0.28)	(0.28)	(0.30)
Constant	-12.71	-3.09^{***}	-4.49^{***}	-3.15^{***}	12.32^{**}	16.30^{**}	16.14^{**}	14.90^{**}	14.40^{*}	7.51
	(45.19)	(0.29)	(1.20)	(0.35)	(5.25)	(7.15)	(7.20)	(7.21)	(7.43)	(318.58)
Observations[a]	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221
Log Likelihood	-4,298.03	-4,229.07	-4,211.21	-4,185.26	-4,174.88	-4,159.75	-4,156.97	-4,090.62	-4,090.21	-4,084.26

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: [a]The number of observations refers to the number of NUTS-2-region pairs;
t statistics in parentheses
Source: Own elaborations

Table 5 Results of ZINB Regression of AI APPLICATION for the Count Part

	Dependent variable: APPLICATION (2011-2020)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IntraRegpc	0.78***	0.86***	0.84***	0.84***	0.84***	0.87***	0.86***	0.48***	0.48***	0.47***
	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
InterRegpc		0.40***	0.36***	0.42***	0.41***	0.45***	0.45***	0.53***	0.53***	0.52***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
DISTANCES			-0.37***	-0.23**	-0.25**	-0.26**	-0.27***	0.03	0.02	0.02
			(0.11)	(0.11)	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)	(0.10)
POP					0.13***	0.16***	0.16***	0.32***	0.32***	0.31***
					(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
GDPpc						-0.34***	-0.32***	-0.02	-0.03	-0.01
						(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
RnDpc							0.06**	0.11***	0.11***	0.11***
							(0.02)	(0.02)	(0.02)	(0.02)
POP_dif								-0.15***	-0.16***	-0.17***
								(0.01)	(0.02)	(0.02)
GDPpc_dif									0.02	0.03
									(0.03)	(0.03)
COMPONENT										-0.13
										(0.13)
InterRegpc :DISTANCES				-0.82***	-0.81***	-0.79***	-0.81***	-0.94***	-0.93***	-0.93***
				(0.12)	(0.12)	(0.12)	(0.12)	(0.11)	(0.11)	(0.11)
Constant	2.44***	2.11***	2.21***	2.19***	-1.36	4.80***	4.20***	-5.16***	-4.90***	-5.11***
	(0.05)	(0.05)	(0.06)	(0.06)	(1.17)	(1.56)	(1.58)	(1.76)	(1.80)	(1.84)
Observations[a]	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221	1,221

Log Likelihood	-4,298.03	-4,229.07	-4,211.21	-4,185.26	-4,174.88	-4,159.75	-4,156.97	-4,090.62	-4,090.21	-4,084.26

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Notes: [a]The number of observations refers to the number of NUTS-2-region pairs; t statistics in parentheses
Source: Own elaborations

Table 6 Regression Results of DEVELOPMENT and APPLICATION in the Best Models

	Dependent variable:		
	DEVELOPMENT	APPLICATION	
	logistic	*zero-inflated count data*	
	(1)	(2)	(3)
IntraRegpc	0.41	-1.26	0.47***
	(0.27)	(1.73)	(0.05)
InterRegpc	0.65***	0.59***	0.52***
	(0.25)	(0.11)	(0.04)
DISTANCES	0.63	-0.37	0.02
	(0.76)	(0.50)	(0.10)
POP	9.78	-0.73***	0.31***
	(10.62)	(0.21)	(0.04)
GDPpc	-0.87	-0.32	-0.01
	(0.53)	(0.34)	(0.07)
RnDpc	0.53*	0.07	0.11***
	(0.31)	(0.11)	(0.02)
POP_dif	-0.03	0.06	-0.17***
	(0.16)	(0.11)	(0.02)

GDPpc_dif	-0.15	0.02	0.03
	(0.22)	(0.13)	(0.03)
POP_1_sq	-0.36		
	(0.38)		
POP_2_sq	-0.32		
	(0.37)		
COMPONENT	0.42	15.28	-0.13
	(0.74)	(318.48)	(0.13)
InterRegpc:DISTANCES		1.19^{***}	-0.93^{***}
		(0.30)	(0.11)
Constant	-128.26	7.51	-5.11^{***}
	(151.92)	(318.58)	(1.84)
Observations	1,221	1,221	1,221
Log Likelihood	-78.22	-4,084.26	-4,084.26
Akaike Inf. Crit.	180.45		

*p<0.1; **p<0.05; ***p<0.01

Notes: t statistics in parentheses; Column (2) is a similar logit regression model of the ZINB model for the zero part; Column (3) is the negative binomial model of the ZINB model for the count part. *Source*: Own elaborations

4.3 Robustness tests

This research conducts robustness tests for two regression analyses by using two different methods, respectively. As for the variable: $DEVELOPMENT$, the researcher performs Firth's Bias-Reduced Logistic Regression to make new estimations (Heinze and Ploner 2003; Simensen and Abbasiharofteh 2022). As for the other, the researcher regresses the dependent variable: $APPLICATION$ in a 5-year time window between 2011-2015. These tests aim to investigate whether coefficients in two robustness models maintain similar confidence levels and the same signs as that in two original models (i.e. the logit and ZINB regression).

Results of Table 7 in the Appendix A indicates that coefficients of independent variables remain consistent with that in the original regression model (10) of $DEVELOPMENT$. In addition, regression results of $APPLICATION$ are robust. Table 8 and 9 in the Appendix A indicate that signs and confidence levels of independent variables ($InterRegpc$, $IntraRegpc$, $DISTANCES$,

$InterRegpc\_X\_DISTANCES$) are consistent with that in the original regression model (i.e. the ZINB model).

5 Discussion and Conclusions

Interregional collaborations of co-inventors between NUTS 2 regions encourage co-innovation of AI technology development (TD). This type of collaboration facilitates co-inventors to transfer various technological knowledge across regions (Hagerstrand 1968; Johansson and Karlsson 2019). This finding contributes to the concept of Science-Technology-Innovation (STI) mode based on global pipelines (Bathelt et al. 2004; Alhusen et al. 2021). More particularly, there is no significant effect of the spatial distance of NUTS-2-region pairs on the probability of establishing AI TD collaboration ties. This finding supports conclusions of Kilkenny (2015) and Van der Wouden and Rigby (2019) that geographical distance is less likely to encourage the establishment of innovative collaborations than social and cognitive proximity between specialised inventors across space.

Both intra- and inter-regional collaborations of co-inventors across NUTS 2 regions which have AI co-patents increase the intensity of co-innovation for AI technology application (TA) significantly. For one thing, face-to-face communication encourages co-inventors within regions to impart tacit knowledge and establish mutual trust based on the Doing-Using-Interacting mode (Lundvall 2016; Alhusen et al. 2021). For another, these co-inventors diffuse various knowledge between regions to create application co-inventions for regional diversification (Santoalha 2019). However, interregional collaborations between distant NUTS 2 regions decrease the probability and intensity of AI TA co-innovation because complex applied knowledge loses greatly over distance (Hagerstrand 1968). Put it differently, knowledge of AI TA concentrates within NUTS 2 regions or diffuses between regions and their neighbouring regions. Results contributing to diffusion theories of Rogers (1962) and Hagerstrand (1968) contradict, to some extent, empirical evidence of Bokányi et al. (2021) that a new technology is adopted between distant large towns. Differently, they justify local knowledge diffusion patterns mentioned by Balland et al. (2020) and Haller and Rigby (2020).

Innovation policies, on the one hand, should create incentives for AI inventors in different NUTS 2 regions to conduct research and development collaboratively (Crescenzi et al. 2016). Collaborations among AI professionals and diversified researchers make AI technological breakthroughs by sharing and combining innovative knowledge between various technological communities (Abbasiharofteh et al. 2020). This combination of knowledge is different in fostering co-innovation if this knowledge is produced and diffused across NUTS 2 regions with various territorial characteristics (e.g. Universities, institutions, GDP per capita and R&D employment) (Rodríguez-Pose and Wilkie 2019). Based on various socio-economic contexts of regions, AI Inventors specialise in specific fields of AI technologies in different regions (Balland et al. 2019), and it requires their collaborations to encourage the combination of professional knowledge for technology development.

On the other hand, regional policies could trigger local innovativeness from different industries to collaborate and absorb various knowledge. It requires greater relatedness between existing knowledge of local inventors and new co-innovations to diversify knowledge bases of NUTS 2 regions (Balland et al. 2019). For instance, regional knowledge bases of ICTs strongly support the diversification of AI technologies in those catching-up regions in Europe (Xiao and Boschma 2021). Similarly, collaborations among local inventors within NUTS 2 regions encourage widespread adoptions of AI technologies in different industries and foster AI TA co-innovation.

There is a limitation in this research. The researcher filters out AI patents according to a limited number of available CPC codes of AI technologies from WIPO PATENTSCOPE Artificial Intelligence Index. Some AI patents are omitted, which leads to a limited number of valid observations. We could have analysed texts of each patent document for a more comprehensive and precise classification of co-patents between AI TD and AI TA.

This research omits the effects of technological relatedness of each NUTS-2-region pair on knowledge diffusion of AI technology development and application. In the next research, researchers can construct indices such as regional knowledge bases, technologies relatedness and economic complexity based on relevant data, for instance, scientific papers, granted patents, trademarks and employment data. This proposed research contributes to the extant literature of the Geography of Innovation.

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Appendix A

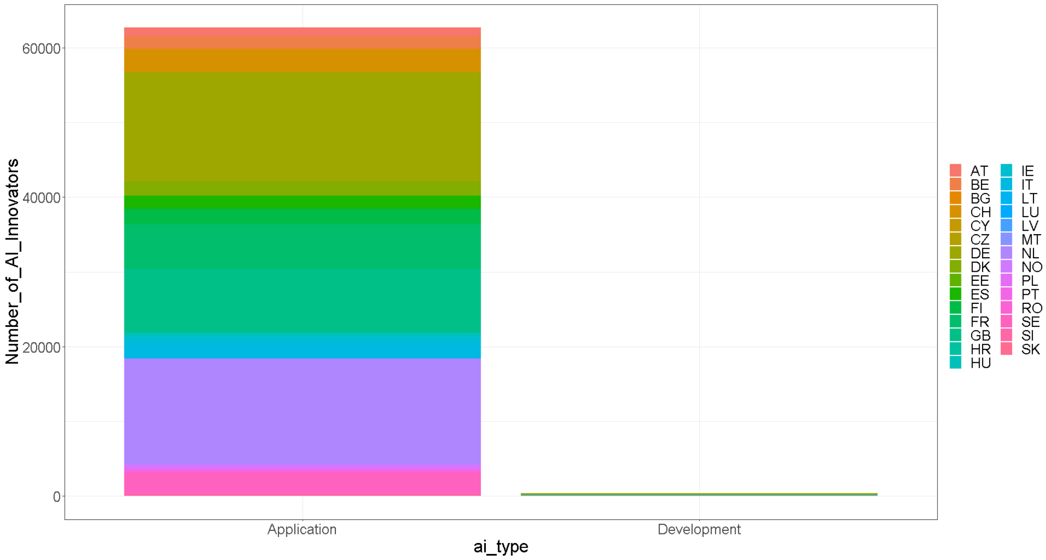

Fig. 7 The Number of inventors of AI Co-patents with At Least Two European inventors by Knowledge Type and Country, 1982-2020, NUTS 2 Region Level
Source: Own elaborations

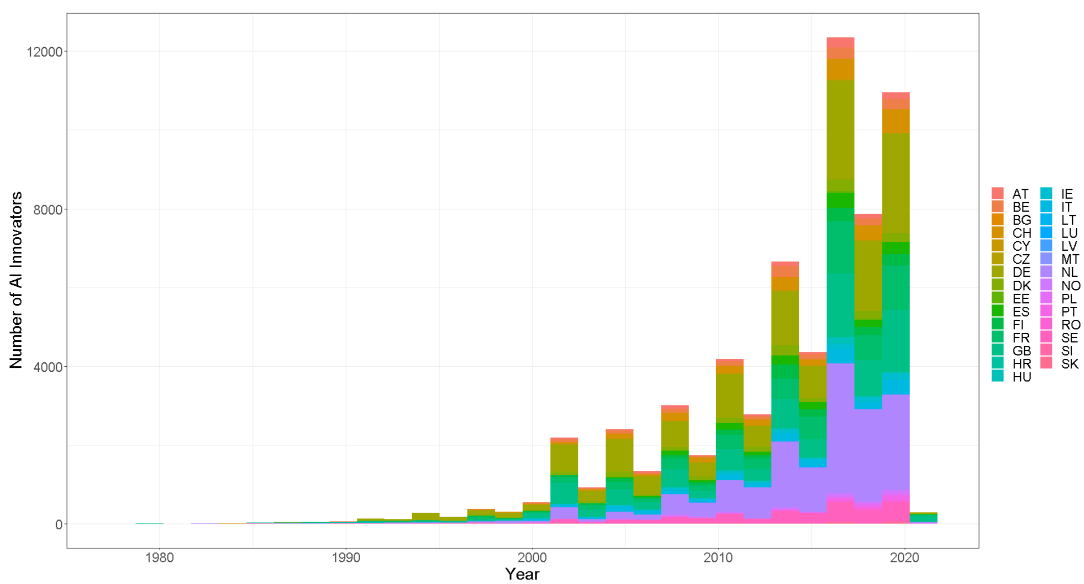

Fig. 8 The Number of inventors of AI Co-patents with At Least Two European inventors by Year and Country, 1982-2020, NUTS 2 Region Level
Source: Own elaborations

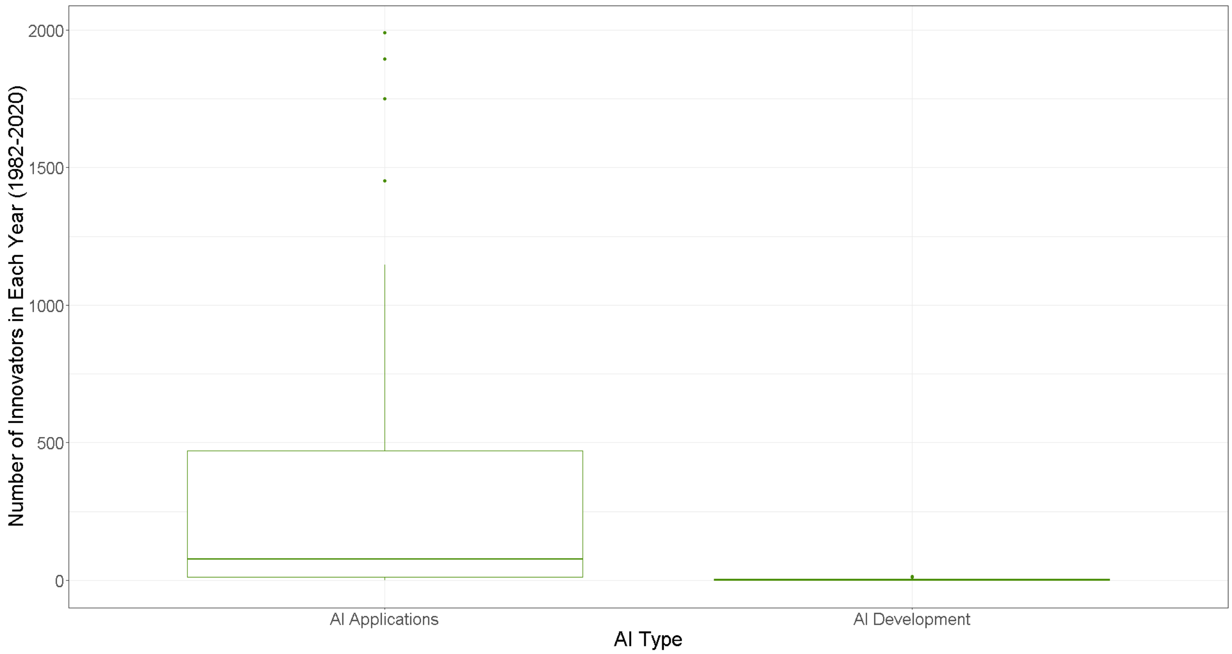

Fig. 9 The Number of inventors of AI Co-patents with At Least Two European inventors in Each Year by Knowledge Type, 1982-2020, NUTS 2 Region Level
Source: Own elaborations

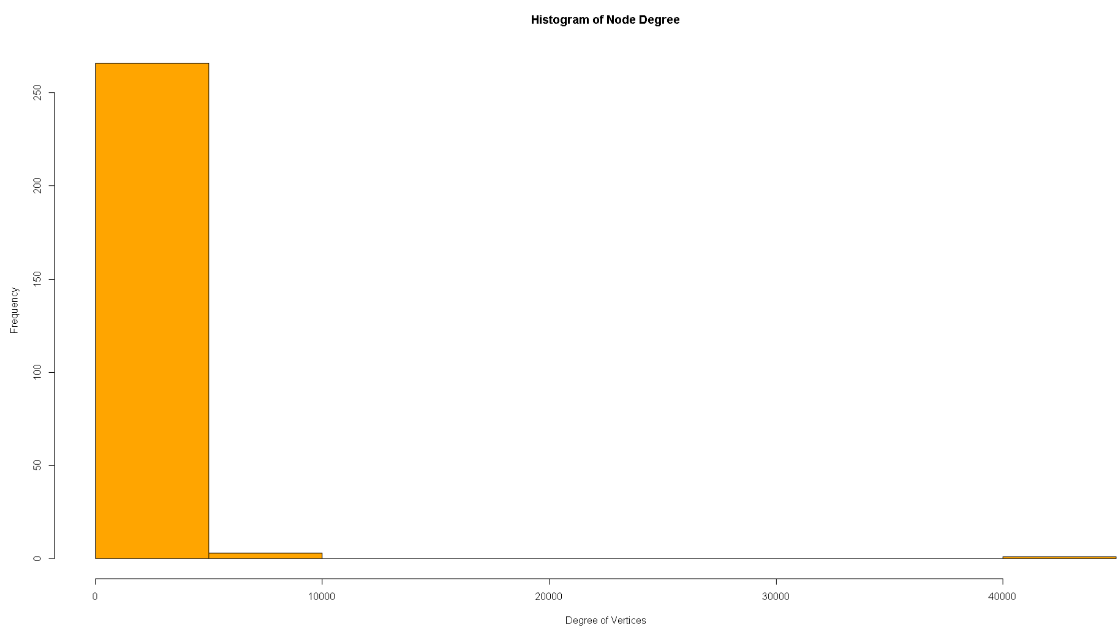

Fig. 10 Histogram of Node Degree in the Collaborative Network between NUTS 2 Regions
Source: Own elaborations

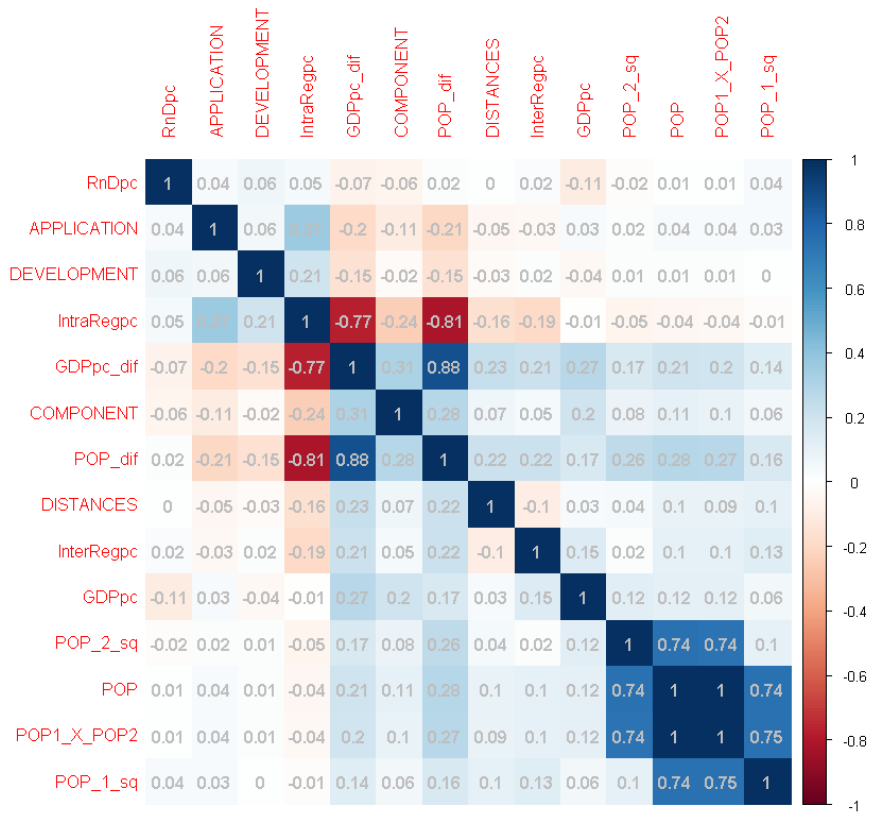

Fig. 11 Heatmap of Correlation Coefficients between Variables
Source: Own elaborations

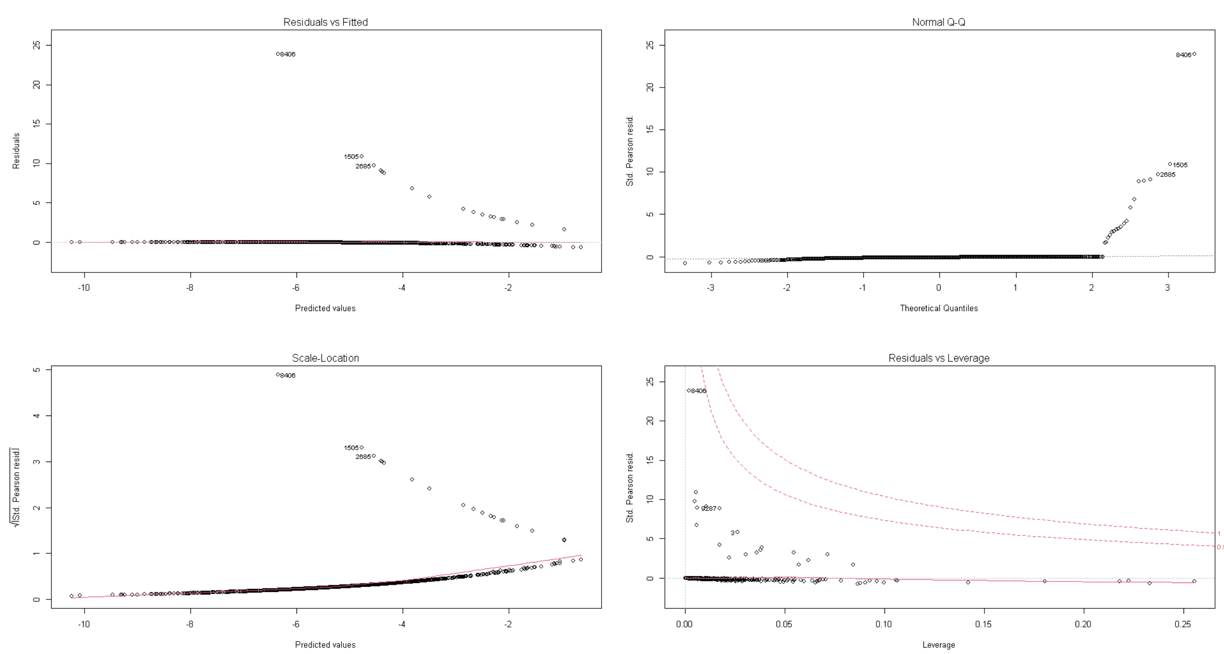

Fig. 12 Assumption Tests of Logit Regression of DEVELOPMENT
Source: Own elaborations

Table 7 Firth's Bias-Reduced Logistic Regression of DEVELOPMENT as Robustness Testing

	Dependent variable: DEVELOPMENT (2011-2020)	
	Coefficient	P value
IntraRegpc	0.37	0.132
	(0.23)	
InterRegpc	0.64***	0.010
	(0.21)	
DISTANCES	0.71	0.330
	(0.64)	
POP	4.84	0.580
	(7.79)	
GDPpc	-0.82	0.127
	(0.44)	
RnDpc	0.43*	0.091
	(0.25)	
POP_dif	-0.03	0.828
	(0.13)	
GDPpc_dif	-0.15	0.475
	(0.18)	
POP_1_sq	-0.19	0.552
	(0.28)	
POP_2_sq	-0.15	0.626
	(0.27)	
COMPONENT	0.34	0.611

	(0.62)	
Constant	-58.85	0.645
	(111.84)	

Note: t statistics in parentheses
*p<0.1; **p<0.05; ***p<0.01

Source: Own elaborations

Table 8 Results of Robustness Tests regarding Regression of APPLICATION for the Zero Part

	Dependent variable: APPLICATION (2011-2015)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IntraRegpc	-2.55	-1.52	-1.34	-1.32	-1.43	-1.45	-1.49	-0.58	-0.59	-0.56
	(3.01)	(1.43)	(1.28)	(1.01)	(1.17)	(1.32)	(1.41)	(0.46)	(0.46)	(0.45)
InterRegpc		0.43***	0.48***	0.30***	0.32***	0.33***	0.34***	0.33***	0.33***	0.34***
		(0.08)	(0.08)	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
DISTANCES			0.71***	-0.61*	-0.58	-0.54	-0.54	-0.59	-0.59	-0.61*
			(0.24)	(0.36)	(0.37)	(0.36)	(0.36)	(0.36)	(0.36)	(0.37)
POP					-0.18	-0.16	-0.16	-0.25*	-0.25*	-0.26**
					(0.11)	(0.12)	(0.12)	(0.13)	(0.13)	(0.13)
GDPpc						-0.21	-0.23	-0.29	-0.29	-0.31
						(0.19)	(0.19)	(0.21)	(0.22)	(0.23)
RnDpc							-0.05	-0.06	-0.06	-0.06
							(0.07)	(0.07)	(0.07)	(0.07)
POP_dif								0.11*	0.10	0.10
								(0.06)	(0.07)	(0.07)
GDPpc_dif									0.01	-0.001
									(0.08)	(0.08)
COMPONENT										0.50
										(0.48)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
InterRegpc: DISTANCES				1.39***	1.38***	1.39***	1.38***	1.42***	1.43***	1.42***
				(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)	(0.31)
Constant	-0.99***	-1.12***	-1.38***	-1.07***	4.05	7.84	8.35*	10.77**	10.76**	11.10**
	(0.18)	(0.15)	(0.19)	(0.18)	(3.18)	(4.80)	(4.80)	(5.22)	(5.32)	(5.40)
Observations	859	859	859	859	859	859	859	859	859	859
Log Likelihood	-2,359.44	-2,317.21	-2,309.48	-2,288.56	-2,285.06	-2,282.01	-2,279.89	-2,261.47	-2,261.31	-2,259.82
Note:										*p<0.1; **p<0.05; ***p<0.01

Source: Own elaborations

Table 9 Results of Robustness Tests regarding Regression of APPLICATION for the Count Data

	Dependent variable: APPLICATION (2011-2015)									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
IntraRegpc	0.63***	0.69***	0.67***	0.68***	0.67***	0.68***	0.67***	0.47***	0.47***	0.46***
	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.05)	(0.05)
InterRegpc		0.32***	0.30***	0.33***	0.32***	0.33***	0.33***	0.39***	0.39***	0.39***
		(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
DISTANCES			-0.28*	-0.11	-0.15	-0.09	-0.10	0.11	0.11	0.11
			(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
POP					0.10*	0.12**	0.11**	0.22***	0.23***	0.23***
					(0.05)	(0.05)	(0.05)	(0.06)	(0.06)	(0.06)
GDPpc						-0.24**	-0.21**	0.01	-0.01	0.02
						(0.10)	(0.10)	(0.11)	(0.11)	(0.11)
RnDpc							0.06*	0.09***	0.09***	0.09***
							(0.03)	(0.03)	(0.03)	(0.03)

POP_dif								-0.09^{***}	-0.11^{***}	-0.11^{***}
								(0.02)	(0.04)	(0.04)
GDPpc_dif									0.03	0.03
									(0.05)	(0.05)
COMPONENT										-0.18
										(0.17)
InterRegpc: DISTANCES				-0.54^{***}	-0.54^{***}	-0.53^{***}	-0.56^{***}	-0.65^{***}	-0.64^{***}	-0.65^{***}
				(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)	(0.16)
Constant	1.98^{***}	1.70^{***}	1.77^{***}	1.75^{***}	-0.99	3.46	2.82	-4.15	-3.93	-4.47
	(0.07)	(0.07)	(0.08)	(0.08)	(1.51)	(2.38)	(2.37)	(2.65)	(2.68)	(2.72)
Observations	859	859	859	859	859	859	859	859	859	859
Log Likelihood	-2,359.44	-2,317.21	-2,309.48	-2,288.56	-2,285.06	-2,282.01	-2,279.89	-2,261.47	-2,261.31	-2,259.82
Note:								$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$		

Source: Own elaborations