МОДЕЛЮВАННЯ ТА ІНФОРМАЦІЙНІ ТЕХНОЛОГІЇ В ЕКОНОМІЦІ Й УПРАВЛІННІ

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ANALYSES OF POVERTY INDICATORS USING PPI METHODOLOGY

Poverty is a negative socio-economical phenomenon which has a destructive influence on not only life quality for people who are caught in a poverty trap but for society in general. Poverty prevents society from realising its potential and leads to social development regression. The first of the sustainable development goals declared by the United Nations in 2025 as global goals of civilisation development until 2030, is to overcome poverty. The growth of poverty rates is observed for the first time in twenty years, and this requires studying the causes and developing policies to prevent this tendency. It is well-known poverty has various forms and national and cultural features, that should be taken into account when solving the poverty problem. One of the relevant tasks in studying this problem is the development of adequate methods of measuring poverty and determining the category of people who are considered poor This study aims to develop a clusterization model using the set of socio-economic indicators in order to identify the poor people cluster. The survey includes 8400 respondents from 7 European countries. Developing the model was carried out using machine learning methods in several steps: 1) data processing and statistical analyses; 2) selection of significant indicators by the classification model; 3) clustering by k-mean algorithm; 4) hierarchical clustering; 5) comparing outcomes of modeling and interpretation of results. The selection of indicators was carried out by classification methods using PPI methodology. Data processing and analyses were performed using Python. Using this approach we can split the population into groups with different living standards levels identifying the poor people group with a simple questionary considering national (local) features. This help to increase the effectiveness and timeliness of poor families' support.

Keywords: **poverty, Sustainable Development Goals (SDGs), PPI methodology, clustering and classification.**

JEL Classification: I32, C53, C55.

Problem statement. Poverty is one of the most important global problems in the world. Eradicating poverty is announced as the goal №1 in the Sustainable Development Goals (SDGs), which were adopted by the United Nations in 2015 as global goals until 2030.

"The World Social Summit identified poverty eradication as an ethical, social, political and economic imperative of mankind and called on governments to address the root causes of poverty, provide for basic needs for all and ensure that the poor have access to productive resources, including credit, education, and training" (United Nations, 2022).

The Multidimensional Poverty Index (MPI) report in 2023 shows that 1,1 billion people in 111 developing countries live in poverty. This is more than double the quality of people who are considered poor according to the poverty threshold of $1,9 per person per day (Global MPI, 2023). Figure 1 shows that by the end of 2023, the number of poor people is approximately the same as in 2019. This means that after 4 years of careful work by the governments of all countries and other organizations, the impact is much less than in the period of 2015-2018.

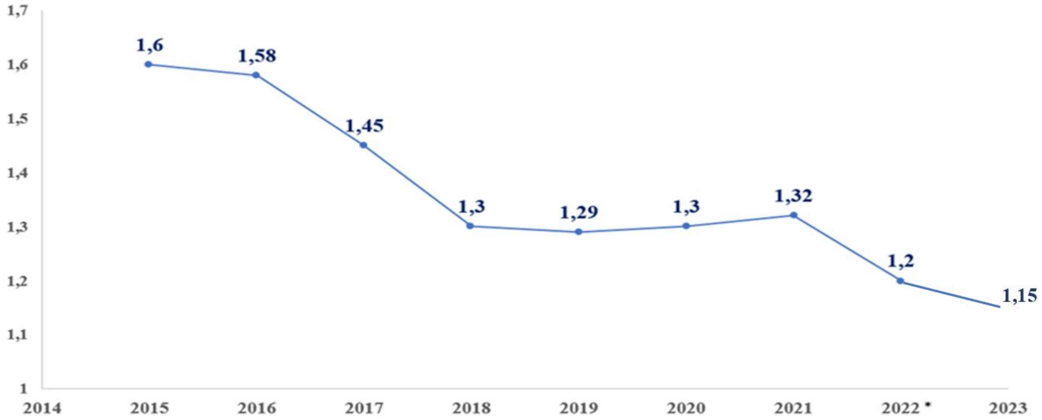

Fig. 1. Poor people dynamics according to MPI, 2015 – 2023 (billions)

Source: (Global MPI, 2023)

Poverty measurement is of key importance in identifying poor people. Several approaches to measuring this multidimensional phenomenon have been proposed and implemented by different authors and organizations.

The most popular indicator of poverty is Multidimensional Poverty Index (MPI) mentioned above. This index is multidimensional and based on the depreciation profile of households and persons (Vollmer & Alkire, 2022). By looking closely at the interlinked deprivations of poor people, this approach to poverty measurement provides insights on how to identify poverty by its multiple dimensions. The indicators which are used to calculate MPI belong to various spheres of life: health, education, standards of living, etc. This index was implemented in 2010 in developing countries by the United Nations initiative and has already covered 111 countries.

The World Bank proposed the index to measure societal poverty (SPL). This one is adjusted to the level of development of any country and calculated by the formula (Vollmer & Alkire, 2022):

$$SPL = 1\$ + 0{,}5 \times MLCPP \quad (1)$$

where MLCPP – median level of consumption per person in a county.

A common feature of these indices is that they are based on data from large-scale national and international household surveys. This information is very detailed and valuable, but such surveys require a lot of resources, including finances, time, human resources, etc. They often take several years to develop and implement.

Analysis of recent research. The dependence of poverty on the level of income and satisfaction of needs was described in the works of Charles Booth (Fried & Elmanharles, 1969). The eradication of poverty by improving the welfare of the population is the subject of F. Hayek's research (Hayek, 1994). Amartya Sen studied poverty through a set of functional capabilities (physical condition, gender, literacy, intelligence, social policy of the state, etc.) (Polly, 2006). Proponents of the theory of welfare and fair distribution, such as J. Keynes and P. Samuelson (Boianovsky, 2019), argue that overcoming poverty requires active state intervention in the socio-economic sphere, increased state spending, expanded budget balancing, achieving a balance of demand and full employment, etc.

The transition to market relations has led to an increased interest in poverty and social differentiation of the population on the part of economists, sociologists and political scientists. They studied the causes, consequences, and ways to overcome poverty and social inequality; proposed methods for measuring their level; and tried to substantiate the peculiarities of the formation of a new social structure of society.

Thus, many scholars have focused on the issue of poverty. Strotmann dealt with the issue of Poverty Index and Happiness (Strotmann & Volkert, 2018). Martin Ravallion studied factors derived from multidimensional poverty that affect the economy of different countries (Ravallion, 2011).

Alfredo Sanchez Carballo, Joel Ruiz Sánchez and Miguel Ángel Barrera-Rojas explored the issues related to inequality and pointed out that poverty has been defined in terms of income, expenditures, and unsatisfied basic needs, as well as multidimensional measurements, through a process in constant evolution (Sánchez et al., 2020).

Among the scientists dealing with the issue of poverty are domestic authors. The most popular of them: Banerjee, A. "The Economics of Poverty. How to free the world from poverty" (Банерджі & Дюфло, 2018), Vikhrov, M. "Arithmetic of poverty: how widespread is poverty in Ukraine, how does it threaten and are there any chances to overcome it?" (Віхров, 2018), Husarevych, N. V. "Assessment of the state of poverty in Ukraine and ways to overcome it" (Гусаревич та ін., 2020), Mishchuk G. Yu. "Social exclusion: problems of defining and assessing the scale in Ukraine" (Міщук & Юрчик, 2019).

Purpose and objectives. Our task is to develop a clusterization model using the set of socio-economic indicators in order to identify the poor people cluster.

In this study, we used the dataset PPI obtained as a result of the project Data Science Capstone (Poverty Probability Index, 2021). The survey includes 8400 respondents from 7 countries that belong to the developed group according to GDP per capita: Germany, France, Italy, Spain, Great Britain, Austria, and Poland. The questionary covers various characteristics of people and indicators of the standard of living (Liberati, Resce, & Tosi, 2022).

The goal of clustering is to divide the set of objects (individuals) into groups (clusters) in such a way that the objects included in the same group are more similar to each other according to certain characteristics than objects from different groups. Selection of the poor people cluster will give "a social profile" of them, that is describing this group in terms of socioeconomic indicators.

Developing the model was carried out using machine learning methods and included several steps:

1) data processing and statistical analyses;
2) selection of significant indicators by the classification model;
3) clustering by k-mean algorithm;
4) hierarchical clustering;
5) comparing outcomes of modeling and interpretation of results.

Data processing and analyses were performed using Python.

The main results of the study.

Data processing and statistical analyses. The survey included about 50 indicators. Given the PPI methodology, this number is very big. This sample of indicators was reduced by the exclusion of some of them. Firstly, those were the indicators that had many missing data, that is 90% and more. These indicators were considered noninformative factors (for instance "bank_interest_rate", "mfi_interest_rate"). Secondly, some indicators didn't have a clear unambiguous interpretation, such as "num_shocks_last_year". Thus, we obtained 28 indicators that were processed using Python.

To detect outliers each variable distribution was tested by the 3-sigma rule. The detected outliers were replaced with the max or min values of those indicators.

All the categorical variables were assigned with the codes. It is worth noting that all these indicators were coding automatically, except the factor "religion".

Codes were assigned to this factor according to the prevalence of religions in European countries. By the Pew Research Center information Christianity is the most widespread religion in this region, therefore Catholicism and Orthodoxy got 0 and 1 respectively. The next codes were assigned to Agnostics (2), Buddhists (3), and people who don't associate themselves with any religion (4).

Then, to estimate the relationship between factors data were tested by the correlation matrix. The analysis identified pairs of factors that were highly correlated. This means that one factor from those pairs should be excluded. Thus, the sample of variables has been reduced to 28 using the correlation matrix and PPI methodology: *Country, Is_urban, Age Female, Married, Religion, Can_calc_percents, Employment_type_last_year, Income_government_last_year, Income_own_business_last_year, Active_bank_user, Cash_property_savings, Has_insurance, Borrowed_for_dail_expenses_last_year, Can_call, Can_use_internet, Phone_ownership, Num_financial_activities_last_year, Literacy, Formal_savings.*

It is worth explaining how we calculated the value of the last variable, which serves as a poverty indicator in our research. The indicator "Formal_savings" means the amount of money, that is enough for one person to live for six months. This is a living wage for six months. This amount depends on the national poverty line defined by the minimum income or expenditures for each country according to PPP (PPP Annual brochure, 2018). Thus, this indicator is calculated by the formula:

$$\textit{FormalSavings} = \textit{PovertyLine} \times \textit{CurrencyValue} \times 180, \qquad (2)$$

It is known the World Bank identified 4 income groups based on GDP per capita. The poverty lines were defined for each of these groups (fig. 2) (World Bank, 2023).

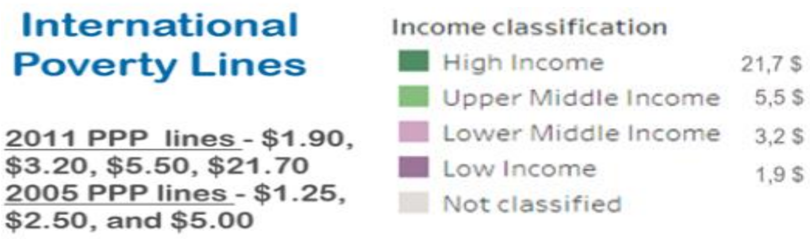

Fig. 2. Income classification and poverty line

Source: World Bank (2023)

The survey in our research includes countries from the high-income group. The PPP line for this group is $ 21,7. This value was corrected according to the national currency rate at 1.07.2020: 0.90479 (EUR), 0.76082 (GBP) and 3.88656 (PLN) (Oanda currency, 2021).

Thus, for countries where the national currency is the euro (Germany, France, Spain, Italy, Austria) the poverty line is 21,7 × 0,90479 = 19,63 (€). For Great Britain, it is 21,7 × 0,76082 = 16,5 (GBP) and 21,7 × 3,88656 = 84,3 (PLN) for Poland.

On the base of these data the values of the indicator "Formal Savings" were calculated by the formula (2), e.g. 16,5 × 180 = 2970 GBP for Great Britain.

Selection of variables by the classification model. In our research, the dependent variable should be an indicator of poverty, which allows identifying poor people. The indicator "Formal_savings" is adequate for this goal and serves the dependent variable.

The most significant factors were selected by an automatic procedure using modules LogisticRegression and RFECV. The optimal number of significant variables is defined by model productivity change. The plot shows that a lot of features don't always improve a model (fig. 3).

The "Model accuracy" serves as an estimation of the model quality. It works in the same way as the coefficient of determination. The dependence the model productivity on the number of variables demonstrates that the productivity of the model decreases as soon as the number of factors is more than 13.

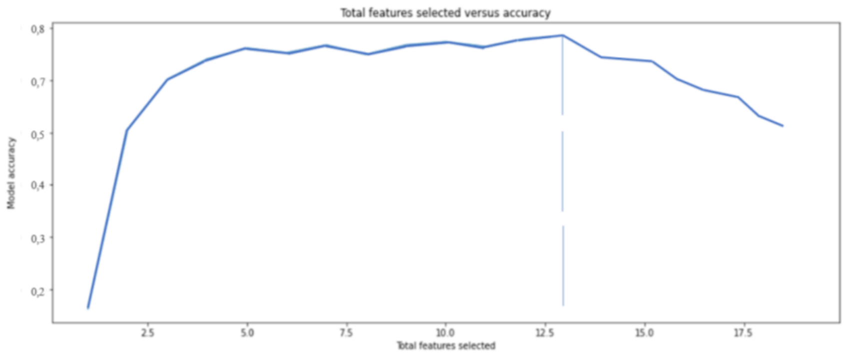

Fig. 3. Classification model accuracy and number of factors

Source: own calculations based on PPI dataset (2021)

Thus, using the classification model we choose13 valuables that have the most significant influence on the poverty indicator "Formal_savings": *country, is_urban, religion, employment_type_last_year, income_government_last_year, active_bank_user, cash_property_savings, has_insurance, can_call, phone_ownerhip, num_financial_activities_last_year, literacy.*

Clustering. In the first stage of the work, we carried out data scaling, which prevents large-scale variables from dominating the definition of clusters. For instance, the factor Age has variation from 0 to 82 at the same time max values of other variables don't exceed 7.

Clustering was carried out using two methods: the K-means algorithm and hierarchical clustering. The parameter k (number of clusters) was selected using the "elbow" and "silhouette" methods.

In hierarchical clustering, the optimal number of clusters was found using dendrogram. All methods showed the expediency of splitting the initial sample into 2 or 3 clusters (fig. 4).

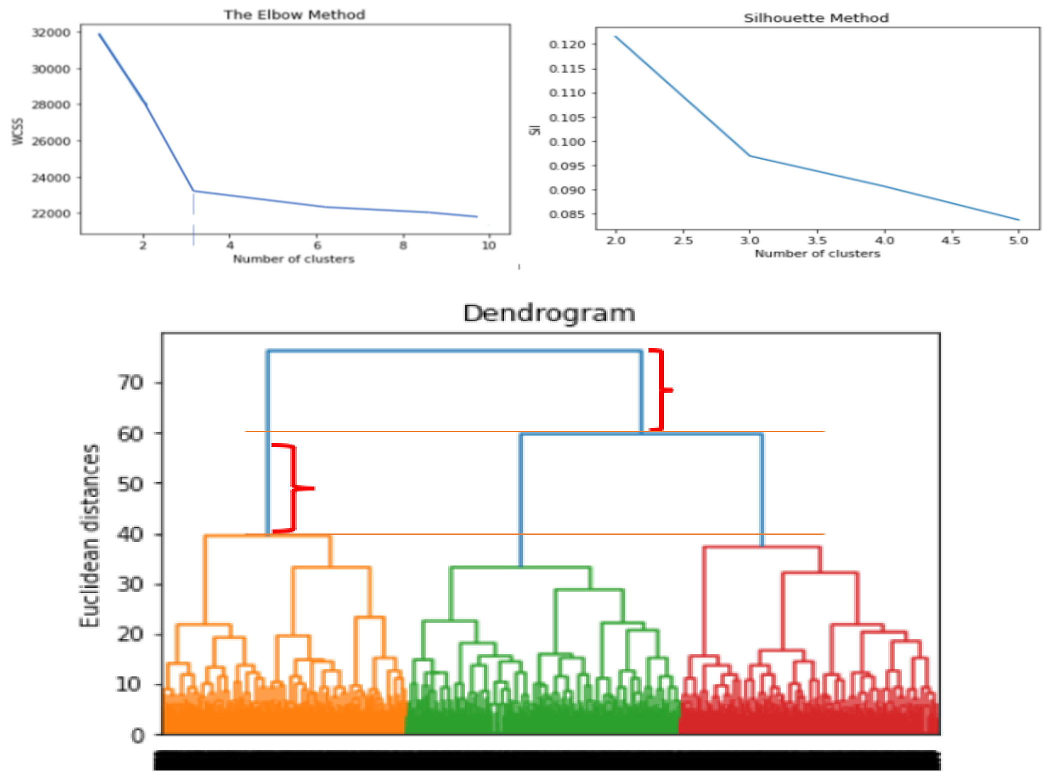

Fig. 4. Number of clusters using Elbow method / Silhouette method / Dendrogram

Source: own calculations based on PPI dataset (2021)

In the modelling process, it turned out that the centroids of the clusters are low-variable on some variables (for example, religion, income_government_last_year). Such variables were eliminated and we obtained a sample of 15 factors.

Thus, we have got 3 samples of variables: 20 (initial data processing result), 13 (according to the classification), and 15 (obtained by elimination of uninformative variables for clustering). Then, models were developed for 2 and 3 clusters and for 3 samples of variables by each method of clustering, that is in general, 6 models of clustering.

To compare the models, we checked the stability of the clusters – whether the same objects were included in each cluster by two clustering methods. The max intersection of clustering results was obtained for the 3-cluster model with the sample of 20 variables (84%) and the 3-cluster model with 15 variables (80%).

This is a high level of similarity clusters and we can consider that they are stable. Given that the model for 20 variables contains low-variable factors, the 3-cluster model with 15 variables was chosen for interpretation.

Clustering. We obtained 3 clusters. They describe groups of people with 15 features including the poverty indicator which varies essentially across clusters.

Table 1 – **Three groups of people including different poverty indicators across clusters**

Indicator	Cluster 1	Cluster 2	Cluster 3
Country	0,3546	0,0718	0,9023
Is Urban	0,1823	0,5753	0,7843
Age	0,6123	0,4855	0,35
Female	0,7705	0,3356	0,5598
Married	0,6751	0,7307	0,5066
Can_calc_percents	0,2767	0,4454	0,8934
Income_own_business_last_year	0,1673	0,3676	0,7865
Active_bank_user	0,0542	0,3259	0,6733
Cash_property_savings	0,1756	0,2755	0,5517
Can_call	0,4557	0,9016	0,9507
Can_use_internet	0,2512	0,7792	0,9345
Phone_ownership	0,3724	0,7237	0,9524
Literacy	0,2620	0,7664	0,8474
Borrowed_for_daily_emerg	0,8845	0,3456	0,8995
Formal_savings (Y)	0,0666	0,3736	0,7702

Source: own calculations based on PPI dataset (2021)

Conclusions. Using this approach we splited the population into groups with different living standards levels identifying the poor people group with a simple questionary considering national (local) features.

Cluster 1.

This cluster has the minimum average value of the poverty line, e.g. it is the cluster of poor people. This cluster includes middle-aged and elderly people who are not urban residents and live most likely in Germany, France, Spain or Great Britain.

In most cases, these are married women with a low level of literacy. Women in Europe are paid almost 15% less than men for the same job (Lomazzi V. et al., 2019).

The pandemic made the situation worse, as the burden on women during the quarantine increased: 30% of women work part-time (this value is much lower for men – 8%). Therefore, for married women with a child, the probability of being below the poverty line is much higher. This conclusion is confirmed by clustering results.

Then, people who entered this cluster don't have their own businesses and have a low level of literacy. They are not active bank clients (they do not take loans/deposits, issue mortgages or exchange currencies), they do not have property savings that can be obtained from renting out an apartment. Also, most people do not have the funds to regularly pay for Internet provider services, or even do not have the opportunity to connect the Internet to their household.

The most important thing is that they took out loans for daily needs and do not have savings that will allow them to live comfortably for another six months.

Thus, people from this cluster are very similar to those people who have financial problems and can live below the poverty line.

Cluster 2.

This cluster includes people living in the same regions as people from the previous cluster: Germany, France, Spain or Great Britain. In general, these are both young people and people of an older generation, most of whom are married men. In general, the level of literacy is at a high level.

The majority of people from this group probably do not have their own businesses and are not active bank clients. Also, most of them do not have savings from renting apartments. More than 75% of people have access to the Internet, but some had loans for daily needs in the previous period (about 35% of people).

In general, almost half of the respondents from this cluster have savings to live comfortably for another six months. Thus, we can consider that it is an average living cost cluster.

Cluster 3.

This cluster includes people of both sexes, both single and married, but more than 78% of respondents live in cities. Geographically, almost all people live in Poland, Italy or Austria.

In general, these people are high-educated. They most likely have private businesses and apartments for rent, and most of them are active bank clients. Almost all respondents have the opportunity to use the Internet, and only about 10% of people borrowed for daily needs.

Almost all people in this cluster are quite young – less than 40 years old. In general, the age factor is a very interesting indicator. According to the results of the Eurostat study, it was found that the younger population is more likely to get rich. Young people are less afraid of being unemployed: 51% of those surveyed in Europe aged 18 to 30 are confident that they will be able to find a new job in two weeks, but only 35% of people over 55 are confident (Halásková, 2019).

It was also found that employees with a long experience did not receive a significant return from their experience. The decrease in earnings of older workers is caused by objective factors, including a decrease in their ability to acquire new skills, modern technologies, deterioration of health, and risk aversion. People reach their maximum salary on average up to 30 years, and after that their earnings increase slightly over time (Halásková, 2019).

In this cluster, almost 80% of the respondents have savings for at least six months to live comfortably. Thus, this cluster can be considered as a cluster of rich people.

In general, the distribution of respondents is the following: the cluster of poor includes 3054 people; the cluster of average living cost – 2999 respondents; the cluster of rich – 2347.

The results of modeling present an approach to the study of poverty as a multidimensional phenomenon addressing the set of socioeconomic indicators associated with it. This approach is based on the clustering population by machine learning methods. The selection of indicators was carried out by classification methods using PPI methodology. One of the main PPI methodology principles is that the set of indicators should be simple: it doesn't contain many indicators and respondents understand clearly and accept all of them.

Applying this approach to the PPI Data Science Capstone dataset allowed us to identify a cluster of poor people with a series of simple questions. The results of clustering are consistent with some of the results of previous studies regarding the interpretation of poverty in terms of the socio-economic characteristics of people's lives.

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АНАЛІЗ ПОКАЗНИКІВ БІДНОСТІ ЗА ДОПОМОГОЮ PPI МЕТОДОЛОГІЇ

Бідність є негативним соціально-економічним явищем, яке має руйнівний вплив не тільки на якість життя людей, які потрапляють в пастку бідності, але для суспільства у цілому. Бідність заважає суспільству реалізувати свій потенціал, призводить до регресу суспільного розвитку. Подолання бідності зазначено ціллю №1 в Цілях сталого розвитку (ЦСР), які були ухвалені ООН у 2015 році як глобальні цілі до 2030 року.Зростання рівня бідності спостерігається вперше за останні двадцять років, що потребує вивчення причин та розробки відповідних заходів запобігання такої тенденції. Відомо, що бідність має різноманітні прояви, має національні та культурні особливості, що потрібно враховувати при вирішенні проблеми бідності. Однією із актуальних задач в дослідженні цієї проблеми є розробка адекватних методів вимірювання бідності і визначення категорії людей, які вважаються бідними. Метою даного дослідження є виявлення кластеру бідних людей на підставі методології PPI за допомогою моделі кластеризації з використанням набору соціально-економічних показників. Відбір показників здійснювався методами класифікації з використанням методології PPI. Інформаційна база дослідження включає дані 8400 респондентів з 7 європейських країн. Розробка моделі здійснювалася в кілька етапів:1) обробка даних та статистичний аналіз; 2) відбір значущих показників за допомогою класифікаційної моделі; 3) кластеризація за алгоритмом k-середніх; 4) ієрархічна кластеризація; 5) порівняння результатів моделювання та інтерпретація результатів. Обробка та аналіз даних здійснювалися за допомогою Python. Використовуючи результати кластеризації можна розділити населення на групи з різним рівнем життя, виділяючи людей з низьким рівнем доходу. Запропонований підхід до оцінювання ймовірності бідності допоможе підвищити ефективність та своєчасність надання допомоги бідним сім'ям.

Ключові слова: **бідність, Цілі сталого розвитку (SDGs), PPI методологія, моделі кластеризації і класифікації.**

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