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EVALUATING AND ENHANCING LOCAL INNOVATIVENESS: A NOVEL APPROACH USING PREDICTIVE MODELS

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Purpose: This study seeks to develop and empirically validate a predictive model for assessing local innovativeness at the municipality level. It responds to the increasing demand among Local Administrative Units for evidence-based insights into the socio-economic and fiscal determinants of innovation and investigates the feasibility of forecasting innovation performance using routinely collected public data.
Design/methodology/approach: The research adopts a quantitative methodological framework, integrating objective administrative data sourced from national institutions (e.g., Statistics Poland, the Ministry of Finance, and the Social Insurance Institution) with subjective data obtained via a CAPI survey conducted among 2,418 enterprises in 144 municipalities in the Kuyavian-Pomeranian Voivodeship. A classical risk scorecard modelling approach—widely employed in the financial sector—was adapted to identify determinants of local innovativeness and to construct a statistical model predicting the Predicted Innovation Rate.
Findings: The study confirms that publicly accessible data can be effectively utilised to forecast local innovation potential. Six key predictors were identified, including tax base structure, average non-agricultural income, the sectoral composition of local enterprises (notably real estate and education), and VAT data related to service imports. Higher levels of innovativeness were associated with a greater presence of education-oriented businesses and higher service imports, whereas a concentration of real estate firms correlated negatively with innovation. The model demonstrated moderate predictive capability and enabled the stratification of municipalities by innovation potential.
Research limitations/implications: As the model was developed using data from a single voivodeship, its generalizability may be constrained. Future research should explore model validation in other regional contexts and incorporate additional qualitative variables to enhance interpretability and predictive accuracy.
Practical implications: The proposed model provides municipalities with a cost-efficient, data-driven tool for monitoring and fostering local innovation. It enables the formulation of targeted development strategies and evidence-based policy interventions.

Social implications: The model has the potential to inform public policy aimed at enhancing regional innovation capacity, reducing territorial disparities, and supporting socio-economic cohesion through the promotion of knowledge-intensive activities.
Originality/value: This paper presents one of the first predictive modelling approaches for evaluating innovativeness at the municipal level, offering a novel, scalable framework of practical relevance to policymakers, local authorities, and development agencies.
Keywords: innovativeness, forecasting, municipality, predictive modelling, risk scorecard Models.
Category of the paper: Research paper.

1. Introduction

The modern economy increasingly relies on innovativeness, which is a key driver of growth for both businesses and entire communities (Freeman, Soete, 1997; Porter, 1990; Schumpeter, 2008; Schumpeter, 1912). Innovativeness is defined as the ability to introduce new, more effective solutions, products, and services that not only improve quality of life but also contribute to economic growth and social development (OECD & Eurostat, 2018; Zastempowski, 2024c). As research highlights, innovations play a decisive role in building competitive advantage at local, regional, and global levels (Porter, 1990; Tidd, Bessant, 2018) while also fostering sustainable economic growth and improving the quality of life for residents of cities and regions (Fagerberg et al., 2006; Schwab, 2017; Tolstov, 2024; Geels et al., 2008; Aghion et al., 2015).

In the era of rapid technological advancement, innovations have become the foundation of knowledge-based economies (Schwab, 2017). For municipalities, cities, regions, and countries competing on the global stage for investment capital, talent, and innovative companies, the ability to effectively implement new solutions is crucial (Woetzel et al., 2018; Katz, Nowak, 2017). The capacity to create and absorb innovations is closely tied to socio-economic factors such as the level of education, employment structure, availability of infrastructure, and the fiscal and investment policies of local governments (Asheim, Gertler, 2009).

Annual innovation rankings of cities, regions, and countries, such as the Global Innovation Index (GII) (WIPO, 2023), European Innovation Scoreboard (EIS) (European Commission, 2023), and local rankings compiled by national research institutes, are important tools for assessing the innovative capacity of these entities. Global rankings like the GII compare the innovativeness of countries based on a range of indicators, including research and development (R&D) spending, the quality of technological infrastructure, access to financing for innovative projects, and international collaboration (WIPO, 2023). At the European level, the EIS evaluates EU countries by analyzing factors such as digitalization, education, and R&D collaboration, identifying both innovation leaders and countries developing in this area (European Commission, 2023a). Meanwhile, regional and local rankings, such as those of the most innovative cities, consider factors specific to municipal entities, such as the availability of space for startups, tax policy, and environmental protection efforts (Naylor, Florida, 2003).

Forecasting innovativeness has become a crucial tool for governments, local authorities, businesses, and investors alike (Mazzucato, 2021; European Commission, 2023). The ability to predict how a given area's innovativeness will develop allows for better urban planning and more efficient resource management. In this context, the use of socio-fiscal and economic data becomes especially important, helping to identify key factors influencing innovativeness and enabling better forecasting of future trends. For example, studies show a strong correlation between R&D spending, the quality of education, the availability of public funding, and the level of urban innovativeness (Mazzucato, 2021). Analyzing such indicators not only helps assess the current situation but also identifies areas where improvements can be made, which is crucial for developing sustainable and modern communities.

Additionally, a systematic literature review (SLR) on measuring, predicting, and forecasting innovation across different territorial levels reveals that most studies on innovation forecasting focus on national or regional levels, while only a small fraction address the local level.

Assuming that most local administrative units (LAUs), such as municipalities, seek information on the conditions or factors necessary to enhance their innovation rates and the measures they should take to motivate and attract companies towards greater innovation, we posed the research question: Can existing data collected by various national agencies, such as statistical offices, the Social Insurance Institution, or the Ministry of Finance, be used to support municipalities in identifying factors necessary to increase innovation rates?

To explore this, the empirical section of our study describes a novel experiment in which we combined objective and subjective data to develop a statistical model capable of predicting the innovation levels of municipalities. We used data from 144 municipalities from one of the voivodeships in Poland.

This paper is organized as follows. The first section provides the theoretical background by exploring measurements and rankings of innovativeness and presenting the results of an SLR on measuring, predicting, and forecasting innovation at various territorial levels. The second and third sections present the research methodology and results, respectively, while the final section discusses the results and their practical implications.

2. Theoretical Background

2.1. The Measurement and Ranking of Innovativeness

Innovation is a remarkably intricate and unique phenomenon (Zastempowski, 2024c; Liczmańska-Kopcewicz et al., 2024) that is an attribute of not just enterprises but also individual regions and entire economies. We can define it as the ability to create, implement, and absorb innovative solutions (Rajapathirana, Hui, 2018; Zastempowski, 2022). It is an activity on various levels that must be undertaken to achieve the final effect of innovation using internal and external resources. The consequence of this activity is the expenditure allocated to the implementation of the entire innovation process and the direct effects of the innovative activity (Biel, 2023), which specialists often use to create international comparisons in the field of innovation.

Defining and measuring innovation, along with selecting the appropriate parameters for accurately assessing innovation levels within spatial units, is a rather complex challenge. Furthermore, Brynjolfsson and Yang (1996) rightly point out that measuring innovation involves specific operational difficulties, such as the absence of universally accepted methods for valuing intellectual capital, the changing nature of innovation over time, and the delayed realization of expected innovation effects, all of which add to the multi-layered complexity of the issue. Similarly, Gault (2018) highlights the importance of the dimension and scope of innovation in the professional management of organizations from a managerial perspective and in evaluating the innovative standing of economic entities, regions, or economies.

As a result, several global and regional rankings have been developed to classify the level of innovation in individual countries. However, it is important to note that these rankings differ in both their objectives and research methodologies. At the global level, the most frequently cited rankings include the Global Innovation Index (GII) (WIPO, 2023), the Bloomberg Innovation Index (BII) (Bloomberg, 2021), and the International Innovation Scorecard (IIS) (CTA, 2023). At the regional level, the European ranking is noteworthy for its methodological foundation, which is based on the guidelines of the Oslo Manual (OECD & Eurostat, 2018). This ranking relies on data from the Community Innovation Survey (CIS) conducted by Eurostat and the European Commission on a biennial basis. The CIS is a statistical survey that provides detailed data on the innovation activities of enterprises in Europe. It collects information on various dimensions of innovation, such as investment in research and development, innovation collaboration, barriers to innovation, and the outcomes of innovation (Zastempowski, 2023). Consequently, the European Innovation Scoreboard (EIS) (European Commission, 2023a) and the Regional Innovation Scoreboard (RIS) (European Commission, 2023b) are derived based on the Summary Innovation Index (SII) and the Regional Innovation Index (RII), respectively. A comprehensive overview of the data collection methods employed by these institutions and the metrics they use to assess innovation is provided in Table 1.

Table 1.
Description of Data Collection and Innovation Measures Used: A Comparison of Key Rankings

Name of the study	Scope of the survey	Innovation measurement framework – thematic groups
CIS	The CIS is a survey about innovation activities in enterprises. The survey is designed to capture the information on different types of innovation, to enable analysis of innovation drivers or to assess the innovation outcomes.	The CIS focuses on the following aspects: - Innovation activities - Innovation expenditure - Innovative products (new to firm, to the market) - Turnover from innovative products - Business process innovation - Incentives for implementation of innovation - Innovation cooperation - Source of financing of innovation - Sources of information on innovation - Innovation barriers
EIS / SII	The EIS provides an extensive comparative analysis of innovation performance among EU Member States, as well as other European countries and regional neighbors. The EIS uses the most recent statistics from Eurostat (for the seven indicators using CIS data) and other internationally recognized sources as available at the time of analysis.	The SII groups 32 indicators into 4 main category of innovation dimensions including 12 subcategories: 1. Framework conditions: - Human resources - Attractive research systems - Digitalization 2. Investments: - Finance and support - Firm investments - Use of information technologies 3. Innovation activities: - Innovators - Linkages - Intellectual assets 4. Impacts: - Employment impacts - Sales impacts - Environmental sustainability
RIS / RII	RII is a synthetic measure of the level of innovation in European regions. The RIS 2023 follows the methodology of the EIS 2023 and uses data for 239 regions across Europe for 21 of the 32 indicators used in the EIS 2023. This index is a weighted average of the measures obtained for individual groups thematic. The metric for a group is the arithmetic mean of the normalized values indicators included in the study.	The RII groups 21 indicators into 3 main blocks including 7 subcategories: 1. Driving forces of innovation: - Human resources - Support government and financial 2. Enterprise activities: - Investments - Connections and cooperation - Intellectual assets 3. Effects of innovative activities: - Innovators - Economic effects
GII	In GII assesses the levels of innovation in 132 world economies. The overall GII ranking is based on two sub-indices that are both equally important in presenting a complete picture of innovation. Each sub-pillar is calculated by taking the weighted average of its individual indicators' scores, which are normalized to again produce scores between 0 and 100.	The GII groups 81 indicators into 2 sub-indices including together 7 pillars: 1. Innovation Input Sub-Index: - Institutions - Human Capital and Research - Infrastructure - Market Sophistication - Business Sophistication 2. Innovation Output Sub-Index - Knowledge and Technology Outputs - Creative Outputs

Cont. table 1.

BII	The ranking process began with more than 200 economies, scored on a 0-100 scale in seven equally weighted categories. Nations that didn't report data for at least six categories were eliminated, trimming the total list to 111. Bloomberg publishes the top 60 economies.	The BII groups indicators into 7 main categories: - R&D Intensity - Manufacturing Value-Added - Productivity - High-Tech Density - Tertiary Efficiency - Researcher Concentration - Patent Activity
IIS	Consumer Technology Association's International Innovation Scorecard has expanded to evaluate 70 countries, including the entire G-20, and all 27 members of the European Union. These countries are then ranked in four ascending tiers: Modest Innovators, Innovation Adopters, Innovation Leaders and Innovation Champions. Point ranges are assigned to each of the 17 categories of innovation factors, grouping countries from grades A to D.	The IIS is a comparative analysis of 40 indicators across 17 categories: - Artificial Intelligence - Broadband - Cybersecurity - Digital Assets - Diversity - Drones & Advanced Air Mobility - Entrepreneurial Activity - Environment - Freedom - Human Capital - R&D Investment - Resilience - Self-Driving Vehicles - Tax Friendliness - Tech Trade - Telehealth - Unicorns

Source: own study based on (WIPO, 2023; European Commission, 2023a, 2023b; Bloomberg, 2021; CTA, 2023).

The use of various approaches to measuring innovation arises from the complex nature of the innovation process and is, therefore, not without certain research limitations. Moreover, as Björk et al. (2023) point out, each innovation is, by definition, qualitatively different from the solution that preceded it. This has three significant implications for the nature of its measurement (Björk et al. (2023):

- Firstly, innovation, as a multidimensional process, is more difficult to measure or compare within and between economic entities than, for instance, the production process.
- Secondly, given the nature of innovation, resources and funds often have a qualitative dimension, which makes it particularly challenging to identify appropriate measures.
- Thirdly, the management and measurement of the innovation process are distributed over time and may be more interdisciplinary than linear measurements.

Regardless of the research methodology adopted or the use of more or less standardized criteria, there is a need for the periodic collection and analysis of data that reflects the quantity and quality of implemented innovations (Srholec, 2011; Hoffecker, 2018; Lema et al., 2021; Anand et al., 2021; Fu, Shi, 2023), particularly in developing countries.

It is also important to note that relatively few studies analyze and rank innovation at the level of smaller territorial units (Jucevičius et al., 2017; Makkonen, 2011; Nordberg et al., 2024), such as municipalities (Local Administrative Units - LAUs). Most studies focus on the Nomenclature of Territorial Units for Statistics (NUTS) levels (European Parliament, 2003):

NUTS 1 (major socio-economic regions), NUTS 2 (basic regions for regional policies), and NUTS 3 (small regions for specific diagnoses). Therefore, it is pertinent to inquire about the current state of knowledge regarding the measurement, prediction, and forecasting of innovation across various territorial categories.

2.2. Insights from the Systematic Review of Literature

To provide a comprehensive review of the literature, we employed a systematic literature review (SLR) methodology proposed by Tranfield (2003). We examined two scientific databases: Web of Science and Scopus. We based our search on the following search string in the title field: (*measurement* OR forecast* OR predict**) AND (*community OR municipality OR voivodeship OR region OR country*) AND *innovati**. The results (as of 11/09/2024) showed 49 documents in Scopus and 36 in Web of Science. In the next step, the following inclusion and exclusion criteria were applied: (1) Document type: Article; (2) Source type: Journal; (3) Publication stage: Final; and (4) Language: English. Finally, as shown in Table 2, 32 articles were identified for further analysis after removing duplicates.

Table 2.
Details of Systematic Literature Review

Criterion	Scopus	Wos
Search string: (measurement* OR forecast* OR predict*) AND (community OR municipality OR voivodeship OR region OR country) AND innovati* in article title	49	37
Document type: Article	29	25
Source type: Journal	28	25
Publication stage: Final	27	23
Language: English	27	23
Total	50	
Net total, after removal duplicates	32	

Source: own study.

The results obtained from the SLR corroborate the earlier observation that most studies on predicting the level of innovation focus on the national or regional level (NUTS 1 - NUTS 3). Only a small part of the studies are those that consider forecasting on the LAUs levels and, therefore, potential local predictors of innovation. Below, we present the key conclusions drawn from the conducted SLR.

The majority of studies are related to the national perspective. For instance, Kumail et al. (2023) address the issue of CO_2 emissions and the role of innovation in reducing them. Their country-level research (1996-2019) suggests that gross domestic product, tourism, and the human development index are strong indicators of innovation and support the growth-led innovation hypothesis.

Erdin and Çağlar (2023) focus on measuring and analyzing the national innovation performance of OECD countries. Their study, based on 2019 GII data, suggests that OECD countries have a greater capacity to create and provide elements that facilitate innovation activities than to produce innovative products. The findings also indicate that OECD countries generally possess a favorable innovation environment and a high level of resources.

Dungey et al.'s (2017) research does not directly address the prediction of innovation levels. Instead, it focuses on the role of correlated innovations and their impact on forecasting real GDP growth in the G7 countries, demonstrating that the effect is positive.

Jurickova et al. (2019), in turn, present the results of a study measuring the technical efficiency of the National Innovation System across a sample of European Union (EU) countries, using data from Eurostat and the World Bank for the period 2005-2016. The following indicators were identified as predictors: the total number of researchers in full-time equivalents, research and development expenditures (in million EUR), scientific journal articles, and patent applications.

Another study that explores the prediction of a country's innovativeness is the one conducted by Lourenço and Santos (2023). The aim of this study was to investigate how Hofstede's cultural dimensions serve as predictors of a country's innovativeness, as measured by the GII. The results suggest that the dimensions of individualism, long-term orientation, and indulgence positively affect a country's innovativeness, while uncertainty avoidance has a negative effect.

Nevezhin et al. (2019) also consider models for forecasting the level of innovation development in countries, as well as the most important factors influencing innovation development. Based on Global Innovation Index (GII) data, their study suggests that institutions, human capital and research, infrastructure, domestic market development, business development, scientific and technological outputs, intangible asset outputs, and the development of creative activities are key influencing factors.

Another group of studies addresses the issue of predicting innovation at the regional level. For example, Boiarynova et al. (2022) and Popelo et al. (2021) propose a method for assessing and forecasting the innovative development of regions, which has been tested using the case of Polish voivodeships. This forecasting approach is based on four key indicators: (1) the number of industrial enterprises that have implemented innovations (units), (2) the volume of innovative products sold by industrial enterprises per economically active person (in euros), (3) the volume of innovative products sold by industrial enterprises as a percentage of the total volume of industrial products sold, and (4) the amount of funding for innovation per economically active person (in euros).

The results presented by Gandin and Cozza (2019) are also noteworthy, as they demonstrate the use of CIS data to predict the innovativeness of regional enterprises in Italy. The identified predictors of innovativeness, defined as obtaining a patent, include company size, sector affiliation, and investment in intangible assets.

The prediction of regional innovativeness is also the focus of research presented by Litvintseva et al. (2017) using Rosstat data from 2002 to 2015, they identify potential predictors of innovativeness for the Siberian Federal District. The key predictors include expenditures on technological innovation by organizations, internal costs of research and development, the number of organizations engaged in scientific research and development, granted patents, and investment in fixed assets .

A regional perspective on innovation is also present in the research by Martinidis et al. (2021), which examines 207 regions of the European Union using RIS and Eurostat data from 2017 to 2020. Their findings indicate that regional innovation (measured by three indicators) is associated with labor force specialization, skills and research networks, and social capital.

The challenges of predicting innovation on a regional scale are indirectly related to the research by Hilmawan et al. (2023). Their study focuses on the opposite relationship, specifically the impact of local government innovation on district development in Indonesia.

The perspective of LAUs is addressed by the fewest studies. For example, Viana et al.'s (2024) research indirectly addresses the issue of innovation at the municipal level by examining the relationship between innovation and regional economic resilience using 14 socio-economic indicators from the most populated Brazilian municipalities. Interestingly, the results indicate that innovation did not serve as a distinguishing factor for classifying regions as resistant or non-resistant.

Prasetyo et al. (2023), in turn, address the issue of measuring the maturity of innovation and technology within the Magelang City community, using data from 2004 to 2019. Their findings suggest that predictors of innovation maturity can be identified in areas such as technology, market, human resources, manufacturing, supply chain, investment, partnership, and risk.

The issue of predicting innovation is indirectly addressed by the work of Albuquerque and Rocha (2019), which focuses on the role of the Third Sector in generating social innovation at a local scale. This is illustrated by social and ecological experimentation initiatives in Portugal.

The work of Gullmark and Clausen (2023) also does not directly address the prediction of innovation at the level of LAUs. Instead, it focuses on identifying factors that promote innovation within local government organizations through a systematic literature review (SLR). The potential for innovation in these organizations is shaped by several factors, including entrepreneurial public sector employees, managers, and politicians; responsiveness to pressures and needs; experiential learning and knowledge sharing; an innovative culture; effective management of innovation processes; and a flat, flexible organizational structure.

The presented SLR results highlight several key points. First, analyses focusing on national and regional perspectives dominate the field. Second, the most frequently used data sources are the GII, Eurostat (CIS, RIS), World Bank, and OECD databases. Third, very little research addresses the prediction of innovation at the LAU level.

Consequently, assuming that most LAUs, such as municipalities, seek information on the conditions or factors necessary to enhance their innovation rates and the measures they should take to motivate and attract companies toward greater innovation, we pose the following research question:

RQ: Can existing data collected by various national agencies, such as statistical offices, the Social Insurance Institution, or the Ministry of Finance, be used to support municipalities in identifying factors necessary to increase innovation rates?

3. Materials and Methods

3.1. Data Gathering

The empirical research was conducted in 2019 in the Kuyavian-Pomeranian Voivodeship in central-northern Poland, as part of the "Regiogmina" project, which was financed by the National Centre for Research and Development. Its aim was to develop a regional policy that would help municipalities and their local government authorities support all initiatives aimed at developing entrepreneurship and innovation.

The implementation of the project allowed for the collection of two data sets. The first included objective data describing the socio-fiscal and economic situation of 144 municipalities in the studied Kuyavian-Pomeranian voivodeship. This data was obtained from four main sources:

- National Official Register of Economic Entities (NOREE): A continually updated repository of information on economic entities in Poland.
- Local Database of Statistics Poland: The largest database in Poland covering the economy, households, innovations, public finances, society, demography, and the environment.
- Social Insurance Institution: A Polish state organization responsible for managing social insurance.
- Ministry of Finance (Tax Office and Tax Administration Chamber): A government body in Poland responsible for drafting the national budget, managing taxes, financing local self-governments, and handling issues related to public debt.

The second data set was derived from a survey conducted using the Computer-Assisted Personal Interviewing (CAPI) technique on a sample of 2,418 enterprises. The companies participating in the survey were randomly selected by the Kuyavian-Pomeranian Statistical Office, based on the NOREE register. The stratified sample, with quotas for sectors according to PKD 2007 (the Polish Classification of Business Activities), subregion (NUTS 3), and municipality (LAU), was representative of the entire population of enterprises in the voivodeship. The data obtained in this manner were subjective in nature, as they were based on the opinions of individuals - either entrepreneurs or managers. It is important to emphasize that all participants were informed that the survey was anonymous. We analyzed the data anonymously and did not collect any personal information. Therefore, in accordance with the guidelines of the National Science Center (2016, p. 2), which form the basis for developing research guidelines at our university (Nicolaus Copernicus University Senate, 2017, p. 5), our study did not require approval from an ethics committee.

Having both types of data - objective and subjective - enabled us to conduct a novel experiment to combine them and build a statistical model. This model, based on objective data that can be periodically collected, allows for the forecasting of an innovation index using a one-time survey and the subjective responses of entrepreneurs.

3.2. Model Event Definition

The central concept in predictive modeling is the modeling of an event. It is the event that is expected to be predicted, as this event is crucial for the business process - in this case, the management of a municipality aimed at creating an environment that motivates companies to be more innovative.

The modeled event was identified using information from the second data set (obtained through the CAPI method). In the study, entrepreneurs and managers were asked whether they had introduced new or significantly improved products or services in the last three years (2016-2018). Based on their responses, we distinguished two statuses for the objective function used in modeling:

- *Innovative:* A company classified as innovative that responded affirmatively to the question.
- *Non-innovative:* A company classified as non-innovative that responded negatively to the question.

The observed statistic that describes the share of innovative companies within a given group (municipality) is designated as Innovation Rate (IR). The forecasted value of this statistic is designated as the Predicted Innovation Rate (PIR).

3.3. Construction of Model Variables

Data for constructing variables that describe enterprises were obtained from aggregated indicators at the municipality level, originating from the first data set, which includes:

- NOREE: Number of enterprises for 2017-2018.
- Local Database of Statistics Poland: Unemployment rates, liabilities, and population statistics for 2017-2018.
- Social Insurance Institution: Number of insured individuals and insurance premiums for 2017-2018, categorized by company size, industry code, and age group.
- Ministry of Finance: Tax and VAT returns for 2017-2018, categorized by company size, industry code, and age group.

As was described (3.2), the model event is associated with the survey conducted in 2019. This setup allows for a classic cause-and-effect analysis, aiming to identify characteristics of municipalities from 2017-2018 that contributed to an increase or decrease in the share of innovative companies in 2019.

A total of 396 variables were developed to describe various factors aggregated at the municipality level. The modeling approach was as follows: using aggregated factors from each municipality for the years 2018 and 2019, the model aims to explain and predict the probability of a company's innovative status observed in 2019.

Specifically, the objective is to determine which conditions or factors municipalities need to satisfy to enhance the Innovation Rate (IR) in a given area. What measures should a municipality take to motivate and attract companies to be more innovative? Can these questions be addressed using existing data collected by various national offices? The goal is to assess whether it is feasible to utilize readily available data - such as information from tax controls, company registries, and mandatory financial reporting - instead of collecting new, costly, and difficult-to-obtain data.

The final modeling dataset consists of 4836 observations, namely, 2418 corresponding to companies surveyed in 2019 and observed data from databases twice in 2017 and 2018, so every surveyed company has two data points in 2017 and 2028. For each company in the survey, 396 variables were calculated for both years. The data was randomly divided into two subsets: Training and Validation, as detailed in Table 3.

Table 3.
Datasets Used in the Modeling Process

Dataset	All	Innovative	Non-innovative	IR [%]
Training	3170	580	2590	18,3
Validating	1666	326	1340	19,6
All	4836	906	3930	18,7

Source: own calculations.

3.4. Method

The method is based on classical risk scorecard models used in the banking environment (Kaszyński, et al., 2020). These scorecards are employed in key processes such as International Financial Reporting Standard 9 (IFRS 9) for provision calculation, Internal Ratings-Based (IRB) for risk-weighted asset calculation, and various credit risk acceptance processes where different types of credit are evaluated.

The methodology for model building adheres to the principles outlined in Basel II documents (BIS-Basel, 2005). It also incorporates well-established methods described in recognized books and articles (Kaszyński et al., 2020; Anderson, 2007; Lessmanna et al., 2013; Thomas et al., 2002; Siddiqi, 2015).

According to the recommendations, the model-building process consists of the following steps (Kaszyński et al., 2020; Anderson, 2007; Lessmanna et al., 2013; Thomas et al., 2002; Siddiqi, 2015):

- *Random Sample and Data Partition:* Two datasets are created - training and validating - using a simple random sampling method (without duplication) in proportions of 60% and 40%, respectively.
- *Binning, Categorization, and Grouping:* Variables are grouped and categorized. Interval variables are split into categories based on entropy statistics, a common technique used in decision tree methods. Nominal variables are also grouped, especially when the number of unique categories is large. After binning, each variable is transformed into a logit variable.
- *Variable Preselection:* Univariate statistics are used to identify non-essential variables, such as those with minimal predictive power or instability over time.
- *Multifactor Analysis:* Multidimensional variable selection is performed using a heuristic method called branch and bound (Furnival, Wilson, 1974).
- *Model Assessment:* There are no universal criteria for model evaluation, but the following are commonly used:
  - *Gini:* The Gini statistic for the model, which measures predictive power, ranges from 0% to 100% (Řezáč, Řezáč, 2011).
  - *R. Gini:* The relative difference between the Gini coefficients of the training and validation datasets. It measures the stability of the discovered rules and the model's predictive power.
  - *GainsXX:* The ability to identify innovative cases within the top percentiles of the sample. It represents the percentage of innovative cases among all cases in the sample (training dataset) that can be identified by focusing on the first XX-percentile of scores.
  - *KS Score:* The Kolmogorov–Smirnov statistic, which measures the stability of the score distributions between the training and validation datasets.
  - *PSI Score:* The Population Stability Index measures the stability of model scores by quantifying the distance between score distributions in the training and validation datasets. Common benchmarks for stability are ≤0.1 or ≤0.5.
  - *Max VIF:* The maximum variance inflation factor for variables, a collinearity measure in logistic regression models. It is based on R-square statistics from a linear regression model where one variable is dependent and the others are independent. Typical benchmarks are <2.5, <3, <5, or <10 (Midi et al., 2010).
  - *Max Pearson:* The maximum Pearson correlation coefficient between all pairs of variables; it is also a measure of collinearity.

- *Max Con Index:* The maximum Condition Index, another measure of collinearity based on the eigenvalues of the covariance matrix. Typical benchmarks are <50, <100, or <150 (Flom, 1999).
- *LiftXX:* Similar to GainsXX, this measures the ability to identify innovative cases in the top percentiles of the sample. It indicates how many times more innovative cases can be identified by focusing on the first XX-percentile of scores compared to a random model.

- *Model Implementation:* It is recommended to calculate all innovation factors, particularly the Predicted Innovation Rate (PIR), on a yearly basis and use this as a measure of innovation change.
- *Monitoring and Testing:* After each annual calculation, some factors may be tested through additional surveys, potentially on a smaller scale or focusing on extreme cases, such as the highest or lowest predicted innovation rates, to verify and monitor the alignment between observed and predicted innovation measures. Furthermore, predicted innovation rates can be used to rank all communes, enabling more in-depth studies of selected communes to understand changes and assess the quality of innovation. Additionally, recommendations tailored to specific communes can be developed to enhance innovation. This can be achieved through partial score analysis, where changes in a commune's characteristics, as identified by the model, could improve its innovation rate by reducing its partial score. These ideas are elaborated on in the following subsections.

4. Results

4.1. Model Statistics

The performance and stability of the predictive model were assessed using several key statistics, which provide insights into the model's predictive power, stability, and collinearity. These statistics are essential for understanding the robustness and reliability of the model.

The model demonstrates an acceptable level of predictive power, as indicated by a Gini coefficient of 24.8% (see Tables 4 and 5). While this value is not particularly high - strong models can achieve a Gini of 70% - it is sufficient for an initial attempt.

Table 4.
Model statistics - Percentage Values

Statistics	Value [%]
Gini	24.8
R. Gini	1.6
Gains1	10.3
Gains2	10.3
Gains3	10.3
Gains4	10.3
Gains5	18.4
Gains10	21.4
Gains50	62.4

Source: own calculations.

Table 5.
Model Statistics - Number Values

Statistics	Value
KS Score	0.0333
PSI Score	0.0410
Max VIF	2.4879
Max Pearson	0.6091
Max Con Index	78.2536
Lift1	10.3448
Lift2	5.1724
Lift3	3.4483
Lift4	2.5862
Lift5	3.6897
Lift10	2.1379
Lift50	1.2483

Source: own calculations.

4.2. Model Scorecard

The final form of the scorecard is presented in Table 6. The overall score for a municipality is calculated as the sum of all partial scores assigned to that particular commune. A lower score corresponds to a higher Innovation Rate.

Table 6.
Model Scorecard

Variable	Condition	Partial score
REVENUE_TAX_BASE_RATIO	not missing (REVENUE_TAX_BASE_RATIO) and REVENUE_TAX_BASE_RATIO <= 0.047520876	50
	0.047520876 < REVENUE_TAX_BASE_RATIO <= 0.0555931914	53
	0.0555931914 < REVENUE_TAX_BASE_RATIO	65
VALUE_ADDED_TAX_RATIO	0.0041976933 < VALUE_ADDED_TAX_RATIO	50
	0.0012027671 < VALUE_ADDED_TAX_RATIO <= 0.0041976933	63
	not missing (VALUE_ADDED_TAX_RATIO) and VALUE_ADDED_TAX_RATIO <= 0.0012027671	68

Cont. table 6.

AVERAGE_INCOME_NON_AGRICULTURAL	12955.666667 < AVERAGE_INCOME_NON_AGRICULTURAL	50
	5025 < AVERAGE_INCOME_NON_AGRICULTURAL <= 12955.666667	55
	2838.7619048 < AVERAGE_INCOME_NON_AGRICULTURAL <= 5025	61
	not missing (AVERAGE_INCOME_NON_AGRICULTURAL) and AVERAGE_INCOME_NON_AGRICULTURAL <= 2838.7619048	63
REAL_ESTATE_INDUSTRY_RATIO	not missing (REAL_ESTATE_INDUSTRY_RATIO) and REAL_ESTATE_INDUSTRY_RATIO <= 0.0245724396	50
	0.0245724396 < REAL_ESTATE_INDUSTRY_RATIO <= 0.0277142263	65
	0.0277142263 < REAL_ESTATE_INDUSTRY_RATIO	69
EDUCATION_INDUSTRY_RATIO	0.0317919075 < EDUCATION_INDUSTRY_RATIO	50
	0.0249221184 < EDUCATION_INDUSTRY_RATIO <= 0.0317919075	62
	not missing (EDUCATION_INDUSTRY_RATIO) and EDUCATION_INDUSTRY_RATIO <= 0.0249221184	64
AVERAGE_IMPORT_VALUE_ADDED	77791.926606 < AVERAGE_IMPORT_VALUE_ADDED	50
	5635.9166667 < AVERAGE_IMPORT_VALUE_ADDED <= 77791.926606	58
	not missing (AVERAGE_IMPORT_VALUE_ADDED) and AVERAGE_IMPORT_VALUE_ADDED <= 5635.9166667	60

Source: own calculations.

4.3. Variable statistics

Tables 7 and 8 present the variable statistics. Based on the Importance statistics, we can conclude that the most significant variable in the model is REAL_ESTATE_INDUSTRY_RATIO, which is related to the real estate market. The descriptions of the remaining measures are provided in the dictionary below.

Table 7.
Variable Statistics – Part 1, Quality of Data

Variable	Type	P. miss [%]	N. unique	P. of mode [%]	Mode
AVERAGE_IMPORT_VALUE_ADDED	INT	0.0	104	13.7	68577.87
EDUCATION_INDUSTRY_RATIO	INT	0.0	196	13.7	0.029813
VALUE_ADDED_TAX_RATIO	INT	0.0	187	13.7	0.006107
AVERAGE_INCOME_NON_AGRICULTURAL	INT	0.0	38	33.8	0.000000
REVENUE_TAX_BASE_RATIO	INT	0.0	188	13.7	0.044976
REAL_ESTATE_INDUSTRY_RATIO	INT	0.0	157	13.7	0.028587

Note: INT - Interval variable; P. miss - % of missing value; N. unique - Number of unique values; P. of mode - % share of mode value. Mode - the most frequent value.

Source: own calculations.

Table 8.
Variable Statistics – Part 2, Predictive Powers and Stability

Variable	Gini [%]	R. Gini [%]	PSI	Importance [%]
AVERAGE_IMPORT_VALUE_ADDED	16.6	1.8	0.006126	11.2
EDUCATION_INDUSTRY_RATIO	14.6	19.8	0.003324	15.7
VALUE_ADDED_TAX_RATIO	12.5	-15.1	0.002246	20.2
AVERAGE_INCOME_NON_AGRICULTURAL	8.4	12.7	0.005536	14.6
REVENUE_TAX_BASE_RATIO	7.7	28.8	0.002399	16.9
REAL_ESTATE_INDUSTRY_RATIO	6.1	25.3	0.000584	21.3

Note: PSI - Population Stability Index; Importance – Percentage share of partial score range in total score range. It measures an influence. Importance of variable.

Source: own calculations.

Table 9.
Variable Statistics – Part 3. Logistic Regression Estimation

Variable	Degrees of freedom	Coefficient	Standard error	Wald Chi-Square	P-value
REVENUE_TAX_BASE_RATIO	1	0.6818	0.2620	6.7687	0.0093
VALUE_ADDED_TAX_RATIO	1	1.0882	0.3317	10.7624	0.0010
AVERAGE_INCOME_NON_AGRICULTURAL	1	0.9851	0.2937	11.2471	0.0008
REAL_ESTATE_INDUSTRY_RATIO	1	2.0419	0.5662	13.0039	0.0003
EDUCATION_INDUSTRY_RATIO	1	0.4995	0.1780	7.8774	0.0050
AVERAGE_IMPORT_VALUE_ADDED	1	0.2848	0.1704	2.7944	0.0946
Intercept	1	6.8612	1.2282	31.2082	0.0000

Source: own calculations.

4.4. Calibration and Forecasting

All data are available on a yearly basis, allowing for the prediction of the average Innovation Rate (IR) for each commune in any future year. The model's outcomes can also generate the Predicted Innovation Rate (PIR), which is calculated using the following formula:

$$PIR = \frac{1}{(1 + \exp(-(-0.031964678 * SCORE + 9.4636582393)))} \tag{1}$$

This formula (1) has been tested through a simple analysis: for all available data, the calculated Innovation Rate (IR) is 18.7%, which matches the average value of the PIR exactly.

4.5. Ranking of Municipalities

The existence of the formula for the PIR provides an opportunity to validate the evolution of predicted Innovation Rates over time and focus on extreme cases, such as municipalities with the highest and lowest PIR. This approach optimizes the costs of advanced research and surveys by allowing for the selection of only a few municipalities for which predicted values can be verified against observed ones.

The data obtained enabled the analysis and ranking of the innovativeness of the 144 surveyed municipalities, as presented in Figures 1-5. In Figure 5 0% means areas without enterprises being surveyed. Even if some municipalities were not included in the survey, so IR is not available for them; due to the predictive model for every forecasted year, it is possible to calculate PIR.

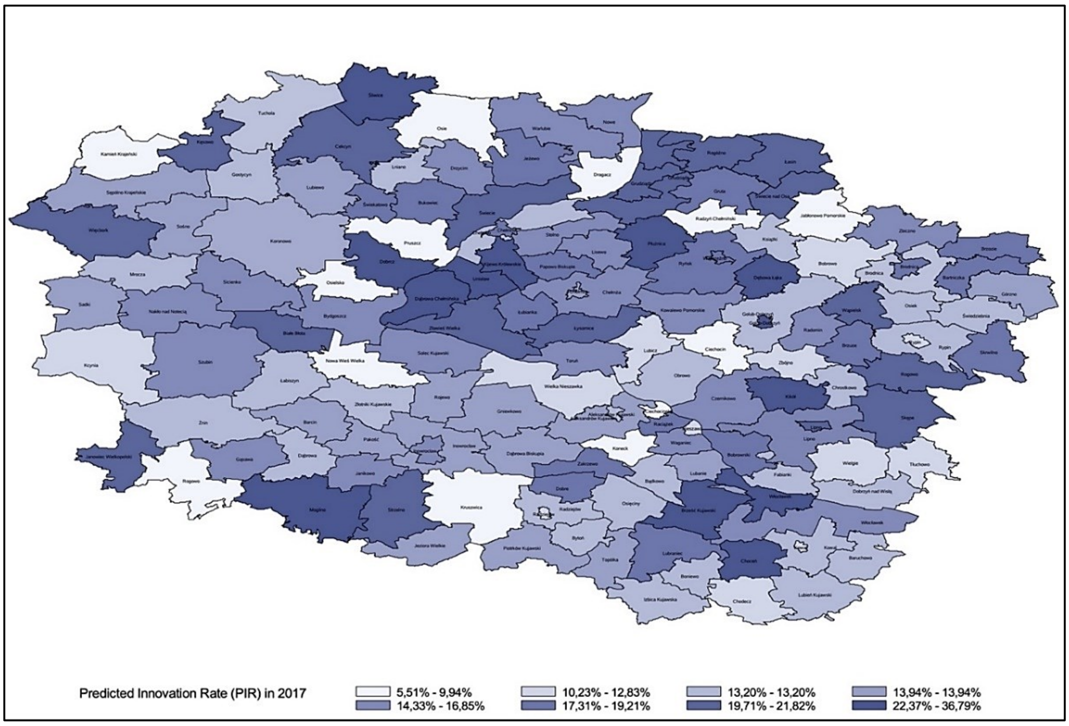

Figure 1. Predicted Innovation Rate in 2017.

Source: own calculations.

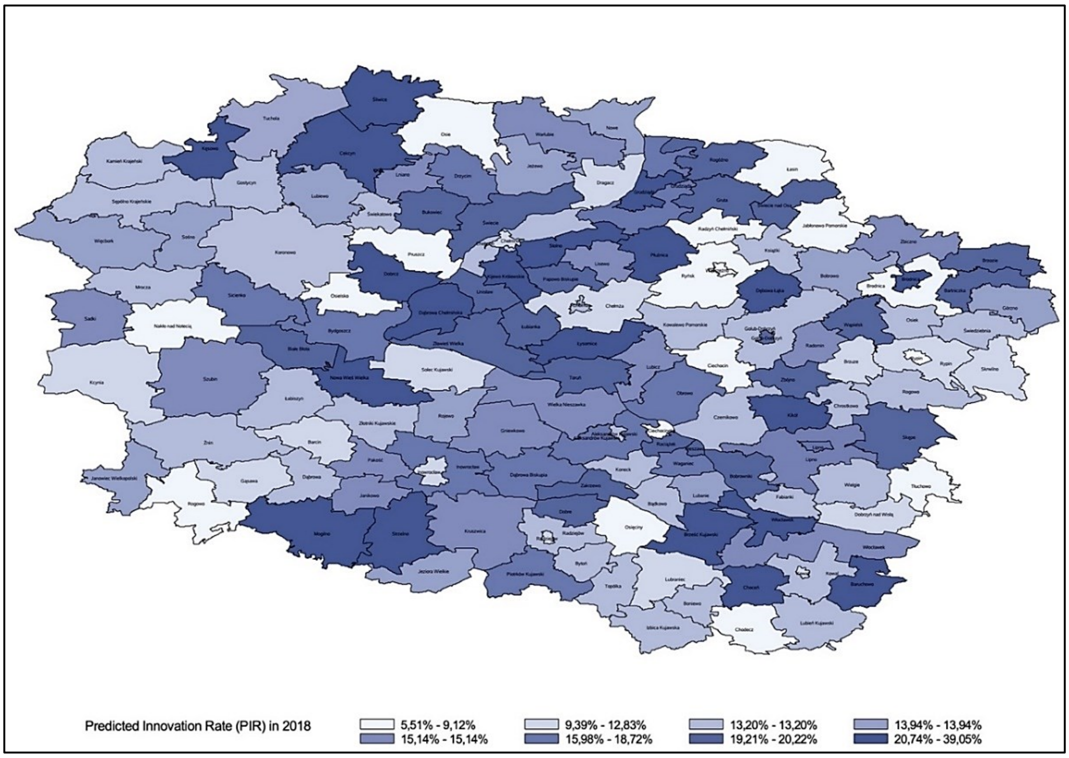

Figure 2. Predicted Innovation Rate in 2018.

Source: own calculations.

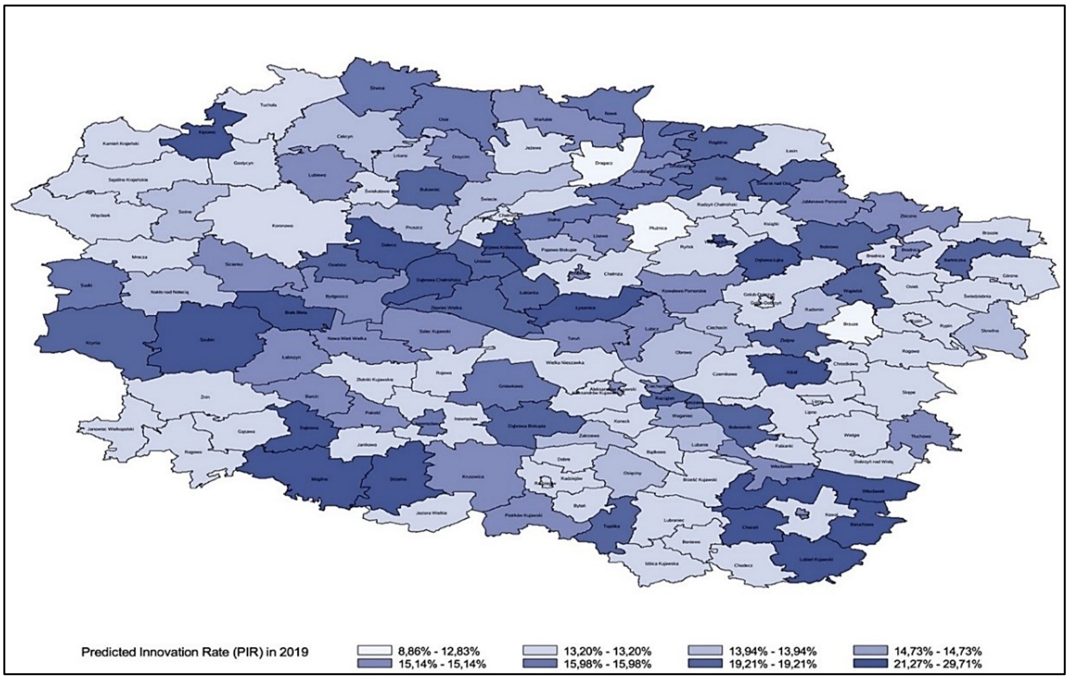

Figure 3. Predicted Innovation Rate in 2019.

Source: own calculations.

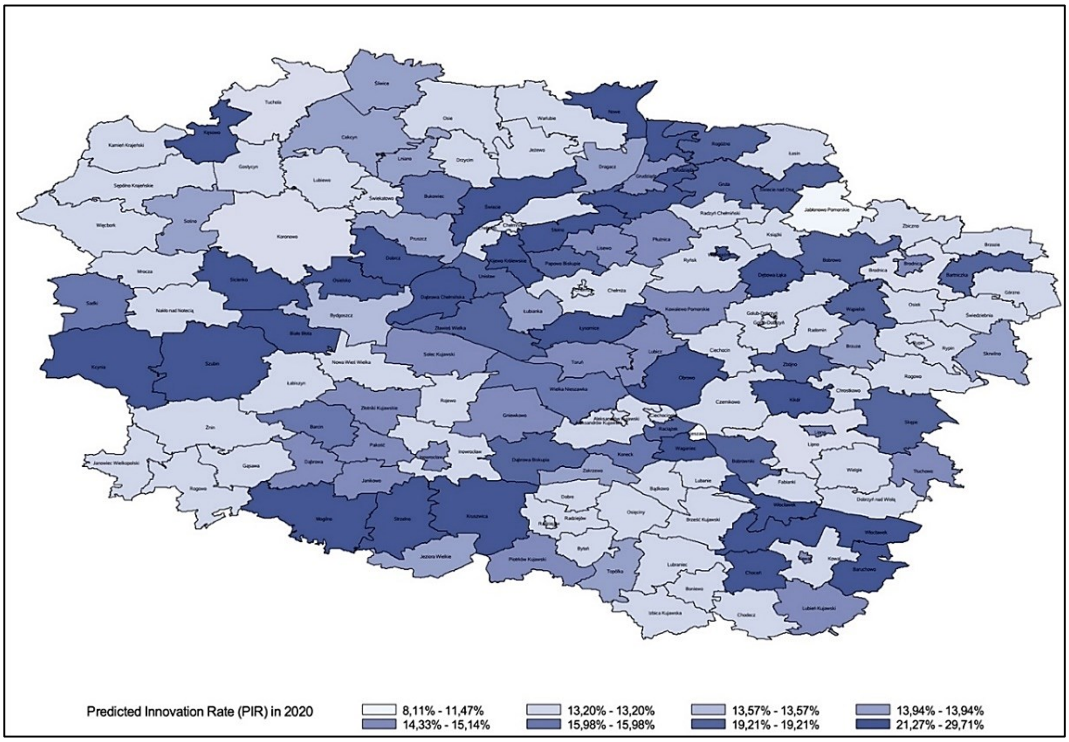

Figure 4. Predicted Innovation Rate in 2020.

Source: own calculations.

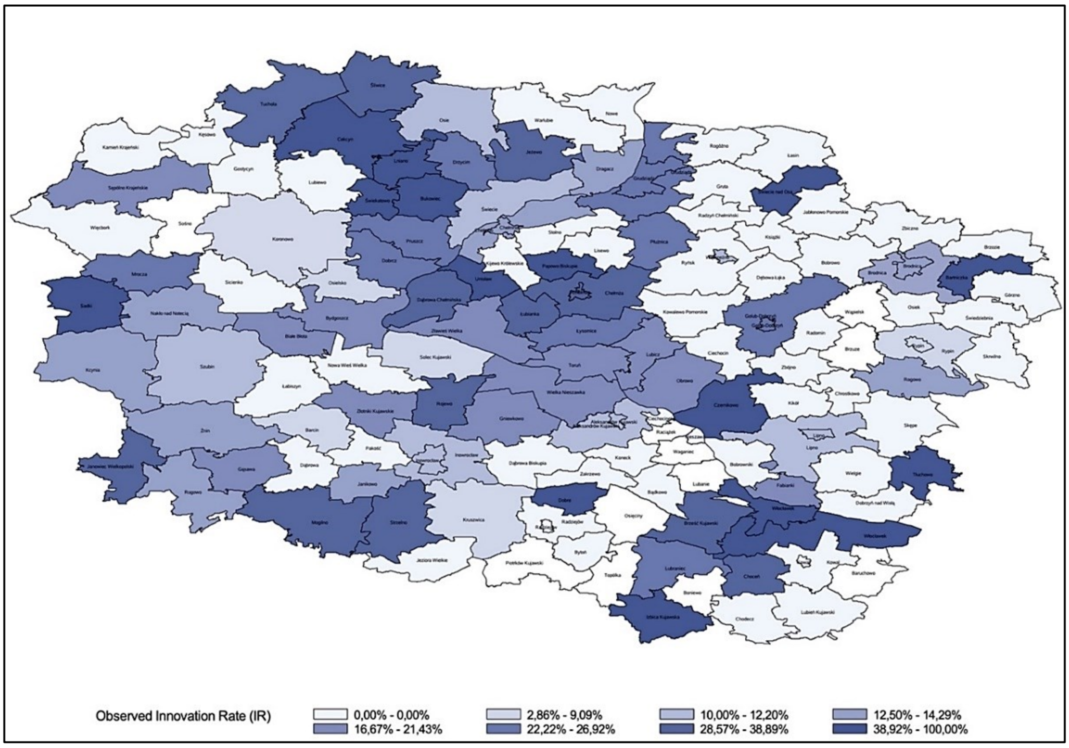

Figure 5. Observed Innovation Rate.

Source: own calculations.

4.6. Variable Descriptions and Reports

A variable category report is highly useful from a business perspective as it helps in understanding the root causes or causal relationships between the characteristics of a municipality and its Innovation Rate. The key statistics in the report are the observed Innovation Rate (IR) and the Share of the Population, which indicates the number of companies within each category.

Below, we present key data regarding the model variables:

REVENUE_TAX_BASE_RATIO (Table 10) - This is the ratio of the total revenue for a municipality from sources within the territory of the Republic of Poland in the CIT (Corporate Income Tax Declaration) tax form to the tax base for small companies. A higher ratio indicates a lower Innovation Rate in the municipality.

VALUE_ADDED_TAX_RATIO (Table 11) - This ratio compares the sum of the amount from VAT - representing the acquisition of value-added tax from taxpayers for services, to the total tax base for small companies. A higher ratio corresponds to a greater Innovation Rate in the municipality.

AVERAGE_INCOME_NON_AGRICULTURAL (Table 12) - This is the average income of a spouse from non-agricultural business activities in the municipality, as declared in the PIT (Personal Income Tax Declaration) tax for small companies. Higher average income correlates with a higher Innovation Rate in the municipality.

REAL_ESTATE_INDUSTRY_RATIO (Table 13) - This measures the share of Social Insurance Institution payers in the municipality from the PKD (Polish Classification of Business Activities) section L - activities related to real estate market services - relative to the total number of Social Insurance Institution payers in the municipality. A higher ratio is associated with a lower Innovation Rate in the municipality.

EDUCATION_INDUSTRY_RATIO (Table 14) - This represents the share of Social Insurance Institution payers in the municipality from the PKD P section - education-related activities - relative to the total number of Social Insurance Institution payers in the municipality. A higher ratio is linked to a greater Innovation Rate in the municipality.

AVERAGE_IMPORT_VALUE_ADDED (Table 15) - This is the average amount for a municipality from VAT, representing the import of services, excluding those purchased from value-added taxpayers, for medium-sized companies. A higher average is indicative of a greater Innovation Rate in the municipality.

The analysis and interpretation of the variable category reports (Tables 10-15) are illustrated using two examples: the most significant variable in the model and the variable that offers the best interpretability.

Table 14 presents a category report for the variable EDUCATION_INDUSTRY_RATIO, which is among the most intuitive variables in the model. This variable can be interpreted as follows: if the ratio of companies involved in the education sector is greater than 0.03, the expected Innovation Rate is approximately 30%. When the ratio falls between 0.02 and 0.03, the Innovation Rate is expected to be 16.6%. If the ratio is less than 0.02, the Innovation Rate is the lowest. In other words, the municipality can enhance its Innovation Rate and encourage its companies to be more innovative by improving conditions for companies in the education sector. This suggests that the presence of educational institutions in a commune can foster creativity among other local businesses. Additionally, the report indicates that the share of companies with the highest Innovation Rate is about 15.5%, implying that there is potential for improvement among the remaining companies in other municipalities.

In turn, Table 13 provides a report for the variable REAL_ESTATE_INDUSTRY_RATIO. It shows that a ratio greater than 0.0024 is associated with a lower Innovation Rate in a municipality. This can be interpreted to mean that companies in the real estate industry are less innovative, and a high concentration of such companies in a municipality can reduce overall innovativeness.

Interpreting variables and their category reports presents the greatest challenge of the project. Future research should focus on identifying variables that offer both strong interpretative value and a significant impact on municipal policies and actions. Ultimately, a refined model can be highly valuable for developing strategies to enhance innovation within municipalities.

Table 10.
Variable Report - REVENUE_TAX_BASE_RATIO

Score	Condition	IR	Share	All	Innovative	Non-innovative
50	not missing (REVENUE_TAX_BASE_RATIO) and REVENUE_TAX_BASE_RATIO <= 0.047520876	19,7%	69,1%	2190	432	1758
53	0.047520876 < REVENUE_TAX_BASE_RATIO <= 0.0555931914	17,8%	19,5%	617	110	507
65	0.0555931914 < REVENUE_TAX_BASE_RATIO	10,5%	11,5%	363	38	325
			100,0%	**3170**	**580**	**2590**

Source: own calculations.

Table 11.
Variable Report - VALUE_ADDED_TAX_RATIO

Score	Condition	IR	Share	All	Innovative	Non-innovative
50	0.0041976933 < VALUE_ADDED_TAX_RATIO	22,7%	39,0%	1236	280	956
63	0.0012027671 < VALUE_ADDED_TAX_RATIO <= 0.0041976933	16,3%	33,8%	1072	175	897
68	not missing (VALUE_ADDED_TAX_RATIO) and VALUE_ADDED_TAX_RATIO <= 0.0012027671	14,5%	27,2%	862	125	737
			100,0%	**3170**	**580**	**2590**

Source: own calculations.

Table 12.
Variable Report - AVERAGE_INCOME_NON_AGRICULTURAL

Score	Condition	IR	Share	All	Innovative	Non-innovative
50	12955.666667 < AVERAGE_INCOME_NON_AGRICULTURAL	23,1%	11,4%	360	83	277
55	5025 < AVERAGE_INCOME_NON_AGRICULTURAL <= 12955.666667	20,2%	29,7%	940	190	750
61	2838.7619048 < AVERAGE_INCOME_NON_AGRICULTURAL <= 5025	17,1%	14,0%	445	76	369
63	not missing(AVERAGE_INCOME_NON_AGRICULTURAL) and AVERAGE_INCOME_NON_AGRICULTURAL <= 2838.7619048	16,2%	45,0%	1425	231	1194
			100,0%	**3170**	**580**	**2590**

Source: own calculations.

Table 13.
Variable Report - REAL_ESTATE_INDUSTRY_RATIO

Score	Condition	IR	Share	All	Innovative	Non-innovative
50	not missing (REAL_ESTATE_INDUSTRY_RATIO) and REAL_ESTATE_INDUSTRY_RATIO <= 0.0245724396	19,6%	68,8%	2180	427	1753
65	0.0245724396 < REAL_ESTATE_INDUSTRY_RATIO <= 0.0277142263	15,9%	15,5%	491	78	413
69	0.0277142263 < REAL_ESTATE_INDUSTRY_RATIO	15,0%	15,7%	499	75	424
			100,0%	**3170**	**580**	**2590**

Source: own calculations.

Table 14.
Variable Report - EDUCATION_INDUSTRY_RATIO

Score	Condition	IR	Share	All	Innovative	Non-innovative
50	0.0317919075 < EDUCATION_INDUSTRY_RATIO	30,6%	15,5%	490	150	340
62	0.0249221184 < EDUCATION_INDUSTRY_RATIO <= 0.0317919075	16,6%	62,4%	1979	328	1651
64	not missing (EDUCATION_INDUSTRY_RATIO) and EDUCATION_INDUSTRY_RATIO <= 0.0249221184	14,6%	22,1%	701	102	599
			100,0%	**3170**	**580**	**2590**

Source: own calculations.

Table 15.
Variable Report - AVERAGE_IMPORT_VALUE_ADDED

Score	Condition	IR	Share	All	Innovative	Non-innovative
50	77791.926606 < AVERAGE_IMPORT_VALUE_ADDED	34,2%	12,7%	404	138	266
58	5635.9166667 < AVERAGE_IMPORT_VALUE_ADDED <= 77791.926606	16,8%	64,4%	2043	343	1700
60	not missing(AVERAGE_IMPORT_VALUE_ADDED) and AVERAGE_IMPORT_VALUE_ADDED <= 5635.9166667	13,7%	22,8%	723	99	624
			100,0%	**3170**	**580**	**2590**

Source: own calculations.

5. Discussion and Conclusions

The conducted experiment, aimed at addressing the research question of whether existing data collected by various national agencies, such as statistical offices, the Social Insurance Institution, or the Ministry of Finance, can be used to support municipalities in identifying factors necessary to increase innovation rates, demonstrated that it is indeed possible. However, several important issues should be emphasized.

First, it is important to consider the potential interpretation of the variables proposed within the scorecard model.

In the case of the variable REVENUE_TAX_BASE_RATIO, which suggests that a higher ratio of a municipality's revenues from sources located within the territory of the Republic of Poland in the Corporate Income Tax (CIT) declaration, relative to the tax base for small companies, is correlated with lower innovativeness in the municipality, several explanations for this phenomenon can be considered.

A higher ratio may indicate that the municipality derives significant revenues from larger companies, which generate most of its income but are less inclined to innovate. Large companies often operate in stable industries and may have less need for innovation compared to small and medium-sized enterprises (SMEs), which are more flexible and adaptable (Mugler, 1998).

This high ratio may also suggest that small companies in the municipality primarily operate in industries with low levels of innovation (e.g., retail and local services). These businesses may contribute less to tax revenues and also engage in fewer innovations due to their presence in less dynamic sectors of the economy.

Furthermore, municipalities that rely heavily on revenues from larger companies may neglect to support smaller businesses. A lack of programs aimed at fostering SME development - such as innovation grants, business incubators, or tax incentives - could result in lower levels of innovation activity among smaller enterprises (Otache, Usang, 2022; Veronica et al., 2020).

Additionally, small companies may face growth barriers (Hvolkova et al., 2019; Kim et al., 2018) such as complex tax regulations, high administrative costs, or insufficient infrastructure support. These obstacles can discourage innovation in smaller businesses and limit their potential for expansion.

The second variable, VALUE_ADDED_TAX_RATIO, indicates that a higher VAT ratio - representing the collection of value-added tax from taxpayers for services - relative to the total tax base for small businesses is positively correlated with greater innovation in the municipality. Several potential explanations for this correlation can be considered.

An increase in VAT related to services may reflect the growth of the service sector, which is often more dynamic and innovative compared to traditional industrial sectors (Audretsch et al., 2020; Del Val Segarra-Oña, Peiró-Signes, 2013; Lütjen, 2019). Services, particularly those connected to digital technologies, consulting, or research and development, typically require continuous innovation, which can enhance the overall innovation of businesses in the municipality.

A higher VAT ratio on services may also suggest that the municipality hosts numerous companies from modern technology sectors such as IT, telecommunications, or biotechnology, which are known for driving higher levels of innovation (Ju et al., 2020). These companies often provide high-value-added services, and their operations can stimulate innovation both within their own enterprises and across the broader local economy.

Additionally, a high VAT ratio for small businesses could indicate the development of many small service enterprises within the municipality. Small service firms frequently need to innovate in order to differentiate themselves in the market and attract customers (Mugler, 1998; Zastempowski, 2024b; Gibson, Van der Vaart, 2008), which may contribute to the overall rise in innovation within the municipality.

The third variable, AVERAGE_INCOME_NON_AGRICULTURAL, suggests that higher average income from non-agricultural business activities in the commune, as declared in the PIT (Personal Income Tax Declaration) for small companies, correlates with a higher innovation rate in the municipality.

Several possible explanations can be considered. First, higher average income from non-agricultural activities may indicate that business owners possess greater financial resources, which can be reinvested in research, development, and the implementation of innovative solutions. Greater financial capacity allows companies to take risks, explore new technologies, or invest in improving products and services (Mugler, 1998; Gibson, Van der Vaart, 2008; Degryse et al., 2012; Kamal, Flanagan, 2014).

Additionally, higher incomes may reflect more advanced and efficient business operations, suggesting that these firms operate in competitive markets or sectors that demand constant innovation to maintain a competitive edge. Successful entrepreneurs are often more inclined to innovate (Romero, Martínez-Román, 2012) in order to differentiate their products or services or enhance operational efficiency.

It is also important to note that municipalities with higher average incomes may attract a more educated and skilled workforce, particularly in industries that depend on specialized knowledge. A highly skilled workforce contributes to innovation by introducing new ideas, leveraging experience, and applying advanced technologies or methodologies.

Another variable, REAL_ESTATE_INDUSTRY_RATIO, measures the proportion of Social Insurance Institution payers in the municipality engaged in real estate market services relative to the total number of Social Insurance Institution payers in the municipality. A higher ratio is associated with a lower Innovation Rate in the municipality.

Here, several potential explanations for this result can also be considered. The real estate industry, while essential to the economy, generally provides fewer opportunities for radical innovation compared to sectors such as technology, manufacturing, or services (Sitek, 2019; Chang et al., 2022). Real estate activities often focus on infrastructure, property management, and transactions, which are typically more stable and less oriented toward innovation. Consequently, a high share of real estate companies in a municipality may lead to a lower overall innovation rate.

Moreover, real estate businesses frequently require substantial capital investments for property acquisition, development, and maintenance. These businesses tend to prioritize financial stability and risk management over innovation. The necessity of protecting large capital investments may make real estate firms more risk-averse and less inclined to adopt new technologies or practices.

Unlike industries that heavily invest in R&D to maintain competitiveness (Belderbos et al., 2004; Park, Lee, 2022), real estate companies may allocate fewer resources to R&D. As a result, this sector may contribute less to the overall innovation activity within the municipality.

The next indicator - EDUCATION_INDUSTRY_RATIO - reflects the proportion of Social Insurance Institution contributors in the municipality engaged in educational activities relative to the total number of Social Insurance Institution contributors in the area. A higher ratio is associated with an increased innovation rate within the municipality.

Several possible explanations exist for the correlation between a higher share of educational activities and greater innovation.

Education is a crucial factor in the creation and dissemination of knowledge. Educational institutions, such as schools, colleges, and universities, foster a culture of learning, critical thinking, and research. This environment is conducive to innovation, as knowledge generated within educational institutions can be transferred to local businesses, encouraging the development of new ideas, products, and services (Zastempowski et al., 2024).

A higher presence of educational institutions likely indicates the existence of a more educated and skilled workforce in the region (Horn, Dunagan, 2018; Audretsch, Belitski, 2021). Skilled workers are better equipped to adopt and implement innovative practices, as they are more prepared to understand and apply new technologies and methodologies. This can contribute to higher levels of innovation within local firms, as businesses benefit from access to a talent pool that drives innovation.

Moreover, it is worth noting that educational institutions often collaborate with companies and research centers to develop innovative solutions (Jones, Patton, 2020; Arroyabe et al., 2022). Such partnerships create an innovation ecosystem where knowledge is shared, research projects are conducted, and enterprises can leverage the expertise of academic professionals. This collaboration fosters creativity and innovation within the local economy (Zastempowski et al., 2024).

It is also worth emphasizing that educational institutions, particularly universities and research centers, are frequently engaged in R&D activities and promote entrepreneurial endeavors (Etzkowitz, 2010). These institutions can support the commercialization of research through startup incubators, spin-offs, and technology transfer offices, which directly contribute to innovation within the local economy (Zastempowski et al., 2024).

In the case of the last variable, AVERAGE_IMPORT_VALUE_ADDED, which indicates the average amount of VAT for the municipality related to the import of services - excluding those purchased from VAT taxpayers - for medium-sized enterprises, a higher value suggests a greater innovation rate within the municipality.

It is important to emphasize that a higher level of service imports may indicate that the municipality has access to more advanced technologies and knowledge. Companies that import innovative services can leverage modern solutions, which fosters the introduction of their own innovations.

Additionally, a high level of service imports may reflect a greater internationalization of local enterprises. Companies that utilize foreign services often gain access to best practices, modern methodologies, and technologies, thereby promoting innovation (Jain et al., 2019; Martínez-Román et al., 2019). Collaboration with international partners can also lead to the transfer of knowledge and expertise.

Firms that import services may be more flexible and willing to adapt to changing market conditions. This dynamism is often associated with a greater propensity to innovate in order to meet customer expectations and market demands.

Finally, the import of services, particularly those related to technology, can act as a catalyst for local innovation. These services may include training, consulting, information technologies, and others that support the development and implementation of innovative solutions by local companies.

Secondly, it is important to emphasize that supporting enterprise innovation is strongly related to the entrepreneurs themselves, including their creativity (Zastempowski, 2024a), market knowledge, and various other criteria, such as industry affiliation. As our results indicate, innovation is also influenced by numerous external factors that can be managed by government and local government institutions. This aspect can be studied and measured using models like the one proposed in this article. It is essential to note that the primary purpose of such a model is to facilitate root cause analysis, wherein causal models (Friston, 2009) are constructed, and analyses are conducted according to the methodology established by Pearl and Mackenzie (Pearl, Mackenzie, 2018).

The essence of this approach is to create an interdisciplinary project team composed of specialists in enterprise management and innovation, as well as data scientists. Throughout the project's various stages, the team should collaboratively identify the most relevant variables that describe the state of the municipality and its enterprises, such as the

EDUCATION_INDUSTRY_RATIO variable, ensuring that the process of enhancing innovation at the municipality level is fully manageable.

Subsequently, the new Predicted Innovation Rate (PIR) should be calculated regularly, on an annual basis, and verified against actual outcomes. Furthermore, in the analysis of what actions the municipality should take to achieve a better innovation indicator, it is essential to implement "do" type actions within the causation ladder (Intervention, as defined in the Ladder of Causation) (Pearl, Mackenzie, 2018). Each intervention should then be assessed to determine whether it has produced the expected effects in terms of changes in the level of innovation.

Finally, the models should be updated, regularly verified, and refined, which will be accompanied by increasing knowledge and experience in innovation management. Moreover, the annual calculations of the PIR indicator will enable detailed analyses for selected municipalities where the indicator is notably low or, conversely, very high.

The model described in this article serves as a proof of concept (PoC) for such a project. A scorecard was selected as the method for constructing the model due to its complete interpretability, allowing it to be understood by a broad audience, including those who may not be familiar with statistics but possess expertise in market knowledge related to enterprises. This accessibility should not create barriers to its implementation. In the future, as analytical support and regular calculations of the PIR become foundational for innovation management, it will be possible to enhance these models using modern machine learning (ML) and artificial intelligence (AI) techniques, with particular attention to the development of Explainable Artificial Intelligence (XAI) (Longo et al., 2024).

Thirdly, it is important to acknowledge the research limitations.

First, although the data from the CAPI study used in constructing the model were based on a representative sample of enterprises in the Kuyavian-Pomeranian Voivodeship, they were not representative at the national level. Therefore, it would be beneficial to conduct research and build models based on samples that are representative of the entire country.

Second, as previously mentioned, the study was conducted in Poland, which, like other countries, possesses its own cultural, political, economic, and social specificities. Thus, it is recommended to expand the geographical scope of the study to include other countries.

Lastly, considering the assumption that most LAUs, regardless of their location, strive to enhance their innovativeness, it would be valuable to propose an analysis of the available data (collected by various national agencies) in the context of building predictive models that account for the specific characteristics of LAU data.

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