

Socio-Economic Situation in Latvia's Municipalities in the Context of Administrative-Territorial Division and Unexpected Impact of COVID-19

Irina Arhipova, Latvia University of Life Sciences and Technologies, Latvia*

 <https://orcid.org/0000-0003-1036-2024>

Gundars Berzins, University of Latvia, Latvia

Aldis Erglis, University of Latvia, Latvia

Evija Ansonska, University of Latvia, Latvia

Juris Binde, Latvian Mobile Telephone, Latvia

ABSTRACT

In this research, the authors analysed how the behaviour of people changed in various phases of the COVID-19 pandemic and how these changes affected the economic activity in municipalities, taking into consideration significant changes in people's habits and employment conditions. The pandemic coincided with the administrative-territorial reform in Latvia, providing a unique opportunity to test and ascertain in a single research both the above-mentioned changes in the economic activity of inhabitants and the viability of the new administrative-territorial division vis-a-vis the new reality. The developed regional planning methodology based on the mobile phone activity data and socio-economic indicators (set of indicators provided by regional development state institutions) is used to categorize the 43 newly formed municipalities into similar groups. It is concluded that the aggregated indicators have a significant impact on the division of municipalities: inhabitants, dynamics indicator, economic development level, mobile phone activity on workdays, holidays, and weekends.

KEYWORDS

COVID-19, Mobile Phone Data, Principal Component Analysis, Regional Development, Regional Economic Activity

INTRODUCTION

The COVID 19 pandemic not only influenced the health of the population, tested the efficiency of national health care systems and spotlighted the weaknesses of these systems, but also revealed significant changes in the models of human behaviour. In the framework of this research, the authors analysed how the behaviour of people changed in various phases of the pandemic and how these changes affected the economic activity in municipalities, taking into consideration significant changes in people's habits and employment conditions. The pandemic coincided with the Administrative-

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*Corresponding Author

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Territorial Reform (ATR) in Latvia, providing a unique opportunity to test and ascertain in a single research both the above-mentioned changes in the economic activity of inhabitants and the viability of the new administrative-territorial division vis-a-vis the new reality. Therefore, the objective of the research was to examine how the

COVID-19 pandemic has influenced the behaviour and the economic activity of people (unloading the capital city, Riga, and increasing activity in the regions and rural areas of Latvia) in terms of whether the new territorial division has increased the economic and social equality among municipal territories throughout the country.

The pandemic has created favourable conditions for remote work and proved that working from home can significantly improve the epidemiological situation. By that creating new social environment for social consensus and dialogue, which requires reconsider approaches to its analysis (Shin, 2016). However, there are jobs, which cannot be performed remotely with sufficient efficiency, and the distribution of jobs that can be performed remotely are unevenly dispersed across municipalities (Fadinger & Schymik, 2020). Situation in Latvia was different, as the majority of inhabitants not only chose to work from home but also changed their place of residence, moving from economic activity centres to areas, which traditionally have been associated with recreation. In 2020, the authors observed a significant decrease of activity in the traditional centres of economic activity and a notable increase in their surrounding areas. This situation allowed us to test the assumption that by significantly activating the business environment, the municipalities surrounding bigger cities could ensure higher economic activity after the pandemic.

Minimisation of socio-economic inequality (difference between municipalities compared by a set of socio-economic indicators) is the aim of the ATR and a significant prerequisite for improving the general welfare of the country. It is also an important aspect for long-term social security and political stability of the state, with the need for development strategies tailored for specific municipal territories (Rodríguez-Pose, 2018). Discussions on the need for administrative-territorial reform began immediately after the restoration of independence of Latvia in 1991. However, the first ATR after the restoration of independence was only implemented in 2009. The aim of the reform was to create economically self-sufficient local governments that would ensure the provision of quality services to the population. As a result of the 2009 ATR, there was a transition from two levels to one level of local government: 26 district councils were abolished, but cities, their rural territories and parishes were merged into 119 counties, and 9 large cities gained the status of republican cities. But already in 2015, the Ministry of Environmental Protection and Regional Development of Latvia encouraged to significantly reduce the number of counties again. One of the proposed options was to reduce the number of counties to 49, preserving 9 cities of national importance.

At the beginning of 2019, the Cabinet of Ministers of Latvia adopted a declaration envisaging the implementation of local government reform by 2021, merging administrative territories into more sustainable and economically stronger units, modeling the development plan of Pierīga municipalities separately. The initially prepared ATR reform project envisaged reducing the number of counties from 119 to 35, thus the new map of counties and parishes was largely similar to the former map of districts of Latvia.

Latvia has chosen to implement its ATR in two phases – first, by defining the conditions for the development and equality of the new administrative units, and then by carving out detailed plans on how to tailor development strategies for individual municipal territories.

The purpose of the ATR is to improve the capacity of municipalities significantly. According to the Law on Administrative Territories and Populated Areas adopted by the Saeima on 10 June 2021, Latvia will have 43 administrative units (municipal territories) instead of the existing 119 municipalities by the end of 2021. The Law introduces two types of municipal territories – city municipal territories (cities) and county municipal territories or counties (“novadi” in Latvian), dividing the latter into towns and parishes (“pagasti” in Latvian). The populated areas of Latvia include cities, towns, villages, hamlets and farmsteads. As the word “pilsēta” in Latvian applies to

both cities and towns, the new law makes a division between the two by introducing the term city (“valstspilsēta” in Latvian) and town (“novada pilsēta” in Latvian). The Law grants the city status to 12 cities. To preserve, strengthen and sustainably develop cultural and historic local identities of the population, a separate law will define the affiliation of municipal territories to the historical regions of Latvia – Vidzeme, Latgale, Kurzeme, Zemgale and Sēlija.

The need for the reform is justified by the fact that many local governments have failed to provide full range of social services to meet the needs of their inhabitants. Moreover, municipal administrative expenditures per capita are rather high, suggesting inefficient use of state budget funds. As a result, many local governments cannot assume financial obligations to ensure development of their respective administrative territory. The goals of the reform go hand in hand with the need for a more efficient network of educational, healthcare, social, transport and utilities infrastructure. Structural changes will also help develop areas with high potential for economic activity, with the type of infrastructure that would meet the needs of various businesses.

Since 2016, the University of Latvia has been collaborating with the Latvian mobile telecommunications company, Latvian Mobile Telephone (LMT), to analyse the statistics of mobile network events in a variety of aspects. LMT is a leading mobile network provider in Latvia providing technological innovations and broader network services. Despite that network, convergence could provide some level of uncertainty that should be considered during the analysis of data from these networks (Shin & Jung, 2012). In the framework of this collaboration, the authors have analysed regional economic activity and population mobility, as well as the compliance of inhabitants with the restrictions aimed at containing the COVID-19 pandemic. Mobile networks as infrastructure for actor-network analysis could be used to map it with socio-technical and socio-economic activity (Shin & Kweon, 2011). The authors have developed an approach for automated processing of real-time data, not only providing information about the actual situation in Latvia, but also allowing for preventive actions and forecasts based on Big Data (Arhipova et al., 2021). The approach developed by the University of Latvia and LMT fully complies with the General Data Protection Regulation (GDPR) of the European Union. At the same time, it allows to precisely assess the behaviour of inhabitants, for example, determine concrete locations, movements and times of activity (Arhipova et al., 2020). However technological development could provide more reliable and consistent approaches to data protection and tracking of personal data usage by using blockchain technologies for socio-economic analysis (Shin & Ibahrine, 2020).

The objective of this research is to offer a methodology for assessing and planning the impact of administrative-territorial reforms, as well as to assess the impact of administrative division on socio-economic equality in Latvia, taking into consideration the impact of the COVID-19 pandemic on people's behaviour.

The paper consists of the following parts: description of the administrative-territorial reform in Latvia and the current territorial division; overview of the literature background; description of results provided by the analysis of socio-economic indicators of municipal performance; analysis of regional economic activity using mobile data; description of the relationship between mobile phone activities and socio-economic indicators, as well as the impact of the pandemic on regional economic activity; conclusions and outline of directions for future research.

BACKGROUND

The COVID-19 pandemic has influenced the behaviour, habits and health of the population. An increasing number of studies suggest that the scope of this phenomenon's impact on various population groups depends on the socio-economic status of these groups (Martin et al., 2020). One of the ways to investigate the socio-economic impact is to analyse municipalities, regions or local territories through available indicators describing the socio-economic situation. For reliable quantitative, data-driven analysis disruptive technologies leading to discover associative rules between socio-economic

indicators and data collected with disruptive technologies such as Internet of Things, Internet of Medical Things, Industry 4.0, Artificial intelligence, and Big Data (Abdel-Basset, Chang & Nabeeh, 2021). Most potential ariseal-time IoT (Internet of Things) data collected using a 5G mobile network, that allow to map social events with real-time data (Shin, 2019). Other ways of collecting data emerges because of high individual's adoption rate of mobile devices such as smartphones and tablets, data from these devices are widely used for telemedicine purpose (Baudier et al., 2021). But it can't be used for analysis of economic development due to GDPR and other restrictions for use of personal data for data analysis. Despite that, one of available data Big Data source for measuring population activity is aggregated mobile phone activity data from mobile stations with geographic mapping to municipal territories. Analysis of correlation between socio-economic data and municipal territory classification based on mobile activity (mobile activity is all calls and data transfer events on mobile station level) data done using machine learning correlation visualization methods (Friendly, 2002).

Several studies prove that its influence on municipalities with different socio-economic conditions is disproportionate (Armillei, Filippucci & Fletcher, 2021). Some studies show that some social-economic indicators are showing greater impact of pandemic that others, especially indicators related to investment amount and corporate profits in region (Alankar et al., 2022). Many social-economic indicators are available with time lag and therefore closer to phenomenon analysis methods such as analysis of sentiment in social networks could be used (Kaur et al., 2021). Where sentiment analysis could be calculated automatically using sophisticated Machine Learning sentiment natural language processing methods (Chen et al, 2018). This method seems very effective but can't be used for regional development analysis due to location attribution problems for social network published information. However, using real-time data Actor-Network analysis methods is an appropriate analysis method for analysing socio-economic behaviour and activity (Shim & Shin, 2019). There are several machine learning methods could be used for classification of municipalities, but it is important that selected machine learning methods are explainable and transparent such as Principal Component Analysis (Jolliffe, 2002).

Studies also suggest that regional development has a direct relation to the quality of regional governance (Ganau & Rodríguez-Pose, 2021), and that successful management of the pandemic is related to the quality of regional governance (OECD, 2020). The quality of regional governance is closely connected to the availability of local resources and their capacity, which, in turn, is related to the region's economic activity (Bassam, 2013) and the size of the population.

The COVID-19 pandemic hits Latvia during the active phase of the ATR. As a result, municipalities were merged to form larger administrative-territorial units with bigger economic capacity and larger populations, notably decreasing the total number of municipalities. This provided an opportunity to verify whether the newly formed municipalities will be functioning in improved socio-economic conditions than before. Municipal diversity presented a major difficulty for describing municipalities and their reactions to the pandemic, the quality of regional governance or socio-economic situation (Xu, Duan & Xu, 2018) in cases where the authors had chosen to use proxy indicators of location-related mobile phone activity (Arhipova et al., 2020). The aim was to measure regional development and to group the traditional indicators of regional development with the help of statistical analysis methods. Such approach not only provides objective classification of municipalities based on the model of their actual behaviour, which is based on objective measurements of population activity, but also connects these measurements with the traditional statistical data, in turn providing an opportunity to identify success factors for regional development in specific groups of municipalities.

To study the impact of administrative-territorial reforms on socio-economic situations in different countries, a variety of approaches is available. For example, a group of authors (Przybyla, Kachniarz & Ramsey, 2020) investigated a hypothesis that administrative status in Poland has a notable influence of investment expenditure on urban development. In Finland, the government is ready to implement another nation-wide reform that would further reduce the number of municipalities and increase their mean populations. The issue of borders is an important aspect in the process of

de-institutionalisation (Zimmerbauer, Suutari & Saartenoja, 2012). To understand the relationship between administrative decentralization and economic growth, a group of researchers examined the experience of administrative reform in China. The study concluded that administrative decentralization significantly (by about 3.3 per cent) increases GDP per capita (Gong, Liu & Wu, 2021). Another study analysed the role of local governance and the consequent outcomes of the implementation practices (Menzori, Nunes de Sousa, & Goncalves, 2021). An empirical analysis, conducted in Western Balkan countries in the period of 2006-2016, assessed the correlation between the most important institutional quality indicators on GDP per capita and economic growth in these countries (Nedic et al., 2020).

A recent trend in Western economies shows that general welfare reforms go hand in hand with rationalization of local administrative structures – mergers and amalgamation processes are leading to reduction of administrative levels and units, subsequently rearranging municipal boundaries. A group of authors have developed mathematical models to analyse the amalgamation policy decisions implemented in Italy. The obtained results can provide useful tools for stakeholders and policy makers (Bruno, Genovese & Piccolo, 2017). Changing borders of urban areas is a complex task because the relevant data are heterogeneous, and there is little consensus on the correct measurement of results. Any change of physical borders leads to eventual adjustment of administrative boundaries. In Italy, an investigation of the area-population relation was conducted, proposing a practical application for relating administrative and alternative boundaries (Alviolo (Massi), 2020).

SOCIO-ECONOMIC INDICATORS CHARACTERISING MUNICIPAL PERFORMANCE

Different statistical data can characterise the economic activity in municipalities. Since the beginning of the 20th century, theories of regional economic development have attempted to distinguish a single development factor as the main prerequisite for development. Even though the most important factors characterising economic activity can be identified, they must be assessed in context, as highlighting of a single factor presents significant shortcomings and limitations. For example, the study “How Regions Grow? Trends and analysis” (OECD, 2009) analyses coherences among six indicators – the GDP growth rate, productivity, population changes, employment, labour force activity and level of economic participation. The findings of this OECD study suggest that the interconnected indicators of productivity and innovation are the most significant development factors, followed by the indicators of infrastructure availability, population and employment. It is also concluded that declining population does not automatically lead to inevitable economic recession and stagnation. When the number of inhabitants is declining, the role of productivity, innovation and labour force activity indicators becomes increasingly crucial.

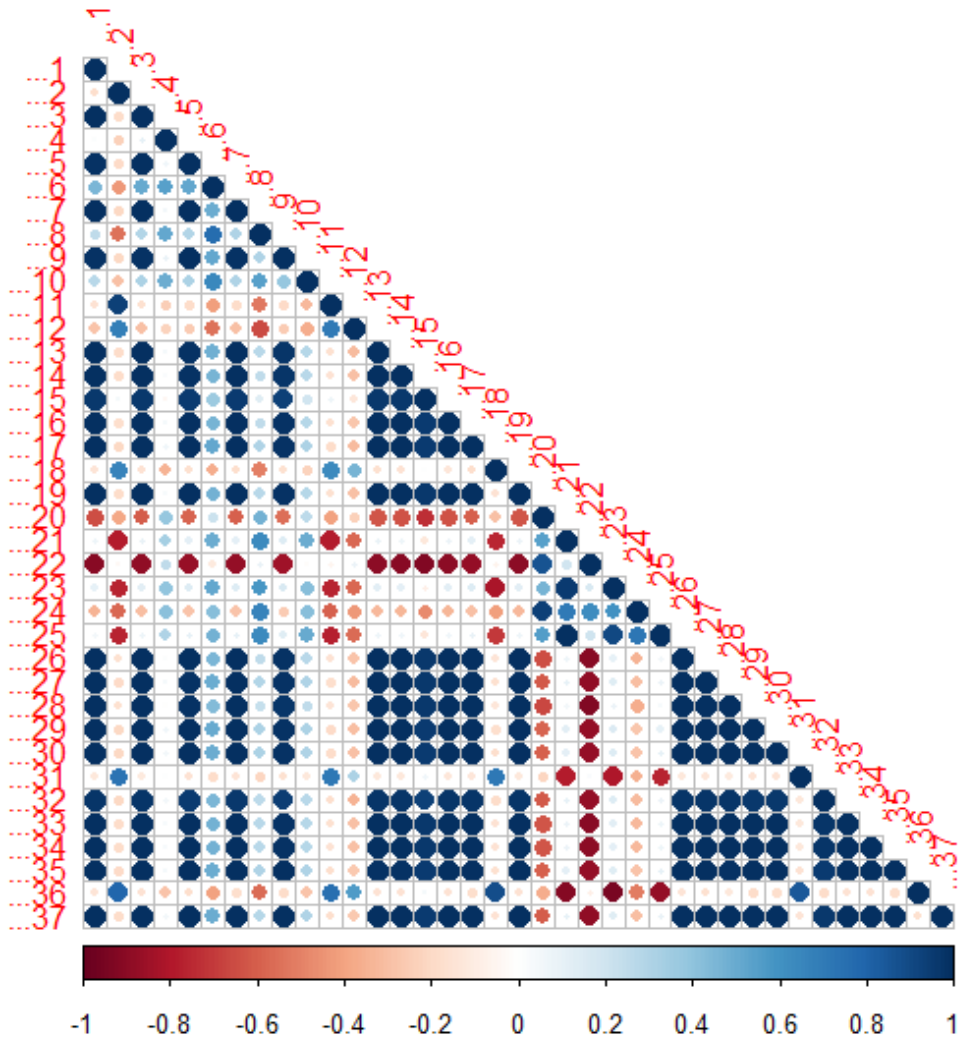
To monitor and assess regional development, Latvia applies the Territorial Development Index (TDI) statistics and the Regional Development Indicators Module (RAIM) (State Regional Development Agency Republic of Latvia, 2020). The TDI illustrates the development level in a respective year, comparing the development level of individual municipalities with the country's average development level. It is a generalized indicator, which is calculated separately for planning regions, cities and counties (“novadi” in Latvian). The TDI calculation is based on eight different statistical indicators, of which the most important are: the number of economically active companies and individual entrepreneurs per 1000 inhabitants, unemployment rate, Personal Income Tax (PIT) per capita, and population changes. While conducting a research for the purposes of this report, the authors had to consider the limited availability of statistical information, because not all of the above-mentioned indicators could be obtained along the lines of administrative units. This research is based on the new administrative-territorial model of the ATR, which divides Latvia into 43 municipal territories. To conduct comparable statistical analysis, the authors selected and analysed 37 socio-economic indicators that could be aggregated or calculated for 43 municipalities based on 2018 data and that might suggest economic activity:

1. Population over working age at the start of the year.
2. Working age population at the start of the year.
3. Population at the start of the year.
4. Total municipal budget revenues (EUR).
5. Number of Personal Income Tax (PIT) payers based on registered domicile.
6. Total municipal budget expenses (EUR).
7. Number of students in general education schools (includes pre-schools, primary and secondary schools).
8. Number of pupils in pre-schools.
9. Number of pre-schools.
10. Population under working age at the start of the year.
11. Municipal electricity consumption (kWh).
12. Number of PIT payers based on the registered domicile of the employer.
13. Municipal budget revenues from PIT (EUR).
14. Number of new-borns.
15. Total municipal budget tax revenues (EUR).
16. Withheld sum of PIT (based on the registered domicile of the employee) (EUR).
17. Municipal budget revenues from Real Estate Tax (EUR).
18. Withheld sum of PIT (based on the registered domicile of the employer) (EUR).
19. Number of general education schools.
20. Total sum of foreign direct investments (EUR)
21. Municipal budget capital expenditure (EUR)
22. Absolute population change per year due to natural migration.
23. Absolute population change per year.
24. Subsidies from municipal fiscal equalization fund (percentage of all municipal budget revenues).
25. Population change per year (percentage).
26. Population change per year due to natural migration (percentage).
27. Municipal budget expenditure on remuneration in percentage of all municipal expenses.
28. Population changes per year due to migration (percentage).
29. Area (km²).
30. Sum of project funding from EU funds (EUR).
31. Unemployment rate (percentage).
32. Sum (EUR) of project funding from EU funds per capita.
33. Municipal electricity consumption (kWh) per capita.
34. Withheld PIT sum (EUR) per capita, based on the registered domicile of the employer.
35. Total municipal budget tax revenues (EUR) per capita.
36. Total sum of foreign direct investments (EUR) per capita.
37. Absolute population changes per year due to migration.

Rather than measuring the socio-economic welfare of municipalities per se, the above-mentioned factors were chosen with an aim to assess the economic activity in a specific municipal territory with maximum precision. The study analyses the new division of 43 administrative-territorial units based on 2018 data. Figure 1 shows the extent of collinearity of the entire dataset by plotting all 37 covariates with strong mutual correlations – 32 out of 37 variables show at least one correlation over 0.7; other 6 variables have at least one correlation over 0.5.

For the above-mentioned reason, it is necessary to remove multicollinearity from the dataset of Latvia's municipalities in 2018 in relation to the administrative reform, and preserve maximum variance. The Principal Component Analysis (PCA) was performed with the Varimax rotation method and as a result, a dataset of three realized principal components (PC) scores instead of the original 37 covariates was ended up. PCA selects covariate linear combinations with the maximum variance,

Figure 1. Graphical visualization of a correlation matrix of 37 variables (blue for positive correlations, red for negative correlations). Circle colour intensity and size is proportional to the correlation coefficients



called Principal Components (PCs). The first three PCs account for 91.6% of the original dataset variance, where the first PC is strongly correlated (absolute value over 0.9) with 22 of the original variables. The second PC is correlated (absolute value over 0.6) with nine of the original variables, and the third PC correlated (absolute value over 0.5) with six of the original variables (Table 1).

This first principal component PC1 can be viewed as a measure of the *Inhabitants* descriptive component; the second principal component PC2 can be viewed as a measure of the *Dynamics indicators* component, or the component, which characterises the development dynamics of a specific municipal territory. The third principal component PC3 can be viewed as a measure of the *Economic development level* in a specific municipality (electricity consumption, taxes, and investments).

PC1 describes the socio-economic status of the population and characterises the standard of living. With the help of these indicators, it can be possible mutually to compare various counties. In the process of forming new municipal territories, the set of these indicators can help identify

Table 1. Rotated Component Matrix (coefficient absolute value below 0.4 is suppressed)

Socio-Economic Indicators	Component (PC)		
	1	2	3
Population over working age at the start of the year	.997		
Working age population at the start of the year	.996		
Population at the start of the year	.996		
Total municipal budget revenues (EUR)	.995		
Number of Personal Income Tax (PIT) payers based on the registered domicile of the employee	.995		
Total municipal budget expenses (EUR)	.994		
Number of pupils in general education schools	.994		
Number of pupils in pre-schools	.993		
Number of pre-schools	.992		
Population under working age at the start of the year	.991		
Municipal electricity consumption (kWh)	.990		
Number of PIT payers based on the registered domicile of the employer	.990		
Municipal budget revenues from PIT (EUR)	.989		
Number of new-borns	.989		
Municipal budget revenues from taxes total (EUR)	.989		
Withheld sum of PIT (based on the registered domicile of the employee) (EUR)	.988		
Municipal budget revenues from Real Estate Tax (EUR)	.986		
Withheld sum of PIT (based on the registered domicile of the employer) (EUR)	.985		
Number of general education schools	.982		
Total sum of foreign direct investments (EUR)	.974		
Municipal budget capital expenditure (EUR)	.968		
Absolute population change per year due to natural migration	-.930		
Absolute population change per year	-.699	.427	.516
Subsidies from municipal fiscal equalization fund (% of all municipal budget revenues)		-.952	
Population change per year (%)		.923	
Population change per year due to natural migration (%)		.920	
Municipal budget expenditure on remuneration in % of all municipal expenses		-.905	
Population changes per year due to migration (%)		.899	
Area (km ²)		-.884	
Sum of project funding from EU funds (EUR)		-.866	
Unemployment rate (%)		-.825	
Sum (EUR) of project funding from EU funds per capita		-.665	
Municipal electricity consumption (kWh) per capita			.761
Withheld PIT sum (EUR) per capita, based on the registered domicile of the employer	.407		.738
Total municipal budget tax revenues (EUR) per capita		.509	.721
Total sum of foreign direct investments (EUR) per capita			.721
Absolute population changes per year due to migration	-.413	.581	.594

inequality aspects and help in objective decision-making regarding strategies for improving the quality of local governments.

PC2 set of indicators describes development dynamics in a municipal territory, also indirectly showing the institutional quality of municipalities.

PC3 set of indicators describes economic and business activity in a municipal territory; it can be applied in designing and development planning process of the ATR. The component scores of 2018 for all municipalities are given in Appendix 1.

ANALYSIS OF REGIONAL ECONOMIC ACTIVITY USING MOBILE DATA

The dataset of this study contains data on unique users and mobile phone activity collected from 1238 LMT base stations across Latvia. The location of each mobile base station is mapped using GPS coordinates and attributed to a specific municipal territory. Each activity registered at a mobile base station is attributed only to one municipal territory at a time, depending on the actual geographical location of the specific activity and the distances between base stations. If a mobile base station is located in a certain municipal territory, all mobile activity is attributed to this municipal unit and aggregated according to one of the two models of territorial division (119 or 43 municipalities) used in this analysis. Mobile activity data for 2018 and 2020 is used, with 15-minute intervals by days and hours for each mobile station.

The PCA was performed on three datasets that consist of covariates – linear combinations of the total number of mobile phone activities and the total number of unique users in a municipality, on different days of the week in the course of one year:

- The 1st dataset consists of covariates for 119 municipalities (division model before the ATR) based on 2018 data;
- The 2nd dataset consists of covariates for 43 municipalities (new division model designed in the ATR) based on 2018 data;
- The 3rd dataset consists of covariates for 43 municipalities based on 2020 data.

The applied Kaiser-Meyer-Olkin (KMO) test produced values between 0.8 and 1 for the analysed time-period, indicating that sampling was adequate. The first two PCs account for:

- 77.7% of the original dataset variance for the 1st dataset,
- 79.9% of the original dataset variance for the 2nd dataset,
- 96.3% of the original dataset variance for the 3rd dataset.

In all datasets, the first PC has the highest values on workdays, but lower values on weekends and in June, July and August. In turn, the second PC has the highest values on weekends and in summer months, but lower values on workdays. The component loadings describe how much each of the observed variable contributes to a particular principal component. Large loadings (positive or negative) indicate that a variable strongly correlates to a particular principal component. The sign of a loading indicates either positive or negative correlation between a variable and a principal component.

Municipal territories with strong economic activity have high correlation with the first PC, otherwise correlate highly with the second PC. These values, or loadings, are given for 43 municipalities in component matrixes for 2018 (Appendix 2) and 2020 (Appendix 3), containing component loadings that indicate correlation between the variables of mobile phone activity in a municipality and the components.

Measure of Municipalities Performance in the Context of New Administrative-Territorial Division

Municipalities in Latvia fall into eight categories based on economic activity (Arhipova et al., 2020):

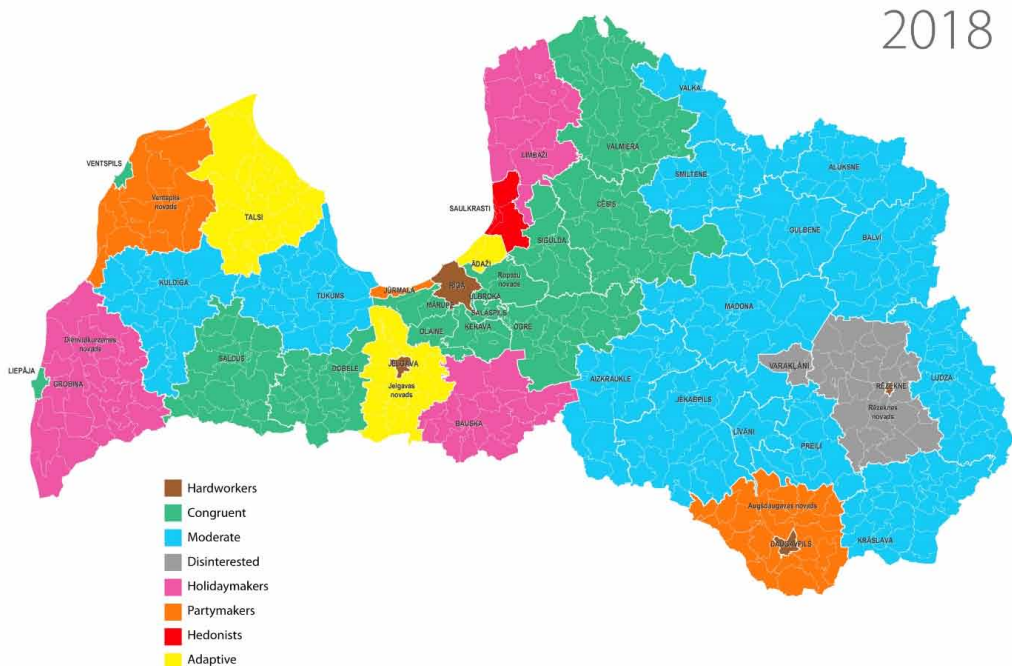
- Hard workers with high activity on workdays, but average-low activity on holidays/weekends.
- Congruent with high and average-high activity on workdays and average activity on holidays/weekends.
- Adaptive with average-high activity on workdays and holidays/weekends. This group is characterised by even development, but without strong local centres.
- Moderate with average economic activity on workdays and holidays/weekends.
- Holidaymakers with average-low activity on workdays, but average-high activity on holidays/weekends.
- Party makers with low activity on workdays, but high activity on holidays/weekends.
- Hedonists with minimal activity on workdays, maximum high activity on holidays.
- Disinterested with low activity on workdays and average activity on holidays/weekends (Fig. 2).

Figure 2. Categorisation of Latvia's 119 municipalities (pre-ATR division) into groups, 2018 (Arhipova et al., 2020)



The analysis of mobile network statistics and our municipal economic activity maps clearly demonstrate that amalgamation of smaller counties is a decision based on data. After amalgamation, an increasing number of counties fall into the *Congruent*, *Moderate* and *Adaptive* categories, there are no counties in the *Disinterested* and *Hedonist* categories, and only a few *Party makers* counties remain (Fig. 3).

Figure 3. Categorisation of Latvia's 43 new municipalities into groups, based on 2018 data before ATR



COVID-19 Impact on Regional Economic Activity

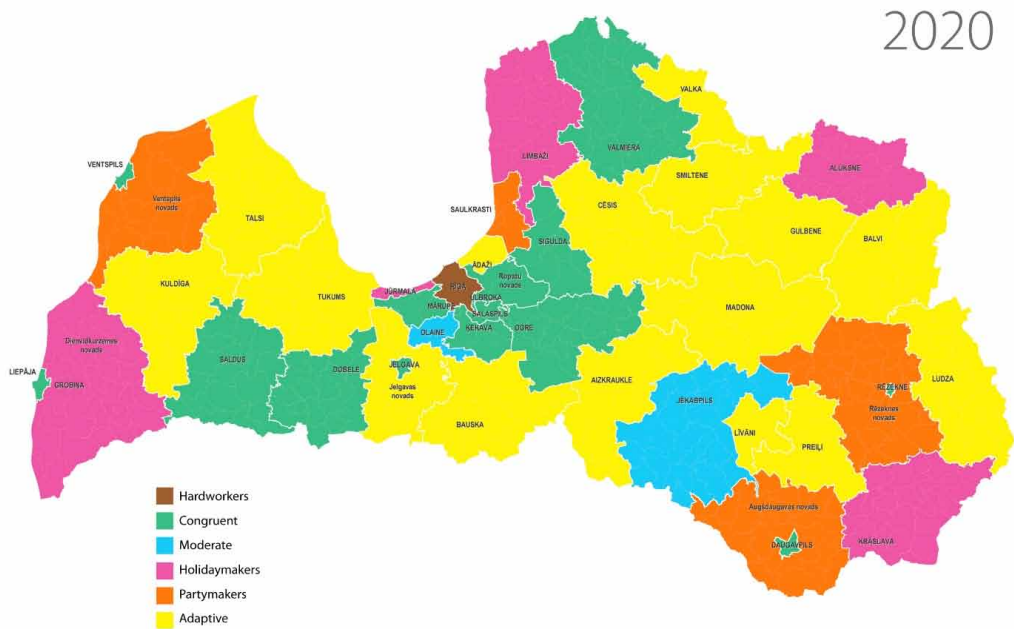
The COVID-19 crisis provided a unique opportunity to validate the developed ATR assessment and regional development planning approach, which combines statistical indicators and mobile network activity measurements in a single model. To validate the model, it is essential to look at municipal territories based on the new administrative-territorial division of the ATR before and during the Covid-19 pandemic. The pandemic significantly changed the behaviour of the population and the economic activity in various Latvian municipalities. Therefore, two maps of the new administrative-territorial division of Latvia were developed for the purposes of this study. The first map is based on 2018 data, containing 43 newly established municipalities (division model before the ATR). The second map contains 43 new municipalities based on 2020 data, with a visible impact of the pandemic (Fig. 4). The data obtained in the study show that if the ATR were introduced already in 2018, the counties would have had a significantly higher potential for smooth development already in 2018 – the number of *Disinterested* counties would have decreased significantly, and a larger number of *Adaptive* counties would have appeared, leading to a more efficient development of the country. The impact of COVID-19 in 2020, however, showed a significantly different picture than expected.

The economic activity of counties has changed significantly due to COVID-19. The number of self-sufficient, or *Adaptive*, counties has significantly increased, and the number of *Hard workers* has decreased. There is a logical explanation for this: the pandemic and the following restrictions motivated inhabitants to change their pattern of behaviour rapidly. They moved to live outside the centres of economic activity – started to work remotely from holiday homes and hotels in the country, thus shifting the economic activity away from cities whilst preserving their jobs. The second trend is that the population reduced mobility and spent both workdays and holidays in the boundaries of the same municipality, thus increasing economic activity on holidays in the areas outside cities.

The restrictions introduced by the central government to contain the pandemic have had a significant impact on human behaviour, and such behavioural changes were not the result of the ATR or special activities by local governments. They permitted to see how people would change their behavioural territory. In the perception of many people, the centres of economic activity were not suitable for living in circumstances of the pandemic, and the choice was in favour of moving to areas with lower population density.

In analysing the newly formed municipal territories, it is important to look at the situation before and during the COVID-19 pandemic, as it has significantly changed the behaviour of inhabitants and the economic activity in various municipal territories of Latvia. Therefore, the authors developed two maps of new administrative-territorial division. The first map includes 43 municipal territories based on 2018 data, i.e. before ATR (Fig. 3). The second map includes 43 municipal territories based on 2020 data and shows the impact of the pandemic (Fig. 4).

Figure 4. The division of Latvia's 43 municipalities into groups, 2020



Currently, the biggest question is whether the effect of the pandemic is here to stay in terms of people remaining in the regions to live and work. In any case, this crisis and the increased opportunities to work remotely provide a unique opportunity for regions to implement sustainable local development strategies to attract well-educated inhabitants with high level of income. Regardless of significant decrease of activity during the COVID-19 pandemic, Riga was the only territory to maintain the *Hard workers* status. In turn, 14 of the newly formed municipal territories fell into the *Congruent* category. The number of *Adaptive* municipalities increased to 16, clearly marking those territories where population migration takes places mostly within the municipality. It means that people work, study, live, shop and relax predominantly in the same territory. Therefore, the economic activity on

different days of the week and in different seasons helps us outline the profile of each municipality (Table 2).

Table 2. Groups of municipalities characterised by mobile phone activity

Municipalities group	Component loading		Number of municipalities		
			factual in	Along the lines of the new administrative-territorial division in	
	PC1: Workdays	PC2: Weekends/holidays	2018	2018	2020
Hard workers	0.8–1.0	0.0–0.2	10 (8%)	4 (9%)	1 (2%)
Congruent	0.8–1.0	0.2–0.6	30 (25%)	13(30%)	14 (33%)
Adaptive	0.6–0.8	0.6–0.8	-	3 (7%)	16 (37%)
Moderate	0.4–0.8	0.2–0.6	42(35%)	14 (33%)	2 (5%)
Holidaymakers	0.4–0.6	0.6–0.8	21 (18%)	3 (7%)	5 (11.5%)
Party makers	0.0–0.4	0.6–1.0	12 (10%)	3 (7%)	5 (11.5%)
Hedonists	- 0.2–0.0	0.8–1.0	1 (1%)	1 (2.5%)	-
Disinterested	0.0–0.4	0.2–0.6	2 (2%)	2 (4.5%)	-
Phenomenon	0.4–0.8	0.0–0.2	1 (1%)	-	-
Total:			119 (100%)	43 (100%)	43 (100%)

When analysing the new municipal units, it is important to look at the situation before and during the COVID-19 crisis, as it significantly changed the behaviour of people and the economic activity in various municipalities in Latvia – unloading Riga and other centres of economic activity and increasing activity in the regions and rural territories. The maps clearly show that merging and amalgamation of administrative units leads to greater economic equality throughout the country. An increasing number of municipalities now fall into the category of *Congruent*, *Moderate* and *Adaptive* (a new category that has emerged after the implementation of the ATR); there are no *Disinterested* and *Hedonist* municipalities, and very few typical *Party makers* (Fig. 5).

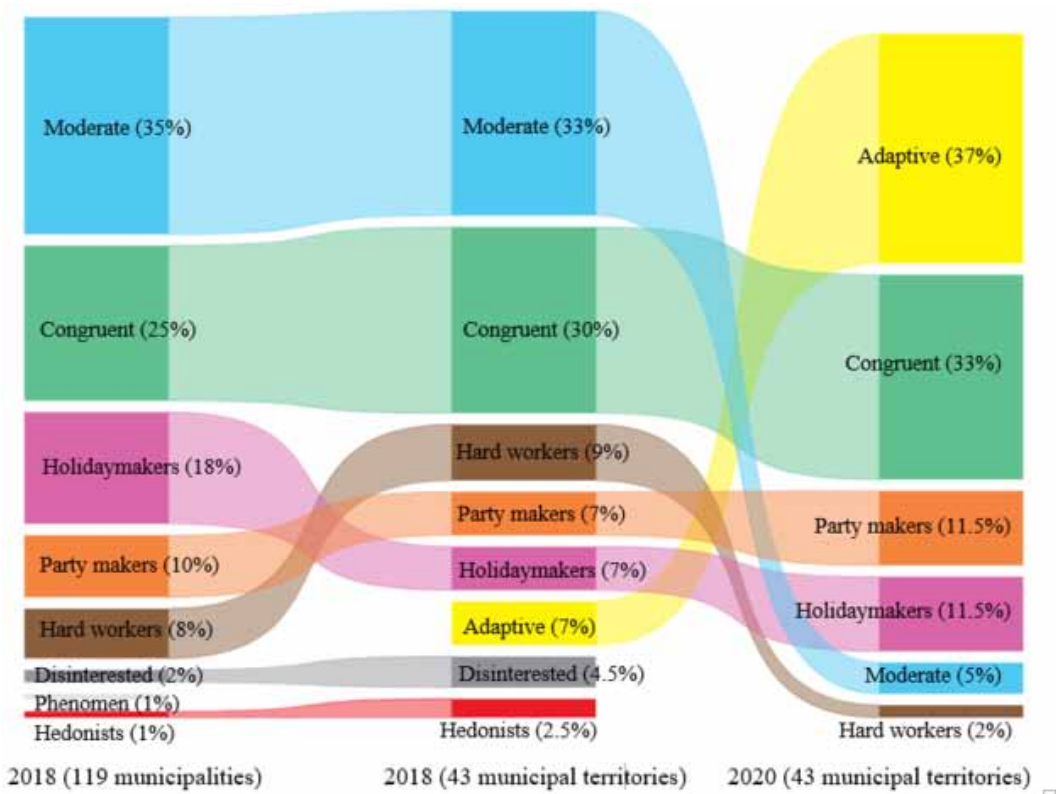
It would be interesting to analyse and forecast, if the impact of COVID-19 will remain after the pandemic and increasing number of people will live and work (also remotely) in the regions. In any case, this crisis provides an opportunity for regions to attract new professionals and inhabitants with high income.

On the one hand, the proposed ATR assessment approach / method allows us to objectively assess changes in population behaviour and, in exceptional cases like the COVID-19 pandemic, to ensure that the method objectively reflects population behaviour. On the other hand, in the context of the ATR and long-term planning, it can be seen that the population can rapidly change their patterns of behaviour if favourable preconditions are created. At present, the sustainability of changes in human behaviour brought about by COVID-19 will depend on the actions of both local and central governments.

RELATIONSHIP BETWEEN MOBILE CALL ACTIVITIES AND SOCIO-ECONOMIC INDICATORS

While analysing the statistical indicators of the aggregated characteristics with Kruskal-Wallis test, we established that there are 29 factors from 37 socio-economic indicators, which have a significant

Figure 5. Comparison of mobile phone activity of municipality groups according to the territorial division, 2018-2020



impact on categorizing mobile data into eight cluster groups in 2018 (Appendix 4). Upon calculations, the authors concluded that the values of the 29 characteristics significantly differ among the eight groups of municipal territories. After selecting the given characteristics, we categorized them according to the affiliation of municipalities to the cluster groups of mobile data: the eventual division of municipalities based on economic activity in 2018 – grouping of 43 municipalities (Figure 3).

The average values for each aggregated component in municipality groups $X1=Inhabitants$, $X2=Dynamics\ indicator$, $X3=Economic\ development\ level$ (Appendix 1) and mobile phone loadings on workdays $Y1$ and holidays/weekends $Y2$ (Appendix 2) are provided in Figure 6.

While conducting the analysis of statistical indicators of the aggregated characteristics with Kruskal-Wallis test, it was established that $X2=Dynamics\ indicator$ has a significant impact on the division of eight cluster groups of mobile data (Table 3).

Dynamics indicator or $X2$ indicates changes in development trends on workdays. As shown in Figure 6, the set of dynamics indicators is very pronounced for *Hard workers* and *Hedonists* with above-average indicators and for *Holidaymakers*, *Moderate*, and *Disinterested* with significantly above-average indicators. Such a statistical result indicates that in the case of small counties, such as *Hedonists*, a small influence in one of the sets of components can significantly affect the development dynamics and the economic activity of the county. In the case of *Hard workers*, the component of *Dynamics indicator* indicates high economic activity, which does not always result in the economic indicators of the municipality and its inhabitants' welfare. It shows that the inhabitants work in the economic development centres but live outside them – in *Holidaymakers* or *Hedonists* municipalities. A *Hard workers* municipality with insufficient recreational opportunities can be regarded as one of the consequences of such statistical observations, where residents choose to spend holidays and

Figure 6. Average values of aggregated characteristics of municipality groups.

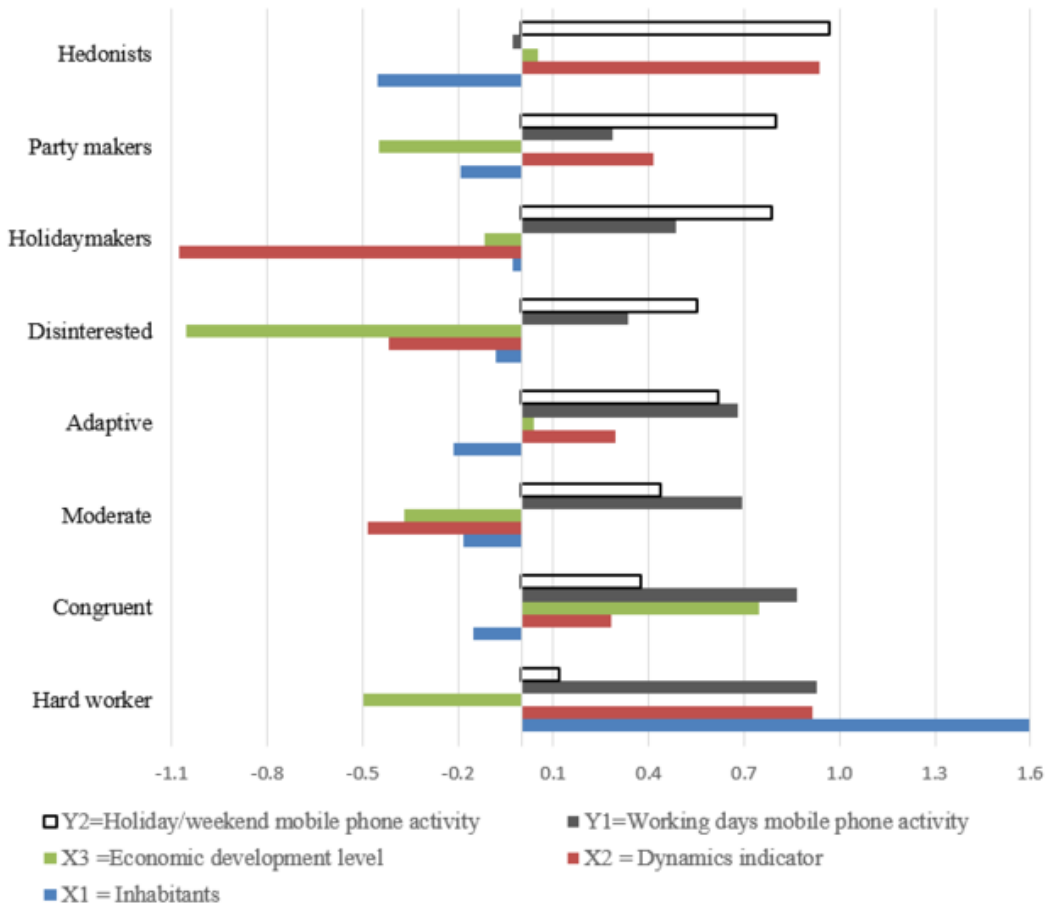


Table 3. Hypothesis Test Summary (Independent-Samples Kruskal-Wallis Test)

#	Null hypothesis H_0	p-value	Decision
1	The distribution “ $X1 = Inhabitants$ ” is the same across 8 categories of municipalities	0.230	Retain H_0
2	The distribution “ $X2 = Dynamics\ indicator$ ” is the same across 8 categories of municipalities	0.038	Reject H_0
3	The distribution “ $X3 = Economic\ development\ level$ ” is the same across 8 categories of municipalities	0.119	Retain H_0

spend money outside economic development centres, thus reducing the influx of funds into the economies of these centres and slowing down their economic development rate (where investment is an essential component). On the one hand, the model “earn in one place, spend in another” has a positive effect on reducing inequality. On the other hand, it poses a long-term risk to regions with imbalanced development models.

To find correlations between socio-economic aggregated component $X1=Inhabitants$, $X2=Dynamics\ indicator$, $X3=Economic\ development\ level$ and mobile phone loadings on workdays $Y1$ and on holidays/weekends $Y2$, the multivariate regression was performed to measure the degree at which the three independent variables $X1$, $X2$ and $X3$ and the two dependent variables $Y1$, $Y2$ are linearly related (Table 4).

Table 4. Multivariate Tests: mobile data $Y1=Workday\ mobile\ phone\ activity$, $Y2=Holiday/weekend\ mobile\ phone\ activity$ dependent of $X1=Inhabitants$, $X2=Dynamics\ indicator$, $X3=Economic\ development\ level$.

Effect		Value	F	Sig.	Partial Eta Squared
Intercept	Pillai's Trace	.991	1951.020	0.000	0.991
$X1=Inhabitants$	Pillai's Trace	.083	1.679	0.200	0.083
$X3=Dynamics\ indicator$	Pillai's Trace	.041	.800	0.457	0.041
$X3=Economic\ development\ level$	Pillai's Trace	.242	5.897	0.006	0.242

It can be concluded that changes in mobile data $Y1=Workday\ mobile\ phone\ activity$, $Y2=Holiday/weekend\ mobile\ phone\ activity$ significantly depend on $X3=Economic\ activity\ level$, where multi-variate test is significant at $p < 0.05$. The measure of the effect size is the Partial Eta Squared (PES), which gives the proportion of the total variance that is accounted by the differences of co-variables. PES gives the amount of variance in all dependent variables that is accounted for by covariate differences. The highest value of $PES=0.242$ suggests that a proportion of the variance in $Y1=Workday\ mobile\ phone\ activity$ and $Y2=Holiday/weekend\ mobile\ phone\ activity$ is accounted by the covariate's differences.

Using the PCA method to group the socio-economic indicators of municipal territories, it can be identified more clearly the dimensions of the ATR formation and administrative-territorial planning, where the connections between socio-economic indicators for inhabitants $X1$, municipality development dynamics indicators $X2$ and economic development indicators $X3$ on workdays $Y1$ and holidays $Y2$, which were determined using mobile load calculations. This allows us to proactively anticipate deviations from the adopted development plans in municipal territories and take timely measures to safeguard the welfare of these territories before the effects of the deviations are visible in statistical indicators.

In the context of regional development planning and administrative-territorial reforms, the essential aspect that should be given the closest attention is the mobile phone activity dynamics in a given territory on workdays. This aspect indicates long-term development perspectives of economic activity in a municipal territory and provides directions for municipal development strategy, pointing at possible sources of revenues and investments to ensure growth and development, as well as the amount of aid needed in the future. Based on our proposed methodology for assessing the development perspectives of municipalities, we can predict changes in these indicators and forecast the amount of subsidies, unless the proposed development plans clearly highlight measures to increase population activity and provide a clear focus for strategic development. The parameter estimates for multiple regression analysis are given in Table 5.

Changes in mobile data $Y1=Workday\ mobile\ phone\ activity$ at the significance level of 0.05 depend on $X3=Economic\ development\ level$. Changes in mobile data $Y2=Holiday/weekend\ mobile\ phone\ activity$ at the significance level of 0.1 depend on $X1=Inhabitants$. Significant indicators confirm that the activity of the population on workdays depends on the level of economic activity $X3$ of the municipality, which is one of the most critical sets of factors and includes indicators such as electricity consumption per capita, the amount of investment per capita, and population changes.

Table 5. Parameter estimates for multiple regression analysis

Dependent Variable		B	Std. Error	t	Sig.	Partial Eta Squared
Y1 = Workday mobile phone activity	Intercept	.699	.033	21.073	.000	.921
	X1=Inhabitants	.051	.034	1.514	.138	.057
	X2=Dynamics indicator	.035	.034	1.051	.300	.028
	X3=Economic development level	.068	.034	2.026	.050	.098
Y2= Holiday/ weekend mobile phone activity	Intercept	.467	.031	14.835	.000	.853
	X1=Inhabitants	-.059	.032	-1.856	.071	.083
	X2=Dynamics indicator	-.041	.032	-1.281	.208	.041
	X3=Economic development level	-.005	.032	-.159	.875	.001

Therefore, municipalities, which have chosen to increase employment opportunities and attract businesses as part of their development strategy in order to promote economic activity and improve the welfare of the population, must follow these indicators and develop plans contributing to the increase of activities related to these indicators. Those municipalities, which base their development strategy on recreation or residential quality, should understand that their inhabitants will most likely work in a different municipality. Therefore, local governments of these territories must focus on the set of indicators X1 characterized by the natural increase of population and municipal tax revenues. However, any of these one-sided approaches poses long-term risks to balanced development of municipalities. As tax revenues and investments flow into those municipalities where people reside, economic development centres will eventually run short on income and lose capacity to develop their infrastructure. Therefore, one of the recommended models of regional development includes promoting an increase of activity on workdays and weekends / holidays alike. It would lead to the formation of self-sufficient and harmonious municipalities that provide employment and recreation opportunities not only to its own residents but also to inhabitants of neighbouring municipalities. This, in turn, would increase mobility of competences and distribute financial resources more evenly over a wider area.

CONCLUSION

A regional reform is a highly complex process that involves many stakeholders and influence groups. Therefore, decisions must be based on the most objective information available. The Latvian ATR and regional development planning methodology, which offers a PCA method using sets of 37 indicators divided into three groups and combined with mobile data-based assessment of population activity, provides a good basis for a public debate on regional development options and territorial division. At the national level, developed data model clearly shows that the current administrative-territorial division of 119 municipalities does not foster smooth long-term development and improvement of welfare. Indirectly concluding, it may be largely due to long delays in objective data analysis and decision-making based on data, and to the population-based tax system, which does not promote even development.

The consequences of the COVID-19 crisis allowed to test offered model and identify possible scenarios if employment, economic activity and social services were sufficiently developed outside the traditional development centres. The crisis implicitly confirmed the validity of the model.

Various statistical data can characterise the economic activity in municipalities. Even though it is possible to identify the most significant factors indicative of economic activity, it must be regarded

them in context. Moreover, conducting research for the purposes of this paper, the authors had to consider the limitations of statistical information since not all of the described indicators were available along the lines of municipal territories. Therefore, to conduct comparison of statistical analysis, the authors used indicators that can be aggregated or calculated with regard to the new municipal division of 43 municipal territories.

When analysing the selected statistical indicators, the authors established that the following three aggregated factors have a significant impact on the division of municipalities into eight cluster groups based of mobile data: *Inhabitants*, *Dynamics indicator* and *Economic development level*.

The 43 newly formed municipalities can be categorized into eight groups based on the mobile phone activity data and socio-economic indicators. The connections between socio-economic indicators for inhabitants, municipal development dynamics and economic development indicators on weekdays and holidays, which were determined using mobile load calculations, allow us to proactively anticipate deviations from the adopted development plans in municipal territories and take timely measures to safeguard the welfare of these territories before the effects of the deviations are visible in statistical indicators.

The findings provide several theoretical contributions:

- classical statistical socio-economic factor analysis alone not giving an understanding of the actual situation and impact on economic development on municipal level because available social-economic data are not providing necessary dynamics and must be used together or verified with more real-time data such as mobile activity data;
- mobile activity data is linked with the geographic territory. Therefore, analysis based on mobile activity data in municipality provides reliable explanation and mapping with economic activity in the same territory;
- there is no one single socio-economic indicator that could explain economic development level of municipality, however factor clusters in combination with human-readable cluster or class label (*Inhabitants*, *Dynamics indicator*, *Economic development level*) provide understanding and interpretations of the results.

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APPENDIX A - COMPONENT SCORES: AGGREGATED VALUES OF STATISTICAL INDICATORS IN 2018

Table 6. Component scores: aggregated values of statistical indicators in 2018

Municipality	X1=PC1 Inhabitants	X2=PC2 Dynamics indicator	X3=PC3 Economic development level
Ādaži county	-0.43976	1.36871	0.53464
Aizkraukle county	-0.11671	-1.2973	0.75364
Alūksne county	-0.28518	0.61779	-1.1555
Augšdaugava county	-0.12687	-0.20143	-1.26313
Balvi county	-0.17619	-1.13114	-0.5387
Bauska county	0.00188	-0.34915	-0.20482
Cēsis county	0.0413	-1.44414	0.41007
Daugavpils city	0.33041	1.0372	-1.60515
Dienvidkurzeme county	0.04738	-2.69951	0.49549
Dobele county	-0.1122	-0.27938	-0.06955
Gulbene county	-0.26137	0.35575	-0.32921
Jēkabpils county	0.02935	-1.73041	0.34376
Jelgava city	0.01481	1.11727	-0.29179
Jelgava county	-0.17168	0.37619	-0.30601
Jūrmala city	-0.09247	1.21526	0.12647
Ķekava county	-0.33465	0.85856	1.67351
Krāslava county	-0.19201	-0.30924	-0.88909
Kuldīga county	-0.16282	-0.35636	-0.52586
Liepāja city	0.12922	1.05053	-0.55083
Limbaži county	-0.13598	-0.17792	-0.63581
Līvāni county	-0.36413	0.73313	-0.93945
Ludza county	-0.15446	-1.34724	-0.38957
Madona county	-0.10541	-1.05973	-0.09464
Mārupe county	-0.37822	0.93797	3.39339
Ogre county	0.04889	0.37993	-0.16012
Olaine county	-0.36307	0.93142	0.38455
Preiļi county	-0.18119	-1.03786	-0.51661
Rēzekne city	-0.19667	1.04741	-0.40669
Rēzekne county	-0.08218	-0.41552	-1.05687
Rīga city	6.2296	0.45715	0.31766
Ropaži county	-0.38024	0.74386	3.23643
Salaspils county	-0.36893	1.15305	0.08466
Saldus county	-0.14399	0.02014	-0.37748
Saulkrasti county	-0.45362	0.93603	0.05007
Sigulda county	-0.16652	0.17228	0.83343

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Table 6. Continued

Municipality	X1=PC1 Inhabitants	X2=PC2 Dynamics indicator	X3=PC3 Economic development level
Smiltene county	-0.26158	-0.39147	0.36096
Talsi county	-0.0266	-0.86388	-0.11404
Tukums county	0.03995	-0.54651	-0.24768
Valka county	-0.36777	0.75046	-0.98048
Valmiera county	0.11983	-1.86051	1.32615
Varakļāni county			
Ventspils city	-0.07018	1.01208	-0.47094
Ventspils county	-0.35995	0.22651	-0.20491

APPENDIX B - ROTATED COMPONENT MATRIX: COMPONENT LOADINGS IN 2018

Table 7. Rotated component matrix: component loadings in 2018

2018	Component	
	Y1=PC1 (Workdays)	Y2=PC2 (Holidays)
Hard workers	0.8 - 1.0	0.0 - 0.2
Rēzekne city	.910	.065
Rīga city	.973	.131
Daugavpils city	.865	.135
Jelgava city	.960	.137
Congruent	0.8 - 1.0	0.2 - 0.6
Salaspils county	.907	.229
Liepāja city	.935	.236
Ķekava county	.895	.342
Ogre county	.872	.344
Ventspils city	.875	.368
Mārupe county	.887	.389
Ropaži county	.869	.403
Valmiera county	.852	.408
Olaine county	.833	.423
Dobele county	.832	.431
Cēsis county	.829	.431
Sigulda county	.838	.442
Saldus county	.839	.447
Adaptive	0.6 - 0.7	0.6 - 0.7
Talsi county	.694	.605
Ādaži county	.668	.612
Jelgava county	.680	.636

continued on next page

Table 7. Continued

2018	Component	
	Y1=PC1 (Workdays)	Y2=PC2 (Holidays)
Moderate	0.4 - 0.8	0.2 - 0.6
Balvi county	.716	.255
Līvāni county	.768	.301
Ludza county	.541	.392
Gulbene county	.789	.410
Preiļi county	.604	.412
Aizkraukle county	.774	.430
Madona county	.734	.431
Jēkabpils county	.786	.445
Smiltene county	.787	.454
Alūksne county	.716	.463
Krāslava county	.407	.494
Kuldīga county	.771	.505
Valka county	.589	.544
Tukums county	.713	.597
Disinterested	0.0 - 0.4	0.2 - 0.6
Rēzekne county (incl. Varakļāni county)	.336	.553
Holidaymakers	0.4 - 0.6	0.6 - 0.8
Bauska county	di	.693
Dienvidkurzeme county	.460	.815
Limbaži county	.402	.845
Party makers	0.0 - 0.4	0.6 - 1.0
Jūrmala city	.378	.859
Augšdaugava county	.254	.639
Ventspils county	.233	.907
Hedonists	- 0.2 - 0.0	0.8 - 1.0
Saulkrasti county	-.028	.969

APPENDIX C - ROTATED COMPONENT MATRIX: COMPONENT LOADINGS IN 2020

Table 8. Rotated component matrix: component loadings in 2020

2020	Component	
	PC1 (Workdays)	PC2 (Holidays)
Hard workers	0.8 - 1.0	0.0 - 0.2
Rīga city	.969	.202
Congruent	0.8 - 1.0	0.2 - 0.6
Jelgava city	.956	.275
Daugavpils city	.920	.351
Mārupe county	.921	.361
Liepāja city	.918	.374
Rēzekne city	.884	.419
Salaspils county	.880	.430
Ventspils city	.875	.456
Ropaži county	.866	.468
Ķekava county	.853	.483
Valmiera county	.830	.546
Dobele county	.820	.555
Saldus county	.816	.564
Ogre county	.809	.566
Sigulda county	.810	.573
Adaptive	0.6 - 0.7	0.6 - 0.7
Jelgava county	.747	.645
Cēsis county	.741	.661
Smiltene county	.736	.657
Ādaži county	.729	.650
Kuldīga county	.729	.671
Valka county	.713	.645
Madona county	.710	.689
Gulbene county	.709	.686
Bauska county	.698	.683
Preiļi county	.622	.768
Tukums county	.644	.754
Ludza county	.600	.747
Balvi county	.630	.747
Talsi county	.652	.744
Aizkraukle county	.692	.710
Līvāni county	.672	.685

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Table 8. Continued

2020	Component	
	PC1 (Workdays)	PC2 (Holidays)
Moderate	0.4 - 0.8	0.2 - 0.6
Olaine county	.786	.563
Jēkabpils county	.784	.611
Holidaymakers	0.4 - 0.6	0.6 - 0.8
Limbaži county	.512	.847
Krāslava county	.491	.843
Dienvidkurzeme county	.563	.813
Jūrmala city	.539	.785
Alūksne county	.588	.699
Party makers	0.0 - 0.4	0.6 - 1.0
Augšdaugava county	.430	.885
Rēzekne county (incl. Varakļāni county)	.416	.881
Ventspils county	.255	.936
Saulkrasti county	.047	.971

APPENDIX D - HYPOTHESIS TEST SUMMARY (INDEPENDENT SAMPLES KRUSKAL-WALLIS TEST)

Table 9. Hypothesis test summary (Independent Samples Kruskal-Wallis Test)

#	Null hypothesis H_0	p-value	Decision
1	The distribution “ <i>Population over working age at the start of the year</i> ” is the same across 8 categories of municipalities	0.105	Retain H_0
2	The distribution “ <i>Population of working age at the start of the year</i> ” is the same across 8 categories of municipalities	0.065	Retain H_0
3	The distribution “ <i>Population at the start of the year</i> ” is the same across 8 categories of municipalities	0.065	Retain H_0
4	The distribution “ <i>Total municipal budget revenues (EUR)</i> ” is the same across 8 categories of municipalities	0.014	Reject H_0
5	The distribution “ <i>Number of Personal Income Tax (PIT) payers based on registered domicile</i> ” is the same across 8 categories of municipalities	0.010	Reject H_0
6	The distribution “ <i>Total municipal budget expenses (EUR)</i> ” is the same across 8 categories of municipalities	0.010	Reject H_0
7	The distribution “ <i>Number of pupils in general education schools</i> ” is the same across 8 categories of municipalities	0.013	Reject H_0
8	The distribution “ <i>Number of pupils in pre-schools</i> ” is the same across 8 categories of municipalities	0.005	Reject H_0
9	The distribution “ <i>Number of pre-schools</i> ” is the same across 8 categories of municipalities	0.035	Reject H_0
10	The distribution “ <i>Population under working age at the start of the year</i> ” is the same across 8 categories of municipalities	0.006	Reject H_0
11	The distribution “ <i>Municipal electricity consumption (kWh)</i> ” is the same across 8 categories of municipalities	0.005	Reject H_0

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Table 9. Continued

#	Null hypothesis H_0	p-value	Decision
12	The distribution “Number of PIT payers based on the registered domicile of the employer” is the same across 8 categories of municipalities	0.003	Reject H_0
13	The distribution “Municipal budget revenues from PIT (EUR)” is the same across 8 categories of municipalities	0.045	Reject H_0
14	The distribution “Number of new-borns” is the same across 8 categories of municipalities	0.003	Reject H_0
15	The distribution “Total municipal budget tax revenues (EUR)” is the same across 8 categories of municipalities	0.004	Reject H_0
16	The distribution “Withheld sum of PIT (based on the registered domicile of the employee) (EUR)” is the same across 8 categories of municipalities	0.002	Reject H_0
17	The distribution “Municipal budget revenues from Real Estate Tax (EUR)” is the same across 8 categories of municipalities	0.010	Reject H_0
18	The distribution “Withheld sum of Personal Income Tax (based on the legal address of the employer)(EUR)” is the same across 8 categories of municipalities	0.001	Reject H_0
19	The distribution “Number of general education schools” is the same across 8 categories of municipalities	0.459	Retain H_0
20	The distribution “Total sum of foreign direct investments (EUR)” is the same across 8 categories of municipalities	0.016	Reject H_0
21	The distribution “Municipal budget capital expenditure (EUR)” is the same across 8 categories of municipalities	0.005	Reject H_0
22	The distribution “Absolute population change per year due to natural change” is the same across 8 categories of municipalities	0.123	Retain H_0
23	The distribution “Absolute population change per year” is the same across 8 categories of municipalities	0.344	Retain H_0
24	The distribution “Subsidies from municipal fiscal equalization fund in % of all municipal budget revenues” is the same across 8 categories of municipalities	0.025	Reject H_0
25	The distribution “Population change per year (%)” is the same across 8 categories of municipalities	0.017	Reject H_0
26	The distribution “Population change per year due to natural change (%)” is the same across 8 categories of municipalities	0.035	Reject H_0
27	The distribution “Municipal budget expenditure on remuneration in % of all municipal expenses” is the same across 8 categories of municipalities	0.045	Reject H_0
28	The distribution “Population changes per year due to migration (%)” is the same across 8 categories of municipalities	0.020	Reject H_0
29	The distribution “Area (km ²)” is the same across 8 categories of municipalities group	0.030	Reject H_0
30	The distribution “Sum (EUR) of project funding from EU funds (ELGF, ELFLA, EZF)” is the same across 8 categories of municipalities	0.043	Reject H_0
31	The distribution “Unemployment rate (%)” is the same across 8 categories of municipalities	0.048	Reject H_0
32	The distribution “Sum (EUR) of project financing from EU funds (ELGF, ELFLA, EZF) per capita” is the same across 8 categories of municipalities group	0.001	Reject H_0
33	The distribution “Municipal electricity consumption (kWh) per capita” the same across 8 categories of municipalities	0.147	Retain H_0
34	The distribution “Withheld PIT sum (EUR) per capita based on legal address of employer” is the same across 8 categories of municipalities	0.001	Reject H_0
35	The distribution “Total municipal budget tax revenues (EUR) per capita” is the same across 8 categories of municipalities	0.001	Reject H_0
36	The distribution “Total sum of foreign direct investments (EUR) per capita” is the same across 8 categories of municipalities	0.016	Reject H_0
37	The distribution “Absolute population changes per year due to migration” is the same across 8 categories of municipalities	0.406	Retain H_0

Irina Arhipova is the professor of Econometrics at the Department of Management Systems of the Faculty of Information Technologies at Latvia University of Life Sciences and Technologies (LLU). Irina Arhipova is one of Latvia's most experienced researchers in Econometrics and Experimental Economics, the author of over 150 scientific articles, a frequent speaker at international scientific conferences and a guest lecturer at foreign universities.

Gundars Berzins is the professor and the Dean of the Faculty of Business, Management and Economics at the University of Latvia. He holds a doctorate in management science and as a leading researcher has participated in many research projects and has authored a number of international scientific publications. His research interests include business strategies and regional policy. He has previously held the post of Chancellor of the University of Latvia. His passion is the importance of strategy and strategic thinking in business. He is excited at reading lectures on "Management theories", "Business Strategy and Policy Management" and "Strategic and Operational Planning".

Aldis Erglis is a researcher at the University of Latvia, Faculty of Business, Management and Economics. The topic of his Doctoral thesis is Dynamic Management of the Organization – Linking Strategy to Operations. Aldis Erglis has a unique experience in complex IT solution development and programming, data analysis and visualisation.

Evija Ansonska has obtained an MA degree in Political Science at the University of Latvia, has studied political science in Denmark. Currently, she is the Head of Marketing and Communication at the University of Latvia, Faculty of Business, Management and Economics and a research assistant. Evija Ansonska has a 17-year experience in communication and project management. As a project manager and a research assistant, Ansonska has participated in different research projects.

Juris Binde is the CEO of Latvia's leading mobile telecommunications operator Latvia Mobile Telephone (LMT), and a professor at Vidzeme University of Applied Sciences (ViA). On a regular basis, Juris Binde speaks at scientific and professional conferences, is the author of tens of research publications, a number of which have been published in internationally reviewed journals on management science and business management, information technologies, data processing and the Internet of things.