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Mental health and well-being of late working age and older adults in Estonian urban and rural areas

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Annotation

Mental health and well-being of late working age and older adults in Estonian urban and rural areas

The distribution of mental health and aging problems among the Estonian population negatively reflects the large sectors of the population. The most vulnerable group is elderly people. This analysis has been conducted to see transformations of aging within the outlying group of late working age and older adults (56+) in rural areas. Prepared and held logistic regression models based on the Estonian National Mental Health Study to help with identifying effects of environmental and other contextual variables on the target group in different types of settlements.

In the study, four dependent and 14 independent variables were selected. Dependent variables represent four mental health related health conditions: registered mental health disorders, self-feeling of health condition, depression risk and life satisfaction. Independent variables are divided for 4 groups: general social-economic factors, lifestyle habits and social connections, psychological profile and risk factors and environment. Based on 16 logistic regression models, environmental variables reveal less importance compare to other three groups of variables. In particular, green infrastructure only had a positive statistically significant influence on life satisfaction among rural elderly people. Additionally, a positive statistically significant effect from green infrastructure was shown in the reduction of depression risk among rural late working age and older adults. The reverse effect has been found in an urban elderly group of people but elaborated due to specifics of the blue infrastructure variable. While social media use among elderly people was not proven as a positive side effect of communication, satisfaction with friends as a face-to-face communication tool was proven in both groups.

Keywords: mental health, late working age, elderly, environmental factors, well-being

CERCS Code: S230 - Social geography

Lühikokkuvõte

Hilise tööea ja vanemate inimeste vaimne tervis ja heaolu Eesti linnades ja maal

Vaimse tervise probleemid ja vananemine on teemad, mis mõjutavad Eesti elanikkonda ja ühiskonda väga oluliselt. Üks haavatavamaid rühmi on eakad. Selle uurimistöö eesmärk on mõista, mis mõjutab vaimset tervist inimese hilisemas tööeas (56+) ja vanemaealiste rühmas. Eesti rahvastiku vaimse tervise uuringu viidi läbi logistilised regressioonimudelid, et selgitada keskkonna- ja muude kontekstuaalsete muutujate mõju sihtrühmale Eesti linna- ja maapiirkondades.

Analüüsi kaasati neli sõltuvat ja 14 sõltumatut muutujat. Sõltuvad muutujad esindavad nelja vaimse tervisega seotud olukroda või hinnangut: registreeritud vaimse tervise häired, üldise terviseseisundi enesehinnang, depressioonirisk ja eluga rahulolu. Sõltumatud muutujad mudelites jagunevad 4 rühma: üldised sotsiaal-majanduslikud tegurid, elustiili harjumused ja sotsiaalsed seosed, psühholoogiline profiil ja riskitegurid ning keskkond. Tulemused 16 logistilise regressioonimudeli põhjal näitasid, et võrreldes kolme teise muutujate rühmaga selgitasid keskkonnatunnused inimese vaimset tervist suhteliselt vähe. Eelkõige avaldas rohetaristu statistiliselt olulist positiivset mõju maal elavate eakate eluga rahulolule. Lisaks ilmnes rohelise infrastruktuuri positiivne statistiliselt oluline mõju depressiooniriski vähenemisele maapiirkondade hilises tööeas ja vanemaealistes. Vastupidine efekt leiti linnas elavate eakate seas, kuid seda nn sinitaristu (veealad) muutuja kaudu. Sotsiaalmeedia kasutamine eakate seas ei omanud uuritud vaimse tervise seisunditele ja hinnangutele mõju, küll aga olid nii linnas kui ka maal olulise positiivse mõjuga sotsiaalsed suhted, mõõdetud sõpradega rahulolu kaudu.

Märksõnad: vaimne tervis; hiline tööiga, vanemaealised, keskkonna tingimused, heaolu
CERCS kood: S230 - sotsiaalgeograafia

1. Introduction

Aging has become a worldwide process of population transformation. Based on diverse sources, the total ratio of the elderly population is estimated to be between 16% and 22% by 2050 (Lee et al., 2019; Tseng et al., 2019). According to the World Health Organization (2022), among the group of people over 60 years old, one-fifth of them have psychiatric diseases or mental health disorders. These limitations, encompassing factors like the decline in their social and economic status and the onset of chronic physical illnesses, are contributing to a compromised state of overall well-being (Beard et al., 2016). With advancing age, a discernible escalation occurs in the incidence of chronic illnesses, diminished mobility, and the emergence of mental health disorders among the older demographic group (Kawai et al., 2021; Kiselev et al., 2019; Strand et al., 2021). The limitations of basic activities affect life quality and life expectancy. In the Estonian context, healthy life years at birth stay at 59,2 (Healthy Life Years | Statistikaamet, 2022).

Thereby, this study focuses on the late-working age and older adults group of Estonian residents and their mental health conditions. This target group has a high meaning in the Estonian context. In particular, in the European Union structure, Estonia is revealed as having one of the highest levels of depression, at 6%–9.7% of middle-aged and older adults, and the eldest are reaching up to 37%–51% (Laidra, 2016). Observing which factors are related to these numbers and finding patterns could explain reasons for the Estonian context.

The general structure of mental health aspects frames the mental health continuum, including physical, emotional, mental, social, environmental, and spiritual health. This helps with studying individuals' well-being and mental health in a different successful way due to including multiple factors for its measurement (Iasiello et al., 2022). Due to physical and psychological factors, aging individuals tend to be less satisfied with their lives. Thus, the mental health continuum transforms into a negative part. Also, environmental variables include diverse fields, which can positively affect people with diverse mental health disorders. The fundamental groups are centered on the physical and social environments (MacAllister et al., 2016; Ware et al., 1983). Several studies also provide evidence of the relationship between mental health disorders and green and blue areas (Gascón et al., 2018; Aliyas, 2019; Andreucci et al., 2019; Lee et al., 2019). The social environment is structured with abilities to communicate with other individuals via diverse tools. There is evidence that the absence of social communication, whether personal or digital, affects emotional and physical health, and the lack of these interactions could cause increased inflammation in the patient (Grolli et al., 2021). Although digital life for older groups of people meets difficulties with usage skills (Hasan & Linger, 2016), they might teach them, thus triggers as inflammation might be reduced. Thus, digital life as social life becomes a valuable part of well-being.

Another remarkable factor of environment can be viewed as a type of settlement. Several researchers (Mamplekou et al.,2010; Bonnell et al.,2022) prove that rural elderly have less depression than the same age group from urban settlements. This elaborates on different styles of life with different influential environments.

Based on these findings, I am assuring of the need for research about relations between a mental health-related continuum of Estonian late working age and older aged people in urban and rural settlements and their impact on life through the various indicators (including environmental) of the Estonian National Mental Health Study (Laidra et al., 2023). Estonian National Mental Health Study was conducted in 2021–2022 to provide population-wide data on mental health in the context of the SARS-CoV-2 pandemic. These findings will be discovered with the stated questions:

1) how mental health and well-being-related variables (registered mental health disorders, self-rated general health, depression risk, and life satisfaction) are represented in urban and rural areas?

2) What affects mental health and well-being-related variables of the late working age and older adults population in rural and urban settlements among four chosen groups: general social-economic factors, lifestyle habits and social connections, psychological profile, and risk factors?

3) how do green and blue infrastructure play a role in connection with mental health and well-being-related variables for the studied age groups?

To get answers to the issues raised, I will use the following methodology. Initially, I identified relevant dependent and independent variables from the Estonian Mental Health study for further logistic regression models. Dependent variables have a relation to the mental health continuum as variables of mental health disorders, depression risk, and life satisfaction. They cover most of the types of mental health continuum groups. Additionally, I choose self-reported health conditions as a controversial factor to variables with registered mental health disorders. After that, I group independent variables based on issued purposes. Then, I implement descriptive statistics for chosen groups of models and calculate correlation matrixes for them. In the final step, I analyze the results and elaborate on them in conjunction with the questions stated for this research and external studies from the same field. Therefore, my input includes discovering patterns of worsening mental health continuums in the Estonian older population in different types of residences and providing general conclusions for spatial planning solutions.

This thesis consists of five chapters. The first chapter represents an overview of the literature related to the Estonian context. Here, the main ideas also have been proposed. The second chapter includes the data and methodology based on the Estonian National Mental Health Study, giving answers to the stated questions. In the third part, I observe the results of the research, which represents the main outputs from the statistical analysis. The fourth part is the discussion part, where the main outputs are summarized and presented as thoughts for further research. In the last part, I collect all conclusions as conclusions for proven methodology.

2. Theoretical overview

2.1 Mental health disorders of late working age and older adults

The World Health Organisation has elaborated the definition of mental health disorders as a sufficient disturbance associated with distress or impairment in critical areas of functioning. The most common among them are dementia, anxiety, and major depressive disorder (MDD) (World Health Organization, 2022). The primary mental health disorders among the elderly group are dementia, Parkinson's, Alzheimer's, major depressive disorder (MDD), anxiety, post-traumatic stress, and depression (Serafini et al., 2020). Several studies in diverse scientific fields suggest that SARS-CoV-2 adversely affects both the population with diagnosed mental health disorders as well as healthy individuals, and this virus causes the development of diverse mental health disorders (Grolli et al., 2021; Shenvi, 2020; Mei et al., 2021). Whereas the most vulnerable group of the human population is the elderly people, they require more inclusive approaches to prevent the appearance and development of mental health decreases. Elderly people, especially those who live alone, if they stay in an endless loop of negative thoughts, may have inflamed depression symptoms, which can cause damage to their mental health status (Grolli et al., 2021). These disorders also imply a possibility of suicide (Brown et al., 2020).

Among elderly people, chronic diseases are common and have a trend to drastically increase their numbers through age and over time. Chronic diseases are substantially structured with long-term inflammatory activity, which is a characteristic of the age's immunological senescence. Several studies demonstrate a predisposition to two or more chronic diseases in the age group 65+ (Hung et al., 2011; World Health Organization, 2017; OECD & European Union, 2020).

At the same time, in particular, depression as a disease has a relation to the inflammatory activity in the central nervous system (Feltes et al., 2017). Thereby, we may postulate that the elderly demographic group with several chronic diseases most probably has a strong chance of illness and development of mental health disorders. This follows the threat of pathogens of external factors such as anxiety and depressive conditions during lockdowns of SARS-CoV-2 (Reger et al., 2020). Thus, several studies propose actions toward the reduction of these threats for vulnerable demographic groups. These actions include physical activities, walks in a comfortable green environment, online chatting and calls with relatives and friends, hobbies, and diet (Lee et al., 2019; Andreucci et al., 2019; Song et al., 2022). In particular, well-being can remain stable while aging if social activities remain stable, diet becomes proper and diverse, and movements are presented in daily activities (Mamplekou et al., 2010). These factors could prevent mental health disease activity.

Estonia has a hyper-high level of depression compared to the rest of the European Union countries. This leadership leads to the worst scenario, where mental health disorders are affecting their social status (Tseng et al., 2019). Since older adults play a sufficient role in the economic sphere, improving the depressive level from 37%-51% could lead to economic and market crises. The study by Abuladze (2020) discovered developing depressiveness among women is almost 50% higher than among men. The vulnerability of the elderly creates an extra load on social infrastructures and families simultaneously (De Carvalho et al., 2017). Increasing the load affects the economy as a part of health care services. The need for external health care tends to cause inequality and discrimination based on socioeconomic status and income. However, based on the research of Mozhaeva (2022), the initial healthcare services do not meet differences via environments in Estonia. Thus, rural and urban area residents are consuming the same level of health care services, and this might demonstrate even distribution of mental health disorders.

The definition of the elderly as a group of people of certain ages meets two ways. In a scientific way, Orimo et al. (2006) define the elderly as people above 65. People aged 65 to 74 are referenced as “early elderly” and 75 and above as “late elderly”. Since the life expectancy of people is rising every year, there are opinions that people should be considered elderly when they reach 70 years of age (Orimo et al., 2006). Desrosiers et al.(2004) defined four aging groups: 55-64, 65-74, 75-84, and 85+. According to Europa (2022), people in Estonia have the right to a pension if they were born between the years 1953 to 1960. For people born in 1953, the age for pension is 63 years. Based on this pension reform, the age of retired individuals will reach the level of 65 years already in 2027 (Europa, 2022). However, being retired usually does not follow physical and psychological fatigue and incompetence with working load. Studies about mental health disorders mainly take into consideration the late working age group as a transmitted cohort (Nakagawa et al., 2020; Abuladze et al., 2020). Additionally, the healthy life years (disability-free life expectancy) in Estonia is 59,2 years (Healthy Life Years | Statistikaamet, 2022). This means that, on average, physically, people from 59,2 years old are limited from a whole life activity. Usually, younger age groups are not seen as significant groups in mental health analysis. In this thesis, the late working age group (before 65+) is going to be analyzed as a risk group.

It is also worth mentioning that aged demographic groups are shown as a group of active people with wishes for cooperation and social interactions. It leads to a review of the retirement and pension model in general (Song et al., 2022). The ability to work while retired or stay active in social life has a strong relation to the prevention of mental health disorders. Work as a place of communication has a positive relation to the well-being of the elderly especially (Cheng et al., 2023).

Nevertheless, the initial health condition of the elderly is of lower capacity than that of younger demographic groups. It can be presented as a lover's social reaction to a decrease in walking speed (Kawai et al.,2021; Strand et al., 2021; Grolli et al., 2021). One notable aspect is the visible decline in social reactions among the elderly. As individuals age, there is a tendency for a reduction in the quality of social interactions. This isolation can be attributed to a myriad of factors, including physical limitations, changes in social circles, and evolving communication norms. The implications of diminished social interactions extend beyond mere companionship, significantly impacting mental health. Thus, it follows the understanding of the nature of the elderly, their strengths, and their weeks.

As mentioned previously, mental health disorders change the quality of life for older groups of people. Hence, the identification and observation of certain groups of older adults are needed to identify the patterns that cause these threats. Several studies prove that low social and economic variables are affecting life satisfaction (Tseng et al., 2019; Cheng et al., 2023). Thus, the creation of special care for vulnerable demographic groups should be done with the transformation and prevention of these groups' perspectives.

Based on the definition of subjective well-being, life satisfaction is a vital part of the emotional and cognitive units of life in general. Well-being also includes emotional values' positive and negative effects (Diener et al., 1999). Positive transformations in the elderly lives could be viewed through life satisfaction and well-being. Life satisfaction is usually a part of the well-being process, which is an indicator of psychological adaptation and successful aging (Nakagawa et al., 2020). It includes the physical and emotional values of individuals. Generally, they are divided into negative and positive factors, which can affect a person's lifespan. These factors have a significant influence on financial aspects, physical health, and academic performance (Huppert et al., 2018). The significant plunge in the life satisfaction and well-being components generally leads to the country-wide negative trends of social plummet and general dissatisfaction (Ruggeri et al., 2020). In addition, the health care system in Estonia provides extra care for older people with higher social determinants, which directly affect their socioeconomic values (Mozhaeva, 2022). Thus, income, marital status, education, and other determinants are directly related to the life satisfaction and well-being of late working-age and older adults. This proves the need for improving and providing detailed care for vulnerable elderly living alone, having low incomes, and having no children (Grolli et al., 2021; Abuladze et al., 2020). Additionally, to the standard set of indicators, I will use having pets and living alone variables instead of marital status. These options would be more precise in a way of seeing loneliness as an indicator of mental health risks.

2.2 Physical and social environments

Environmental variables can include two major variables: physical and social (MacAllister et al., 2016; Ware et al., 1983). Physical environment could include, at the same time, an indoor environment, such as residential houses, specific buildings, and outdoor parks and neighborhoods. The social environment has formed from diverse social determinants: income, marital status, education, and others. Most of the studies prove a correlation between better quality of variables and better life quality and well-being, including mental health conditions (Robles et al., 2014; Perez et al., 2022). Both variables are interlinked: the absence of positivity in one directly correlates with the persistence of negativity in the other. This conclusion initiates the process of understanding the positive implementations inherent in both physical and social environments.

To commence, it is essential to discern the positive practices within the physical environment, examining their formation, rationale, and the reasons underlying their positive impact. The major groups of natural zones are represented with green (green covers) and blue (water bodies) infrastructures. Several studies show positive trends with greenery in a walkable distance from the residential place. They prove the idea of a positive trend and a strong correlation between mental health disorders and the presence of greenery (Lee et al., 2019; Tseng et al., 2019). However, when it comes to blue areas, it constantly remains constant (De Vries et al., 2016).

Physical environments seem more diverse through the planning project decisions. The study of Andreucci (2019) describes positive changes with different type of green areas and propose ideas about special facilities for elderly with mental health disorders. At the same time, the architecture field follows the postulate that the building environment could negatively affect persons with mental health disorders. This follows the dependents to life satisfaction and well-being in different residential settlements could be diverse and can be patterned (Karakas et al., 2020). Nevertheless, the study of Kliit (2023) based on the Estonian National Mental Health

Study dataset discovered a weak correlation between mental health variables and environments in the Estonian context. This conclusion is stark contrast with several studies in the same field (Lee et al., 2019; Tseng et al., 2019, Pouso et al.,2021). This caused the opposite way of the green area relationship with health variables.

Besides the green and blue infrastructures, the type of settlement plays a role in the development of mental health diseases. Several studies identified correlations between mental health and residential areas, as rural is more beneficial for preserving the development of mental health disorders (Mamplekou et al.,2010; Wang et al.,2021; Bonnell et al.,2022). In this master thesis, one of the goals is to understand these differences in Estonian reality.

The physical environment affects the elderly not only through external activities but with basic existence in their own accommodation. Light and noise pollution are among the key factors that trigger life satisfaction. Besides the external triggers, the elderly demographic group suffers from sleep disorders because they cannot have deep sleep at night as the amplitude of the circadian rhythm is decreased by a change in the biorhythm (Park et al.,2022).

In the way of proving physical environments, in this study, I use tree cover variable, which demonstrates an effect from a group of trees as a more effective formation to health: emotionally as more solid green structure and physically as giving an opportunity to walk through. Additionally, tree canopy has a proven positive impact on mental health (Alvarado et al., 2023; Browning et al., 2019; Zhang et al., 2022). Also, blue infrastructure, which is used as a combination of water body presence, could demonstrate associations with mental health and self-reported health conditions (De Vries et al., 2016).

The next of the most valuable parts of environments was proposed as social environment. This section contains a diverse range of social determinants and emotional well-being from the point of view of the residential place. Pension models can provide different types of health care for elderly with mental health disorders, such as through home services and social welfare home services. In the first way, most of the responsibility relies on the family members, and in the second – responsible authorities. The study of Song (2022) found positive trends in the second group as more affordable space for socialization of elderly. This proves how better communications positively affect the life satisfaction of people with mental health disorders.

While technology has a trend to be distributed worldwide and has a possibility to cover the lack of social connections, the elderly demographic group stays the most triggered in relation to them. Their initial trust in new technologies contains fears about the safety of usage. However, different types of settlements provide different levels of association between the elderly and technologies. Since in urban areas, aging occurs faster than in rural, this provides an environment with diverse digital technologies due to types of occupations, career paths, and skill development (United Nations, 2015). Through the Weck et al. (2023) study with the thematic analysis, we may see general trust in technologies for older adults who are working or recently retired. The interest of this research follows with the identification of four factors of trust: the personal base of trust, the cognitive base of trust, the calculative base of trust, and the institutional base of trust. In addition, supplementary factors were added for a better description of the results.

When the trust stage is successfully formed, the next step could be the increased usage of digital technologies and transferring to digital life in general. Furthermore, the increase in frequency of usage leads to risk factors for mental health disorders and addictions. During the lockdowns of SARS-CoV-2, social media played a replacement role in life communications. Among the elderly with mental health disorders, the presence of digital life reduces deterioration in health status and the course of disease (Grolli et al., 2021; Song et al., 2022). However, different demographic groups have different attitudes towards the social media. These attitudes negatively affect the addiction factor, which can be a trigger for the development of mental health disorders. Late working adults deal with negative emotions from social media usage (Rasmussen et al., 2020). At the same time, Berryman et al. (2017) proposed the lack of a correlation between social media and mental health issues for younger adult groups. This shows that social media has the opposite trend for older age groups.

3. Data and methods

3.1 Data

For this master thesis project, the Estonian National Mental Health Study was used. This study was held to provide broad-wide data on mental health in the Estonian population. This study initially covers 20000 persons in Estonia aged 15 years and older. The study took place as a combination of a three-way survey (January-February 2021, May-June 2021, January-February 2022), a registry study, and subsequent validation. Besides the quantitative part, the study included qualitative research (Laidra et al., 2023). For independent variables, I started to identify possible items that could be sufficient for logistic regression analysis. Firstly, I identified four groups: general sociodemographic, lifestyle and social connections, psychological profile and risk factors, and environmental.

The survey structure contains six major blocks: A-Socio-demographic background, B-Mental health, C-Risk and protective factors, D-COVID-19-related stressors, E-Mental health support during the crisis, F-Anchoring vignettes (Laidra et al., 2023). Each section contains questions that are related to the title of the block. At the same time, some questions were repeated in all three waves, whilst some of them were used only once.

Register study includes variables from different authorities that are related to the study data. This includes data from the population Register, Education Information system, Social insurance board, Unemployment insurance fund, Health insurance fund, and topographic database. These databases have been integrated into the survey data, which gives a comprehensive vision of the analysis results.

The dataset I use has been preset due to the sensitivity of the initial data version. All personal data, which can identify location, personal code, and other personal sensitive data, has been erased due to the privacy and personal limitations to access to this type of data. However, the filtered dataset includes all essential variables for the spatial analysis of the target group. In the beginning, I was introduced to the dataset with 330 variables. However, the initial dataset I worked with for statistical analysis includes 1074 variables for the 19275 individuals. Data variables contain information from five different sources: 896 variables are from the three waves of survey (including items for the Estonian Mental Health Survey), 145 – contextual data from the topographic database, and 33 variables are from the population register and health insurance fund.

For my further statistical analysis, I preprocess data in a way that represents the results of the thesis questions. Therefore, I spent a week going through the three ways of survey data to identify possible integrated items. I also learned the structure and sources (how and with what kind of methods) of these variables that had been collected. Also worth mentioning is that these participants were selected with random sampling for equal coverage in all counties of Estonia.

3.2 Methods of statistical analysis

The methodological part of the thesis includes three essential steps. The first step includes identifying target groups and dependent variables for further analysis. The second step is related to choosing and modifying independent variables, grouping them, and finalizing their number for analysis. The third step includes identifying statistical analysis methods.

In the way of the general pattern of how life satisfaction transforms during all aging stages, there are the most crucial changes related to decreasing life satisfaction, future expectations, and lower social and economic statuses between late working age and older adults (Tseng et al., 2019; Cheng et al., 2023). However, at the same time, well-being is a combination of life expectancy characteristics and satisfaction maintained at the same level (Röcke & Lachman, 2008). Also, based on healthy life years in Estonia (59,2) and age, when chronic diseases are meeting more than they are absent (50), It is worth taking late working age into the analysis (figure 1). Following the plan, I consider the two major cohorts related to the age range 56-75 and 76+. However, to see essential distributions and differences, I decided to prepare four subsets: the first is the entire dataset, the second is the entire dataset for age 56+, the third is for 56+ in rural settlements, and the fourth is for 56+ in urban settlements.

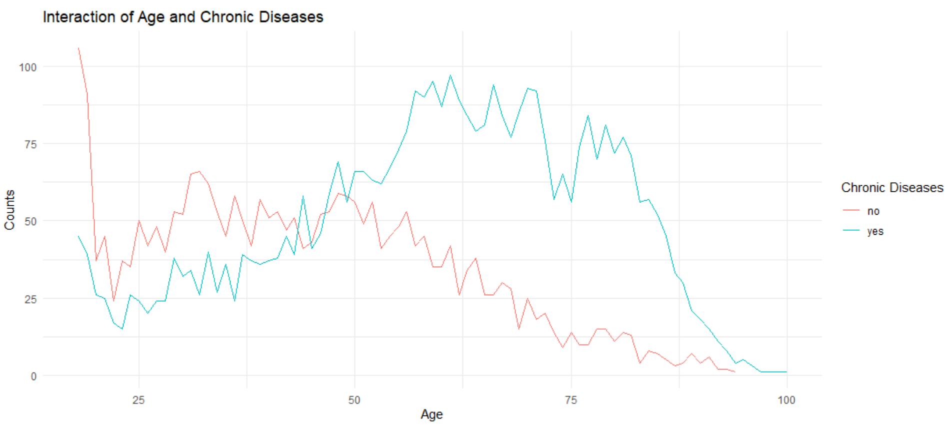

Figure 1. Interaction of age and chronic diseases from the Estonian Mental Health Study data

An essential step towards the analysis part includes the selection of variables for the regression analysis. The focus idea of the analytical part is to reveal how different mental health disorders can be connected with life contextual variables. For this, I use four dependent variables: mental health disorders, self-feeling of health condition, depression risk, and satisfaction with life. These variables represent different ways of mental health observations. They were selected on the basis of the mental health continuum. This is a way more comprehensive analysis of mental health disorders and includes aspects such as emotional, psychological, and social well-being (Joshanloo & Nosratabadi, 2008). In this case, I decided to use the registered mental health disorders variable as directly related to the chosen topic, then depression risk as a predictive factor of the quality of life, and the life satisfaction variable as a general factor related to emotional well-being. Furthermore, a variable of self-rated health condition was added due to the fact that individuals expressed their self-assess of their current state, and this confirmation proves the negative influence on emotional well-being.

The mental health disorders variable is structured from the registered data for 2020 and 2021 about the state of mental health and the survey self-reported information about mental health presence. Since registered data has been presented for two years, I created a merged column for the mental health variables based on registered data from 2016-2020 and 2021. After that, I created a new column with self-reported mental health conditions as self-reported diagnosed mental health conditions from the survey. The question of self-reported diagnosed mental health conditions has been asked in all three waves, and it has an important effect on the image of how individuals can self-esteem their mental health condition. This question includes four options: 1-“no,” 2-“yes,” 3-“don’t know,” and 4-“prefer not to answer.” In this case, the output represents “no” and “don’t know” answers as 0-“no mental health disorders,” and for “yes” as 1-“presence of mental health disorders.” While merging the results of responses from all three waves, I chose the maximum value method (pmax()). Thus, if the presence of mental health disorders appears, then it is marked as 1, and the rest are as 0, so we may still reveal that the person who did not want to give an answer actually has mental health disorders. After this optimization, the variable is represented as binary. This entire combined preprocess of registered and self-reported variables collects the data of all individuals of the selected group who have suffered from mental health conditions as a binary version, where if at least one of the variables mentions the existence of mental health disorders, this represents as 1-“yes,” and the rest marks as 0-“no.”

The variable of self-feeling of health condition comes from the block “Risk and protective factors” and relates to the question “How would you assess your current state of health?”. This question is used in all three waves. The question is represented in the 1-5 range, where the lowest relates to the most positive. For the general report, the outputs from all the wave results were optimized in a binary way, where to 1 were associated answers 1 and 2, and to 0 - the rest. I created one merge based on these modified variables from all three waves. Then, to keep most of the respondents who used to be dissatisfied with their health at least once, I merged them with finding the minimum value element-wise across multiple vectors.

The third variable I use as a dependent variable is depression risk. This variable has been formed using Emotional State Questionnaire 2 (EST-Q2; (Aluoja et al., 1999)). A presented survey contains a depression screening of seven questions in all three questionnaires on mental health block. These questions have a five-range scale of possible options related to different feelings: from 1 – not bothered at all to 5 – constantly bothered. The maximum points are 35, and the borderline risk of depression – is 11. Based on this border value, the binary variable has been established. Further, I merged all three columns with the pmax() function, which reveals individuals who have been discovered with a risk of depression.

The life satisfaction indicator is similar to the self-feeling variable, where the range 1-4 represents the most satisfied to the least. Seeing how satisfied respondents are with life could prove or refute the connections between mental health and aging problems and help confirm life-span patterns among aged groups. This issue was included in all three waves and has been modified to the binary vision as well, where 1 is related to "very satisfied" and "quite satisfied" and 0 includes "not particularly satisfied" and "not satisfied at all." To see everyone who has been dissatisfied with life in one of the questionnaires, while merging, I used the pmin() function.

To avoid misunderstanding while reading the results of logistic regressions, I decided to represent all outputs in one style, where 0 equals the lack of problems, and 1 represents the presence of health problems. Therefore, I mirrored outputs of life satisfaction and self-feeling of health condition.

For independent variables, I started to identify possible items that could be important for logistic regression analysis. Firstly, I identified four groups: general sociodemographic, lifestyle and social connections, psychological profile and risk factors, and environmental. Then I went through data descriptions and surveys to reveal applicable variables. As an output, I selected 5 variables in the general sociodemographic group, 13 variables in the lifestyle and social connections group, 8 – in the psychological profile group, and 15 in the environmental group. After a working discussion with the supervisor, it was decided to delete or optimize some indicators. From the first group, marital status has been correlated with the living alone variable from the second group and then optimized to one comprehensive living alone variable. Income and working status had a strong correlation. Thus, working status has been left and moved to the lifestyle and social connections group. In lifestyle and social connections were deleted: alcohol consumption, smoking (due to being out of focus of this research), living with a partner (correlates with marital status, which has been merged with living alone variable), use electronic devices for leisure (TV, Youtube) (due avoiding overloading models), use electronic devices for work (correlates with working status), relate to someone (due avoiding overfitting). From psychological profiles were removed: corona stress check group (due to being out of focus of this research) and trauma survey check (due to avoiding overloading models). Also, the big five personality traits (neuroticism, extraversion, openness to experience, agreeableness, conscientiousness) remained kept away from this particular research while having strong input to the results of models.

Environment group variables can be divided as data from surveys and topographical databases. Survey variables included information on noise pollution from human activities, noise pollution from transport, lack of light, strong light, lack of greenery, and type of settlements. Additionally, the type of settlement data has been provided by Statistics Estonia, which I use as a classification variable for urban and rural elderly subsets as a variable, which covers most individuals.

The topographical databases were collected as 100-, 500- and 1000-meter buffer radiuses from centroids, which were set on the building of the registered address. The collection of environmental data was carried out by using register data (Statistics Estonia, the Land Administration's vegetation height model, and the Estonian Topographical Database of the Land Board (ETAK)). In Kliit's (2023) research based on the same database, the absence of difference between different buffer radiuses was proved. Several studies have researched the mobility of older adults, and they have revealed that their walking speed has decreased (Kawai et al., 2021; Strand et al., 2021). Based on the average walking speed of older adults and the 15-minute city concept, the distance older adults can walk in 15 minutes is about 729 meters. Thus, for this particular research, 500-metre buffer radiuses seem to be the most suitable. In particular, for this thesis project, I use tree cover on a 500-meter radius as a green infrastructure variable and joined variable for blue infrastructure, which contains as area indicator lakes, rivers, reservoirs, and artificial lakes, as distance to lake and sea in a 500-meter radius. The length of the shoreline was not added to the joined blue infrastructure variable due to a crucial change in value distribution. The road network variable has been removed due to a high correlation with tree cover (-0.56). The same has been performed with a population in a 500-meter radius (-0.49).

Finally, in the presented research, the first group contains 3 variables: gender, age, and education. Lifestyle and social connections group include 7 variables of working status, life alone, having pets, movements, sleeping hours, using electronic devices for non-working communications, and satisfaction with friends. The third group currently contains only two variables: chronic diseases and post-traumatic syndrome (PTSD). The environmental block is structured with a tree cover and blue infrastructure.

Initially, I optimized the variables for some survey variables to match the way of analysis. Optimization includes combining survey answers into smaller ranges, merging with prevalence to different sides (minimum, maximum, the highest value in all answers), factoring and labeling them. Environmental variables included identifying ranges, even 4 ranges (for the tree cover variable), and binary vision (for the blue infrastructure variable).

Identifying statistical analysis methods includes a definition of software to perform analysis, means and methods to achieve solutions. In this study, I use R 4.3.3 software and RStudio as a platform for model calculations. Firstly, descriptive statistics for residents from the total population of the data set, including late working age and older adults in rural and urban settlements, will be calculated. These calculations take into account the number of individuals and their percentage in each subset of data.

In relevant studies, logistic regressions have been used for analysis (De Vries et al., 2016; Grolli et al., 2021; Song et al., 2022; Nakagawa et al., 2020; Abuladze et al., 2020). Thus, in this particular project, I perform a multivalve logistic regression analysis to reveal patterns and answer the questions in this study. This plan is to be implemented with four models in each chosen subset (16 models in total) (table 1). They are conducted jointly with correlation matrixes as additional analysis to reveal the lack of overfitting and relevance of output results. Each logistic regression model includes the number of individuals and probability coefficient (R2 Nagelkerke, which calculates the likelihood of models). All output variables include odd ratio, coefficient interval (CI 95%), signs of significance of variables, and information of reference value for each variable.

For a more suitable and detailed vision, I prepare a table with all the variables I use in this analysis (Annex 1).

Table 1. Models for logistic regressions

	Registered mental health disorders	**Self-rated health condition**	**Depression risk**	**Life satisfaction**
Total	Model 1 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 2 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 3 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 4 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment
Total late working age and older adults (56+)	Model 5 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 6 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 7 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 8 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment
Rural late working age and older adults (56+)	Model 9 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 10 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 11 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 12 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment

Urban late working age and older adults (56+)	Model 13 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 14 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 15 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment	Model 16 • General social-economic factors • Lifestyle habits and social connections • Psychological profile and risk factors • Environment

Note: description of variables in each group is in annex 1

4. Results

Based on the general dataset and subsets for all rural and urban late working age and older adult groups of respondents to the project, The outputs are represented via table format (table 2).

Analyzing the results of descriptive statistics, late working age and older adults in both types of settlement in Estonia have similar distribution patterns of mental health and well-being-related variables. However, a slightly increased number of individuals with registered mental health disorders in the urban type of settlement (48.01 to 45.63 % in rural) places this group of individuals the most compared to the total population and total late working age and older adults. Compared to total population outputs, in rural and urban areas, late working-age and older adults experience deterioration in health status. Remarkably, the depression risk variable shows a decrease compared to the total population, and at the same time, life satisfaction has also increased. This reveals the particular life of this group of people. This proves previous studies' outputs that higher satisfaction with life reduces depressiveness (Abuladze et al., 2020). With aging, life satisfaction levels remain stable or improve compared to younger age groups (Nakagawa et al., 2020). Furthermore, depressiveness is associated similarly in both types of settlement (Danek et al., 2023).

Compared to the total population, late working age and older adults have a sufficient decrease in working status due to retirement and a sufficient increase in chronic disease presence as a subprocess of aging. Notably, rural individuals walk longer than the total population, while urban late working age and older adults have fewer long walks (more than 60 minutes). However, longer walks are more characterized for older residents compared to the total population.

Furthermore, late working age and older adults have a reduction in abilities to use social media devices for general communications. Only about 61.03 to 64.73 % of rural and urban individuals use them for contact with other individuals. Nevertheless, satisfaction with friends has greater value than the total population for both types of settlement. This might lead to the view that face-to-face communication is more reliable and efficient for older groups of individuals.

Table 2. Descriptive statistics for residents from the total population of the data set, late working age and older adults in rural and urban types of settlements

	Total	**Total late working age and older adults (56+)**	**Rural late working age and older adults (56+)**	**Urban late working age and older adults (56+)**
Variables	number (%)			
Registered mental health disorders				
no	5212 (52.7)	2383 (53.05)	1077 (54.37)	1305 (51.99)
yes	4678 (47.3)	2109 (46.95)	904 (45.63)	1205 (48.01)
Self-satisfaction with health				
satisfied	2399 (33.17)	566 (16.49)	247 (16.11)	319 (16.8)
not satisfied	4834 (66.83)	2867 (83.51)	1286 (83.89)	1580 (83.2)
Life satisfaction				
satisfied	5130 (68.74)	2219 (64.45)	990 (64.29)	1228 (64.56)
not satisfied	2333 (31.26)	1224 (35.55)	550 (35.71)	674 (35.44)
Depression risk				
no	5033 (68.86)	2424 (73.23)	1083 (72.98)	1340 (73.42)
yes	2276 (31.14)	886 (26.77)	401 (27.02)	485 (26.58)
Age (years)				
15-35	6445 (33.44)			
36-55	5574 (28.92)			
56-74	4804 (24.92)	4804 (66.21)	2147 (68.05)	2655 (64.8)
75+	2452 (12.72)	2452 (33.79)	1008 (31.95)	1442 (35.2)
Gender				
Male	9672 (50.18)	2915 (40.17)	1401 (44.41)	1513 (36.93)
Female	9603 (49.82)	4341 (59.83)	1754 (55.59)	2584 (63.07)
Education				
Higher	2283 (30.76)	918 (26.94)	363 (24.01)	554 (29.25)
Secondary	4225 (56.93)	2070 (60.76)	934 (61.77)	1136 (59.98)
Basic	914 (12.31)	419 (12.30)	215 (14.22)	204 (10.77)
Working status				
Not working	3527 (47.58)	2504 (72.81)	1132 (73.79)	1371 (72.01)
Working	3885 (52.42)	935 (27.19)	402 (26.21)	533 (27.99)
Living alone				
No	4306 (57.38)	1778 (51.08)	808 (52.13)	969 (50.21)
Yes	3199 (42.62)	1703 (48.92)	742 (47.87)	961 (49.79)
Pets				
No	17916 (92.95)	6806 (93.80)	2887 (91.51)	3915 (95.56)
Yes	1359 (7.05)	450 (6.20)	268 (8.49)	182 (4.44)
Movements (in minutes)				
<15	422 (11.78)	239 (11.85)	114 (12.69)	125 (11.18)
15-30	994 (27.75)	570 (28.26)	255 (28.40)	314 (28.09)
30-60	1152 (32.16)	640 (31.73)	256 (28.51)	384 (34.35)
>60	1014 (28.31)	568 (28.16)	273 (30.40)	295 (26.39)
Sleeping, hours				
<7	932 (17.77)	420 (17.33)	186 (16.80)	233 (17.71)
7-9	3941 (75.14)	1799 (74.22)	826 (74.62)	973 (73.94)
>9	372 (7.09)	205 (8.46)	95 (8.58)	110 (8.36)
Digital for non-working communication use				
No	789 (22.58)	716 (36.91)	339 (38.97)	377 (35.27)
Yes	2706 (77.42)	1224 (63.09)	531 (61.03)	692 (64.73)
Satisfaction with friends				
Not satisfied	1297 (17.54)	515 (15.24)	221 (14.62)	294 (15.76)
Satisfied	6096 (82.46)	2864 (84.76)	1291 (85.38)	1572 (84.24)
Chronic diseases				
No	2677 (39.61)	716 (21.98)	326 (22.39)	390 (21.65)
Yes	4081 (60.39)	2542 (78.02)	1130 (77.61)	1411 (78.35)

PTSD				
No	4081 (77.41)	1975 (77.39)	927 (80.89)	1048 (74.54)
Yes	1191 (22.59)	577 (22.61)	219 (19.11)	358 (25.46)
Tree cover				
low	4819 (25)	1786 (24.61)	288 (9.13)	1494 (36.47)
medium-low	4819 (25)	1824 (25.14)	609 (19.30)	1215 (29.66)
medium-hight	4818 (25)	1850 (25.50)	885 (28.05)	965 (23.55)
hight	4819 (25)	1796 (24.75)	1373 (43.52)	423 (10.32)
Blue infrastructure				
No	12909 (67.01)	4761 (65.65)	2063 (65.39)	2698 (65.85)
Yes	6355 (32.99)	2491 (34.35)	1092 (34.61)	1399 (34.15)

For the elaboration of logistic regression models, I implemented them in connection with the correlation matrix. This is performed to figure out differences and relations between chosen variables for models. Previously, while identifying variables for modeling, I used particular and general correlation matrixes to avoid overfitting models with similar variables. Here, while observing variables with positive or negative correlations, I take into account the meaning of each variable and its representation of the outputs. The significance of outputs is represented via the following ranges: .00 to .30 (.00 to -.30) – negligible correlation, .30 to .50 (-.30 to -.50) – low positive (negative) correlation, .50 to .70 (-.50 to -.70) – moderate positive (negative) correlation, .70 to .90 (-.70 to -.90) – high positive (negative) correlation, .90 to 1.00 (-.90 to -1.00) – very high positive (negative) correlation (Jaadi, 2021). Thus, correlations that are less than negligible are considered to be a lack of overfitting.

However, as it is represented in Figures 2-5, some correlations are higher than negligible levels. The general model for the total population age variable reveals positive correlations to a dependent variable as a self-rated health condition, which means a negative attitude to one's own health among older ages (.36), and an independent variable as chronic diseases, which reveals increase number of chronic diseases among older individuals (.37). Negative correlation is to social media use (-.46) and working status (-.42). The same negative correlation remains in all subsets of this study for both variables.

The dependent variable, "self-rated health condition," stays positively correlated with chronic diseases. This is in line with studies in the medical field, which prove a correlation between the presence of chronic diseases and stresses and worries of own life (Grolli et al., 2021).

Another dependent variable, depression risk, reveals positive correlations with post-traumatic stress disorder (PTSD) and with life satisfaction in all subsets of this study. Whilst life satisfaction and depression risk are both dependent variables, their impacts have different outputs for other variables. Also, depression risk has a negative low correlation with the "satisfaction with friends" variable, which elaborates on a decrease in depression risk while having reliable connections with other individuals. Notably, the depression risk variable demonstrates a positive correlation with registered mental health disorders (.30) only in the urban late working age and older adults subset.

From an environmental group of variables, only tree cover and type of settlement have a negative correlation in all populations and late working age and older adults subsets, which proves the decrease of tree cover areas in urbanized areas.

Also, isolated cases of correlations have been revealed for social media use with working status (.35) in all population datasets, level of education and social media use in rural (.31), and gender with living alone in urban subsets (.31).

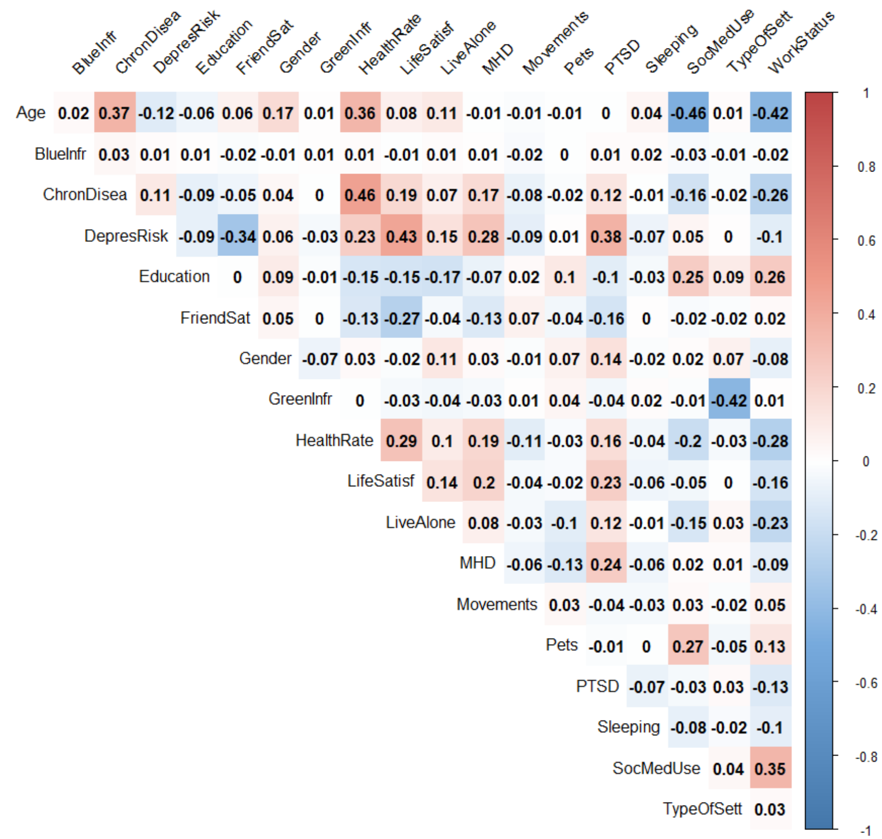

Figure 2. Correlation matrix for the entire dataset

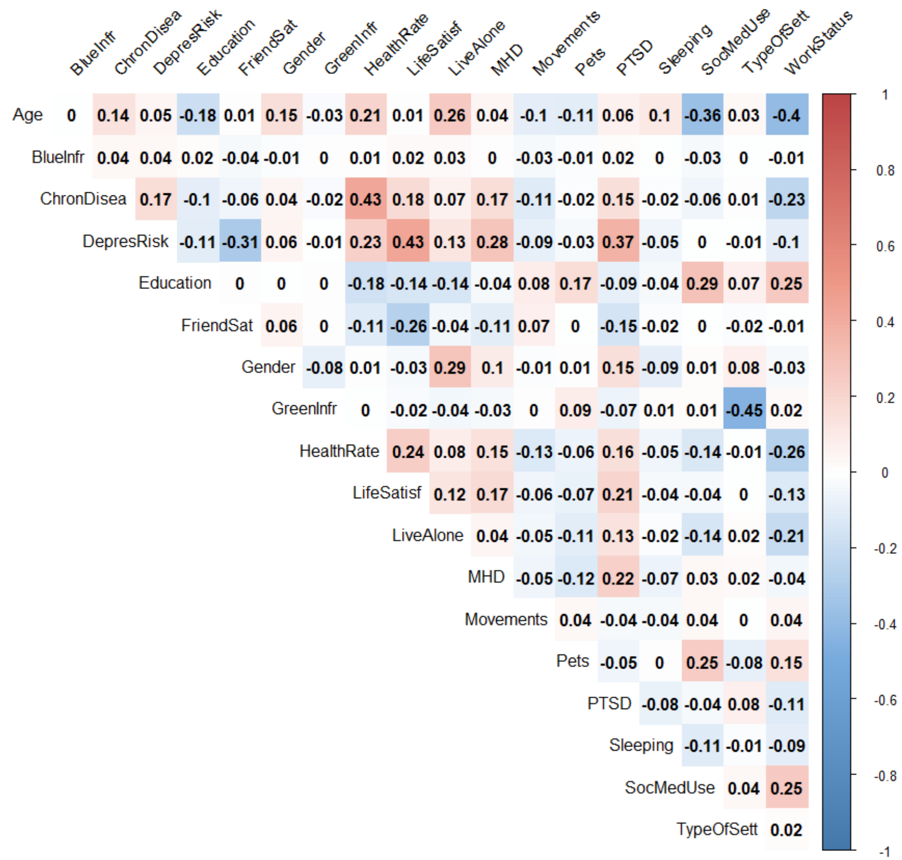

Figure 3. Correlation matrix for the entire late working age and older adults dataset

Range of correlation: .00 to .30 (.00 to -.30) – negligible correlation, .30 to .50 (-.30 to -.50) – low positive (negative) correlation, .50 to .70 (-.50 to -.70) – moderate positive (negative) correlation, .70 to .90 (-.70 to -.90) – high positive (negative) correlation, .90 to 1.00 (-.90 to -1.00) – very high positive (negative) correlation.

Note: Age=age, BlueInf=Blue infrastructure, ChronDisea=chronic diseases, DepresRisk=depression risk, Education=education, FriendSat=satisfaction with friends, Gender=gender, GreenInf=tree cover, HealthRate=self-rated health condition, LifeSatisf=life satisfaction, LiveAlone=living alone, MHD=registered mental health disorders, Movements=movements, Pets=having pets, PTSD=PTSD, Sleeping=sleeping, SocMedUse= digital for non-working communication use (Social media use), TypeOfSett=type of settlement.

Table 4. Binomial logistic regression for the entire dataset (n=2114-2125[1]).

Dependent Variables / Independent variables[2]	Model 1: Registered mental health disorders	Model 2: Self-rated health condition	Model 3: Depression risk	Model 4: Life satisfaction
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age: 36-55	1.04 (0.76-1.42)	2.06 (1.47- 2.89) ***	0.45 (0.32-0.63) ***	1.23 (0.89-1.71)
Age: 56-75	0.90 (0.65-1.24)	2.57 (1.79-3.68) ***	0.26 (0.18-0.37) ***	0.99 (0.71-1.39)
Age: 76+	0.55 (0.36-0.83) **	9.78 (4.89-21.15) ***	0.22 (0.14-0.35) ***	0.81 (0.54-1.23)
Gender: female	1.51 (1.22-1.88) ***	0.74 (0.57-0.95) *	1.46 (1.16-1.85) **	0.74 (0.60- 0.91) **
Education: secondary	0.57 (0.40-0.81) **	0.90 (0.494-1.58)	0.87 (0.58-1.29)	0.98 (0.68-1.40)
Education: higher	0.49 (0.33-0.72) ***	0.52 (0.28-0.93) *	0.67 (0.44-1.04) .	0.58 (0.40-0.86) **
Working status: working	0.84 (0.66-1.07)	0.54 (0.40-0.73) ***	0.64 (0.49-0.84) **	0.64 (0.50-0.82) ***
Living alone	1.16 (0.95-1.43)	1.09 (0.84-1.41)	1.27 (1.01-1.59) *	1.27 (1.03-1.56) *
Having pets	1.01 (0.81-1.25)	0.72 (0.56-0.93) *	0.89 (0.70-1.125)	0.77 (0.61-0.96) *
Movements: 15-30 minutes	0.76 (0.54-1.06) .	1.10 (0.69-1.71)	0.87 (0.60-1.27)	0.88 (0.62-1.23)
Movements: 30-60 minutes	0.89 (0.64-1.23)	0.79 (0.51-1.21)	0.76 (0.53-1.09)	0.83 (0.59-1.16)
Movements: more than 60 minutes	0.65 (0.46-0.91) *	0.57 (0.37-0.88) *	0.66 (0.45-0.96) *	0.96 (0.68-1.35)
Sleeping: 7-9 hours	0.64 (0.50-0.83) ***	0.54 (0.37-0.78) **	0.58 (0.44-0.77) ***	0.50 (0.38-0.65) ***
Sleeping: more than 9 hours	0.56 (0.37-0.85) **	0.45 (0.25-0.82) **	0.67 (0.42-1.06) .	0.53 (0.35-0.80) **
Social media use	1.14 (0.86-1.52)	0.80 (0.52-1.21)	1.29 (0.95-1.77)	1.05 (0.80-1.38)
Satisfaction with friends	0.52 (0.41-0.65) ***	0.34 (0.24-0.48) ***	0.19 (0.15-0.24) ***	0.28 (0.22-0.35) ***
Chronic diseases	1.94 (1.52-2.47) ***	4.86 (3.80-6.23) ***	1.6 (1.24-2.09) ***	1.65 (1.30-2.11) ***
PTSD	2.19 (1.75-2.75) ***	1.74 (1.24-2.46) **	4.48 (3.50-5.75) ***	2.40 (1.90-3.03) ***
Tree cover: Medium-Low	0.79 (0.60-1.04) .	0.89 (0.63-1.27)	0.87 (0.65-1.18)	0.998 (0.76-1.32)
Tree cover: Medium-High	0.82 (0.62-1.08)	0.87 (0.62-1.23)	0.85 (0.63-1.14)	0.97 (0.74-1.28)
Tree cover: High	0.86 (0.65-1.13)	0.82 (0.58-1.16)	0.80 (0.59-1.08)	0.85 (0.64-1.12)
Blue infrastructure	1.04 (0.84-1.27)	0.95 (0.73-1.22)	1.06 (0.85-1.33)	0.93 (0.76-1.14)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

[1] in model 1=2124 ($R^2_{Nagelkerke}$=0.16), model 2 = 2125($R^2_{Nagelkerke}$=0.38), model 3 = 2114 ($R^2_{Nagelkerke}$=0.36), model 4 = 2125 ($R^2_{Nagelkerke}$=0.23)

[2] Reference in independent variables: Age:15-35, Gender: Male, Education: basic, Working status: not working, Living alone: not alone, Having pets: not having, Movements:less than 15 minutes, Sleeping: less than 7 hours, Social media: not using, Satisfaction with friends: not satisfied, chronic diseases: not having, PTSD: not having, Tree cover: Low, Blue infrastructure: not having.

Table 5. Binomial logistic regression for the entire late working age and older adults dataset (n=1153-1164[1])

Independent Variables[2] \ Dependent Variables	Model 5: Registered mental health disorders	Model 6: Self-rated health condition	Model 7: Depression risk	Model 8: Life satisfaction
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age: 76+	0.72 (0.51-0.99) *	3.93 (1.92-8.76) ***	0.89 (0.62-1.27)	0.75 (0.54-1.04) .
Gender: female	1.69 (1.26-2.28) ***	0.53 (0.32-0.86) *	1.11 (0.79-1.54)	0.63 (0.47-0.85) **
Education: secondary	0.56 (0.35-0.89) *	0.54 (0.11-1.81)	0.89 (0.54-1.50)	1.11 (0.70-1.78)
Education: higher	0.43 (0.26-0.73) **	0.26 (0.05-0.89) .	0.53 (0.30-0.95) *	0.61 (0.36-1.03) .
Working status: working	0.98 (0.71-1.37)	0.50 (0.31-0.79) **	0.65 (0.44-0.96) *	0.65 (0.45-0.92) *
Living alone	0.89 (0.67-1.19)	1.22 (0.77-1.93)	1.34 (0.98-1.84) .	1.35 (1.01-1.81) *
Having pets	0.95 (0.68-1.31)	0.74 (0.47-1.18)	1.05 (0.72-1.52)	0.57 (0.40-0.81) **
Movements:15-30 minutes	0.83 (0.52-1.31)	0.94 (0.39-2.15)	0.98 (0.59-1.64)	0.78 (0.49-1.24)
Movements: 30-60 minutes	0.95 (0.60-1.51)	0.86 (0.36-1.91)	0.93 (0.56-1.56)	0.60 (0.38-0.96) *
Movements: more than 60 minutes	0.72 (0.45-1.16)	0.55 (0.23-1.21)	0.78 (0.46-1.32)	0.93 (0.58-1.49)
Sleeping: 7-9 hours	0.70 (0.50-0.99) *	0.32 (0.14-0.65) **	0.59 (0.40-0.87) **	0.56 (0.39-0.81) **
Sleeping: more than 9 hours	0.45 (0.25-0.79) **	0.16 (0.05-0.45) ***	0.60 (0.33-1.09) .	0.57 (0.33-0.99) *
Social media use	1.23 (0.90-1.69)	0.70 (0.39-1.21)	1.26 (0.89-1.79)	0.97 (0.71-1.33)
Satisfaction with friends	0.55 (0.40-0.77) ***	0.28 (0.12- 0.58) **	0.21 (0.15-0.30) ***	0.22 (0.15-0.31) ***
Chronic diseases	1.75 (1.17-2.66) **	9.81 (6.29-15.49) ***	2.67 (1.61-4.63) ***	2.50 (1.63-3.94) ***
PTSD	2.19 (1.61-2.97) ***	1.79 (0.93-3.66) .	4.60 (3.32-6.41) ***	2.54 (1.84-3.52) ***
Tree cover: Medium-Low	0.71 (0.48-1.03) .	0.83 (0.44-1.57)	0.78 (0.51-1.19)	1.03 (0.70-1.51)
Tree cover: Medium-High	0.75 (0.52-1.08)	1.24 (0.67-2.29)	0.89 (0.59-1.35)	0.89 (0.60-1.30)
Tree cover: High	0.88 (0.61-1.26)	0.80 (0.44-1.46)	0.85 (0.56-1.29)	0.91 (0.62-1.33)
Blue infrastructure	0.95 (0.72-1.26)	0.78 (0.50-1.22)	1.13 (0.83-1.54)	1.02 (0.77-1.36)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

[1] in model 5=1164 ($R^2_{Nagelkerke}$=0.14), model 6 = 1164 ($R^2_{Nagelkerke}$=0.41), model 7 = 1153 ($R^2_{Nagelkerke}$=0.32), model 8 = 1164 ($R^2_{Nagelkerke}$=0.27)

[2] Reference in independent variables: Age:15-35, Gender: Male, Education: basic, Working status: not working, Living alone: not alone, Having pets: not having, Movements:less than 15 minutes, Sleeping: less than 7 hours, Social media: not using, Satisfaction with friends: not satisfied, chronic diseases: not having, PTSD: not having, Tree cover: Low, Blue infrastructure: not having.

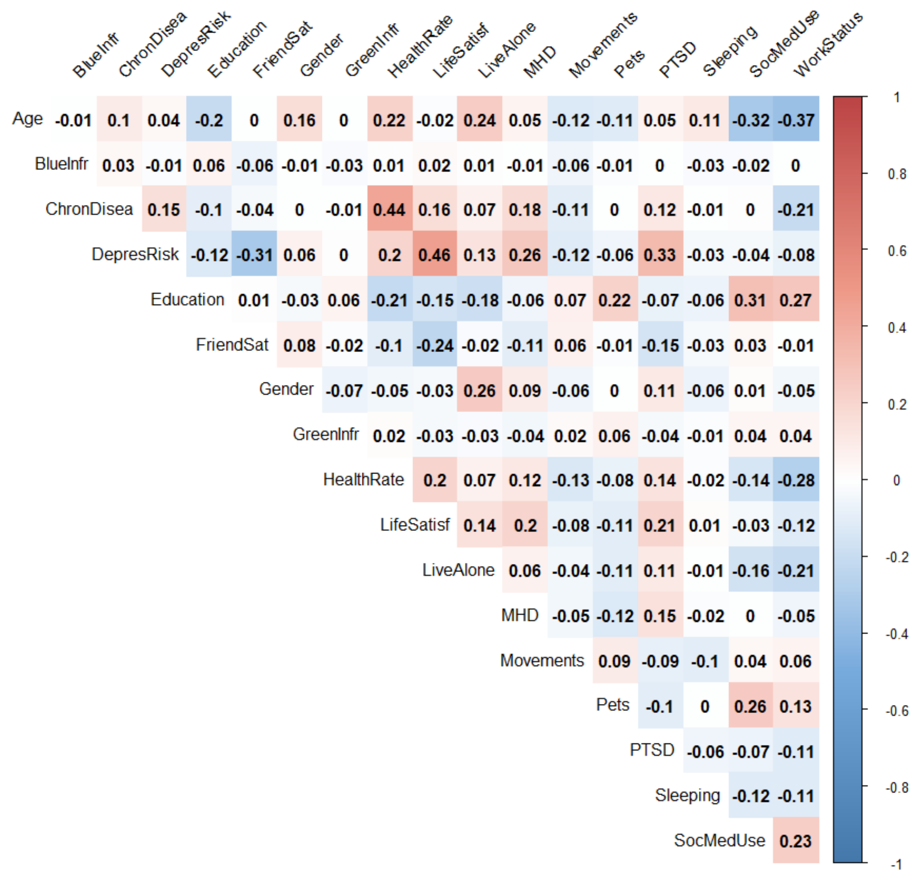

Figure 4. Correlation matrix for the rural late working age and older adults dataset

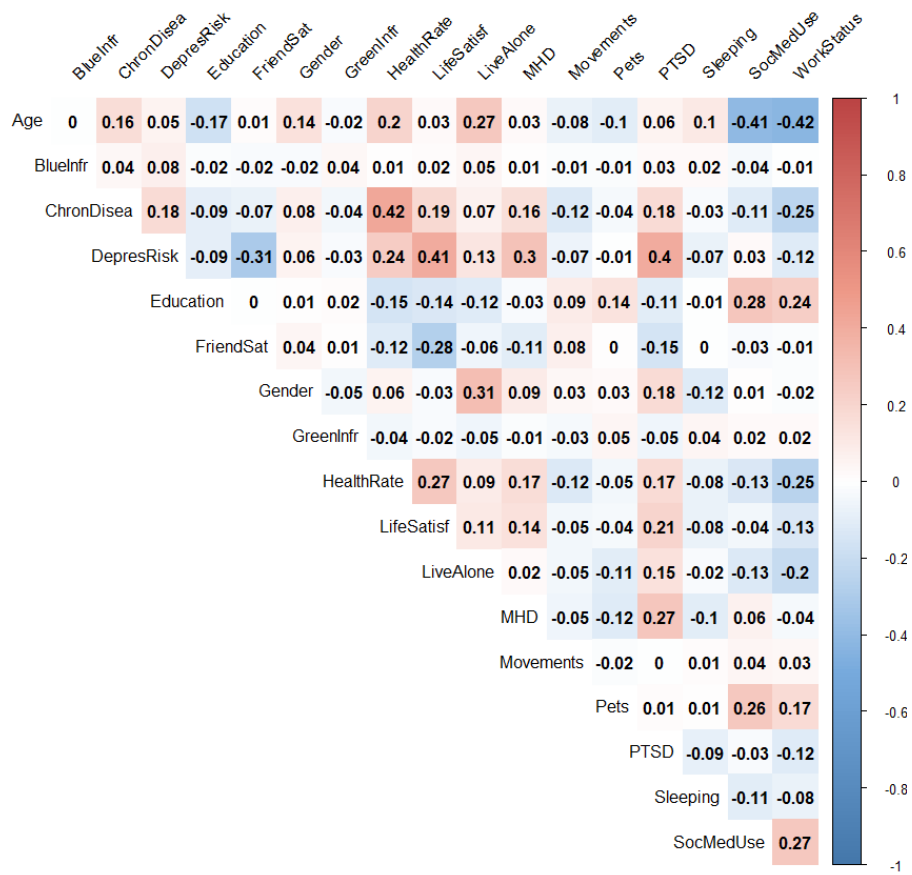

Figure 5. Correlation matrix for the urban late working age and older adults dataset

Range of correlation: .00 to .30 (.00 to -.30) – negligible correlation, .30 to .50 (-.30 to -.50) – low positive (negative) correlation, .50 to .70 (-.50 to -.70) – moderate positive (negative) correlation, .70 to .90 (-.70 to -.90) – high positive (negative) correlation, .90 to 1.00 (-.90 to -1.00) – very high positive (negative) correlation.

Note: Age=age, BlueInf=Blue infrastructure, ChronDisea=chronic diseases, DepresRisk=depression risk, Education=education, FriendSat=satisfaction with friends, Gender=gender, GreenInf=tree cover, HealthRate=self-rated health condition, LifeSatisf=life satisfaction, LiveAlone=living alone, MHD=registered mental health disorders, Movements=movements, Pets=having pets, PTSD=PTSD, Sleeping=sleeping, SocMedUse= digital for non-working communication use (Social media use).

Table 6. Binomial logistic regression for the rural late working age and older adults dataset (n=513-515[1])

Independent Variables[2] \ Dependent Variables	Model 9: Registered mental health disorders	Model 10: Self-rated health condition	Model 11: Depression risk	Model 12: Life satisfaction
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age: 76+	0.70 (0.42 1.17)	5.50 (1.76-21.06) **	0.79 (0.45-1.38)	0.48 (0.28-0.81) **
Gender: female	1.75 (1.13-2.73) *	0.21 (0.09-0.46) ***	1.40 (0.85-2.32)	0.69 (0.43-1.10)
Education: secondary	0.59 (0.30-1.18)	0.81 (0.10-3.98)	0.76 (0.36-1.65)	1.12 (0.54 2.36)
Education: higher	0.33 (0.15-0.72) **	0.44 (0.05-2.32)	0.28 (0.11-0.68) **	0.59 (0.25-1.37)
Working status: working	0.96 (0.63-1.48)	0.42 (0.20-0.86) *	0.68 (0.36-1.24)	0.80 (0.43-1.32)
Living alone	1.16 (0.95-1.43)	1.39 (0.69-2.86)	1.16 (0.71-1.88)	1.37 (0.87-2.17)
Having pets	1.16 (0.72-1.86)	0.63 (0.30-1.29)	1.20 (0.69-2.07)	0.42 (0.25-0.71) **
Movements: 15-30 minutes	0.85 (0.43-1.71)	0.90 (0.25-2.92)	0.48 (0.22-1.03) .	0.45 (0.22-0.92) *
Movements: 30-60 minutes	1.25 (0.63-2.50)	1.08 (0.30-3.49)	0.61 (0.29-1.33)	0.34 (0.16-0.72) **
Movements: more than 60 minutes	0.68 (0.34-1.39)	0.68 (0.19-2.14)	0.38 (0.17-0.83) *	0.70 (0.34-1.42)
Sleeping: 7-9 hours	0.80 (0.46-1.44)	0.32 (0.10-0.91)	0.56 (0.30-1.09) .	0.65 (0.35-1.21)
Sleeping: more than 9 hours	0.76 (0.31-1.84)	0.06 (0.01-0.26)	0.36 (0.13-0.96) *	0.94 (0.38-2.34)
Social media use	1.27 (0.80-2.03)	0.56 (0.23-1.27)	1.16 (0.69-1.96)	0.86 (0.53-1.39)
Satisfaction with friends	0.52 (0.31-0.87) *	0.11 (0.02-0.42) **	0.16 (0.09-0.28) ***	0.17 (0.09-0.30) ***
Chronic diseases	2.25 (1.24-4.32) *	13.17 (6.36-28.53) ***	3.16 (1.53-7.11) **	3.39 (1.76-6.93) ***
PTSD	1.21 (0.71-2.05)	1.35 (0.49-4.33)	3.98 (2.27-7.04) ***	2.49 (1.43-4.39) **
Tree cover: Medium-Low	1.24 (0.54-2.97)	0.61 (0.14-2.41)	0.56 (0.23-1.39)	0.50 (0.21-1.17)
Tree cover: Medium-High	1.13 (0.52-2.56)	0.67 (0.17-2.28)	0.52 (0.22-1.21)	0.33 (0.15-0.74) **
Tree cover: High	1.24 (0.59-2.72)	0.62 (0.17-1.98)	0.58 (0.23-1.16)	0.45 (0.21-0.97) *
Blue infrastructure	0.81 (0.53-1.24)	0.73 (0.36-1.51)	0.60 (0.36-0.98) *	1.25 (0.79-1.96)

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1

[1] in model 9=515 ($R^2_{Nagelkerke}$=0.11), model 10 = 515 ($R^2_{Nagelkerke}$=0.47), model 11 = 513 ($R^2_{Nagelkerke}$=0.32), model 12 = 515 ($R^2_{Nagelkerke}$=0.32)

[2] Reference in independent variables: Age:15-35, Gender: Male, Education: basic, Working status: not working, Living alone: not alone, Having pets: not having, Movements: less than 15 minutes, Sleeping: less than 7 hours, Social media: not using, Satisfaction with friends: not satisfied, chronic diseases: not having, PTSD: not having, Tree cover: Low, Blue infrastructure: not having.

Table 7. Binomial logistic regression for the urban late working age and older adults dataset (n=640-649[1])

Independent Variables[2] \ Dependent Variables	Model 13: Registered mental health disorders	Model 14: Self-rated health condition	Model 15: Depression risk	Model 16: Life satisfaction
	OR (95% CI)	OR (95% CI)	OR (95% CI)	OR (95% CI)
Age: 76+	0.72 (0.46-1.13)	3.42 (1.34-10.08) *	0.96 (0.58-1.58)	0.98 (0.63-1.52)
Gender: female	1.77 (1.17-2.70) *	1.05 (0.52-2.07)	0.91 (0.57-1.46)	0.50 (0.33-0.75) **
Education: secondary	0.56 (0.29-1.08) .	0.28 (0.01-1.88)	0.95 (0.46-2.01)	1.001 (0.53-1.91)
Education: higher	0.52 (0.25-1.06) .	0.13 (0.01-0.88) .	0.81 (0.37-1.83)	0.57 (0.28-1.15)
Working status: working	0.98 (0.63-1.54)	0.53 (0.27-0.99) *	0.63 (0.37-1.07) .	0.57 (0.35-0.92) *
Living alone	0.81 (0.55-1.19)	1.11 (0.59-2.13)	1.52 (0.98-2.34) .	1.42 (0.97-2.11) .
Having pets	0.71 (0.43-1.16)	0.72 (0.37-1.45)	0.92 (0.52-1.61)	0.76 (0.45-1.26)
Movements: 15-30 minutes	0.74 (0.39-1.41)	0.77 (0.19-2.65)	1.77 (0.86-3.82)	1.29 (0.69-2.43)
Movements: 30-60 minutes	0.73 (0.39-1.38)	0.64 (0.16-2.07)	1.33 (0.64-2.85)	0.97 (0.52-1.83)
Movements: more than 60 minutes	0.66 (0.34-1.29)	0.40 (0.10-1.30)	1.38 (0.64-3.07)	1.32 (0.69-2.55)
Sleeping: 7-9 hours	0.63 (0.40-0.99) *	0.26 (0.07-0.76) *	0.56 (0.34-0.92) *	0.48 (0.30-0.76) **
Sleeping: more than 9 hours	0.30 (0.13-0.66) **	0.35 (0.07-1.83)	0.72 (0.32-1.59)	0.36 (0.17-0.74) **
Social media use	1.18 (0.76-1.85)	0.88 (0.37-1.96)	1.37 (0.84-2.27)	1.03 (0.66-1.59)
Satisfaction with friends	0.54 (0.35-0.85) **	0.49 (0.17-1.22)	0.24 (0.15-0.39) ***	0.25 (0.15-0.40) ***
Chronic diseases	1.34 (0.77-2.39)	8.7 (4.75-16.29) ***	2.79 (1.35-6.32) **	2.28 (1.26-4.26) **
PTSD	3.20 (2.15-4.79) ***	2.31 (0.93-6.68) .	5.60 (3.65-8.69) ***	2.60 (1.72-3.94) ***
Tree cover: Medium-Low	0.63 (0.40-0.99) *	0.92 (0.43-1.97)	0.86 (0.52-1.41)	1.24 (0.80-1.93)
Tree cover: Medium-High	0.69 (0.43-1.11)	1.67 (0.77-3.74)	1.02 (0.59-1.74)	1.37 (0.85-2.21)
Tree cover: High	1.04 (0.57-1.86)	0.89 (0.36-2.31)	1.03 (0.52-2.02)	1.18 (0.64-2.17)
Blue infrastructure	1.10 (0.75-1.61)	0.82 (0.44-1.54)	1.69 (1.11-2.58) *	0.85 (0.57-1.24)

Significance codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1

[1] in model 13=649 ($R^2_{Nagelkerke}$=0.19), model 14 = 649 ($R^2_{Nagelkerke}$=0.41), model 15 = 640 ($R^2_{Nagelkerke}$=0.36), model 16 = 649 ($R^2_{Nagelkerke}$=0.27)

[2] Reference in independent variables: Age:15-35, Gender: Male, Education: basic, Working status: not working, Living alone: not alone, Having pets: not having, Movements: less than 15 minutes, Sleeping: less than 7 hours, Social media: not using, Satisfaction with friends: not satisfied, chronic diseases: not having, PTSD: not having, Tree cover: Low, Blue infrastructure: not having.

Upon question 2 of this study, based on logistic regression models the different life habits of urban and rural late working age and older adults have been revealed. In particular, older age groups have more worries about their own health in both types of living areas. For rural females, it is also common to have more mental health disorders than males and be less dissatisfied with their own health. Also, females in urban and rural areas are more likely to have registered mental health disorders than males. Higher education predicts less likelihood of registered mental health disorders in both settlements and has a positive output for depression risk for rural individuals. Moreover, better satisfaction with health connects individuals with higher education for urban residents. Also, life satisfaction increases in both settlements with aging.

From the lifestyle habits and social connections group, working status improves self-rated health in both life satisfaction and depression risk in urban areas only. Living alone decreases life satisfaction in urban and rural types of settlements and also has a negative impact on depression risk in urban areas. Having pets positively affects the life satisfaction of rural older adults only. Walking more than 15 minutes daily improves life satisfaction and reduces depression risk for rural late working age and older adults. Sleeping more than 7 hours has a positive impact with all the dependent variables for urban late working age and older adults, while rural older residents feel an impact only in depression risk.

Social media use has not proven to have any impact as a communication tool. However, satisfaction with friends was revealed as a factor that performs those dependent variables on the positive side for rural and urban elderly individuals (except for urban individuals in self-rated health conditions).

Psychological profile and risk factors group variables have more statistically meaningful outputs for urban elderly people than for rural ones. The presence of PTSD negatively impacts all mental health continuums for urban late working age and older adults, whilst for rural residents, it impacts depression risk and life satisfaction only. Chronic diseases have a high significance in both (except registered mental health disorders for urban elderly people).

For the third question of this study, chosen models revealed only a positive impact of medium-low tree cover on the reduction of registered mental health disorders in the total population dataset. The same remains true for the entire dataset of late working age and older adults. At the same time, different settlements with medium-low tree cover impact the reduction of registered mental health disorders in the urban subset only. Also, medium-high and high tree cover have been found to be positive factors in the reduction of depression risk and increasing life satisfaction for rural late working age and older adults. Unexpectedly, the urban type of settlement is characterized by a negative impact on depression risk from blue infrastructure, whilst in rural areas, it is in reverse.

5. Discussion

The implemented methodological part of this study set the main task as revealing common patterns in mental health continuum variables for Estonian late working age and older adults and identifying particular specifics based on the data collected by the Estonian Mental Health Study. Common cases have been revealed based on the outputs of 16 logistic regression models.

In most of the reviewed studies (Gascón et al., 2018; Aliyas, 2019; Andreucci et al., 2019; Lee et al., 2019), environmental variables (blue and green infrastructures) have positive outcomes for individuals with diverse mental health disorders. Tree canopy especially positively affects individuals of all age groups in reducing mental health disorders (Alvarado et al., 2023; Browning et al., 2019; Zhang et al., 2022). Nevertheless, in my outputs, a tree cover doesn't reveal vital significance in most of the models. Only for the life satisfaction variable for rural older adults does more green infrastructure enhance satisfaction with life. For urban late working age and older adults, it is on a borderline of significance with registered mental health disorders at medium-low level.

The most unexpected output belongs to blue infrastructure and its relation to depression risk. Rural older individuals living within a 500-meter radius of water objects help decrease depression risk. However, this study revealed increased depressiveness while living near water bodies in urban areas. However, it might be explained by the structure of the blue infrastructure variable, which does not include the shoreline and belongs to Estonia's most urbanized areas (Tallinn, Pärnu, Maardu). The shoreline was not included due to significant changes in the variable output distribution. Thus, it can be included in future studies.

In general, environmental factors do not play a sufficient role in the mental health continuum in both types of settlement for late working adults and older aged groups. Chosen environmental factors tend to have a limited impact on mental health and well-being compared to a psychological profile and risk factors, lifestyle habits and social connections, and general socioeconomic factors. Especially, psychological profile and risk factors (chronic diseases and PTSD) have a significant influence on all chosen dependent variables (except for chronic diseases for registered mental health disorders in the urban subset), which proves dependence on emotional human state and physical inflammations (Grolli et al., 2021).

Therefore, in future studies, the overstatements and overvalue of green and blue infrastructure variables should be avoided. In spatial planning, decisions about the better well-being of residents and greenery as a planning tool needed to be revised. More comprehensive spatial planning decisions, such as providing a better social environment, could work more efficiently in this case. Also, multifaceted and long-term planning decisions with a focus on social cohesions might reduce mental health issues. Here, for example, satisfaction with friends has a strong impact on all the chosen variables in both types of settlement (except for self-rated health conditions in urban areas). Thus, the creation of places for community socializing, such as parks with inclusive infrastructures (including benches, walking paths, and gardening), cafes, and shops for late working age and older adults, might support friendship connections, and the output can improve mental health conditions. Physical socializing realization is needed for older adults since the absence of digital life impacts mental health and has a negative impact on older groups living alone in urban areas.

In the observation of features in different types of settlement, lifestyle variables have different outputs. Particularly, working helps with prevention and has a reduction effect on the mental health variables. However, working status mostly influences only urban late working age and older adults, whilst, in rural areas, working status helps only with depression risk. It could be elaborated on the social purpose of work when employees get social contact during the day to cover daily communication needs. In rural areas, it would not work similarly due to the fact that more social tights characterize rural types of settlement. Another reason could be physical loads. The rural lifestyle includes the diverse specter of physical routines, which the urban lifestyle does not include. Movement results in rural areas prove it. Thus, activity as working time helps cope with physical needs, and in urban areas, physical load includes the working activity due to transportation issues. Previously, studies focused on the general population or a smaller range of lifestyle-related factors. In this study, comprehensive and diverse unique variables reveal previously hidden factors related to the mental health continuum in urban and rural areas for late working age and older adults.

Another important finding relates to aging as an impact on the flow of mental health aspects. From the logistic regression models for the entire dataset, I found out that self-rated health conditions become worse with aging. However, depression risk shows a decline with age. These controversial outputs prove the well-being "paradox" when accepting a limited life span and fewer expectations from life in general moderate personal interactions with environments, keeping positive and negative aspects in balance (Nakagawa et al., 2020).

My study also revealed sleeping as a significant factor in the reduction of mental health problems among urban residents. However, for rural individuals, it works only with depression risk. It may be related to external factors such as noise, light pollution, or air quality. All of these variables were not included in the current study but could be taken into further analysis.

In conclusion, the outputs of this study are important for the spatial planning aspect of different types of territories with a focus on the 56+ age group of the population. It elaborates on how mental health variables affect older population groups and in different settlements. This research revealed that environmental factors play the least role in mental health aspects. Social media use does not affect better outputs for them as well. Satisfaction with friends affects significantly and can be a reason for spatial planning changes. Lifestyle and psychological variables are forming the mental health continuum. The types of settlements (urban and rural) show different variables that are significant in terms of mental health. Particularly, having pets and movements are more relevant for life satisfaction in rural areas, sleeping more than 7 hours, active working status, and living alone – in urban. I advise the practical realization of spatial planning activities to be conducted with experimental tools with focus in predominant population group (Urban Living Labs), which might be a tool for general improvements in the Estonian context against mental health disorders. Using my methodology might be a scientific proof analysis for redevelopment and replanning decisions in rural and urban areas.

6. Summary

This study conducted 16 logistic regression models for four group of individuals: total population, total late working age and older adults, rural and urban late working age and older adults. Based on correlation matrix analysis 14 independent variables were chosen and grouped.

The output for the first question proves a reduction in the number of older individuals who are self-satisfied with their health group compared to younger age groups. The same happens with life satisfaction. At the same time, individuals with depression risk are less in older age groups. Also, registered mental health disorders take less place in age comparison but more in the settlement, where urban late working age and older adults have more mental health disorders than their rural counterparts. Aging affects the tragical reduction of self-rated health condition satisfaction in all models. However, life satisfaction increases for 76+ elderly individuals.

For the second question of the analysis, walking more than 15 minutes a day improves life satisfaction and reduces depression risk. Having pets also positively affects the life satisfaction of rural older adults. Rural women have a better estimation of their health even though they have more registered mental health disorders. Having registered mental health disorders tends to urban older women as well. Higher education level decreases the chance of registered mental health disorders for urban and rural older adults. The same is with depression risk in rural areas and with self-rated health condition in urban areas. Working status reveals better self-rated health conditions in rural and urban areas, as in life satisfaction and slight depression risk in urban areas. Living alone has slight statistical significance only in urban areas and only for depression and life satisfaction. Sleeping more than 7 hours has a positive affect with all the dependent variables for urban elderly, while rural elderly people have only in depression risk. The evidence in social connection in between digital communications and better outcomes for mental health-related aspects has not been found. However, satisfaction with friends revealed connection (except for urban in self-rated health conditions). PTSD has a negative impact on all the mental health-related variables in urban areas, while for rural elderly, it statistically affects only depression risk and life satisfaction. Chronic diseases have a strong significance in both groups (except registered mental health disorders for urban elderly people).

The main focus of question three is on the relation to environmental factors: green (tree covers as four levels: low, medium-low, medium-high and high) and blue (water bodies without shoreline) infrastructures in a 500-meter radius. For the whole population models, only the medium-low tree cover level impacts the reduction of mental health disorders. The same stays with late working age and older adults groups models. However, in the context of different types of settlements, a medium-low tree cover level remains significant only for urban citizens. At the same time, the urban type of settlement is characterized by a negative impact on depression risk from blue infrastructure, whilst in rural areas, it is reversed. It might be a result of excluding the shoreline from the blue infrastructure variable. Also, medium-high and high tree cover have been found to be positive factors in the reduction of depression risk and increasing life satisfaction in rural areas.

Hilises tööeas ja eakate inimeste vaimne tervis ja heaolu Eesti linnades ja maapiirkondades

Arina Nosikova

Kokkuvõte

Rahvastiku vananemisest on järgjärgult kujunemas ülemaailmne väljakutse. Prognooside kohaselt tõuseb eakate osakaal kogu rahvastikust 2050. aastaks 16–22%-ni (Lee jt., 2019; Tseng jt., 2019). Depressiooni leviku järgi on Eesti näitajad ühed Euroopa Liidu kõrgeimad, vanemaealistel on levimus 37–51% vahemikus (Laidra, 2016). Samuti on leitud, et vanemaks saades väheneb inimeste eluga rahulolu ja sagenevad depressiivsed sündroomid, mis omakorda on negatiivselt seotud elueaga (Nakagawa et al., 2020; Abuladze et al., 2020). Veel on toodud välja, et sotsiaalse suhtluse puudumine mõjutab otseselt inimeste emotsionaalset ja füüsilist tervist (Grolli et al., 2021). Lee jt (2019) rõhutasid, et füüsiline keskkond (rohelised alad ja sotsiaalne suhtlus) mõjutavad positiivselt eakate inimeste vaimset tervist. Asulatüüpide kontekstis on varasemate uuringute järgi maal elavatel täiskasvanutel vähem depressiooni kui linna vanematel täiskasvanutel (Mamplekou et al., 2010; Bonnell jt, 2022). Käesoleva uurimistöös analüüsin Eesti hilises tööeas inimeste ja vanemate inimeste vaimse tervise aspektide seoseid linna- ja maapiirkondades kasutades selleks Eesti rahvastiku vaimse tervise uuringu (Laidra et al., 2023) andmeid.

Uurimistöös püstitati järgnevad uurimisküsimused:

1. kuidas on esindatud vaimse tervise ja heaoluga seotud muutujad (registreeritud vaimse tervise häired, üldise tervise enesehinnang, depressioonirisk ja eluga rahulolu) linna- ja maapiirkondades?
2. mis mõjutab hilises tööeas inimeste ja vanemaealise elanikkonna vaimse tervise ja heaoluga seotud muutujaid maa- ja linnaasulates neljas tunnuste rühmas: üldised sotsiaalmajanduslikud tegurid, elustiili harjumused ja sotsiaalsed seosed, psühholoogiline profiil ja riskitegurid, keskkond?
3. millist rolli mängivad roheline ja sinine infrastruktuur elukohaümbruses inimese vaimse tervise ja heaoluga seotud muutujates uuritud vanuserühmades?

Töös püstitatud eesmärgi täitmiseks viidi läbi logistilisi regressiooni mudelid kolmes rühmas: kogu elanikkonna seas, 56+ vanuses (vanema tööealise ja vanemaealiste) elanikkonna kohta üldiselt ning seejärel 56+ rahvastiku kohta linna- ja maapiirkondade kohta eraldi. Sõltuvad

muutujad mõõtsid inimese heaolu ja vaimse tervise erinevaid aspekte: üldise tervise enesehinnang, depressioonirisk ja eluga rahulolu pärinesid küsitlusandmetest ning registreeritud vaimse tervise häired küsitlusega seotud registriandmetest. Korrelatsioonimaatriksanalüüsi põhjal valiti välja ja rühmitati 14 sõltumatut muutujat. Väljund on esitatud kokku 16 logistilise regressiooni mudelis.

Töö tulemustest selgub, et rahulolu oma tervisega väheneb vanemaealiste hulgas võrreldes nooremate vanuserühmadega. Sarnane trend ilmneb ka üldise eluga rahulolu puhul. Samal ajal on küsitluses mõõdetud depressioonirisk vanemaealiste seas madalam. Lisaks on vaimse tervise häirete diagnooside esinemissagedus vanemates vanuserühmades väiksem. Siiski on märgata, et linnapiirkondades esineb vaimse tervise diagnoose hilises tööeas ja eakate täiskasvanute seas võrreldes maapiirkondadega sagedamini. Mudelitest selgus aga, et kuigi vanusega rahulolu oma tervisega väheneb kõigis mudelis, siis vanuses 76+ inimeste rahulolu eluga suureneb, mis viitab niiöelda heaolu paradoksile hilisemas elueas (Nakagawa et al. ., 2020).

Huvitav tulemus (teine uurimisküsimus) on, et kõndimine rohkem kui 15 minutit päevas parandab eluga rahulolu ja vähendab depressiooniriski. Lemmikloomade pidamine mõjutab positiivselt ka maapiirkonna vanemate täiskasvanute eluga rahulolu. Maal elavad naised hindavad oma tervist paremini, kuigi neil on rohkem registreeritud vaimse tervise häireid. Registreeritud vaimse tervise häireid on suhtleiselt rohkem ka ka linna vanematel naistel. Kõrgharidustase vähendab registreeritud vaimse tervise häirete võimalust linna ja maa vanemaealistel. Sama on depressiooniriskiga maapiirkondades ja tervise enesehinnanguga linnapiirkondades. Tööga seotus seostub parema terviseseisundiga maal ja linnas, üldise rahuloluga ja väiksema depressiooniriskiga linnapiirkondades. Üksi elamisel on väike mõju depressiooniriskile ja eluga rahulolule ainult linnapiirkondades. Üle 7 tunni magamine avaldab linna eakate puhul positiivset mõju kõikidele sõltuvatele muutujatele, maaelanike puhul ainult depressiooniriskile.

Rahulolu sõpradega seostus reeglina parema vaimse tervisega (välja arvatud linnaelanike üldise tervise enesehinnang). Postraumatiline stressihäire (PTSD) avaldab negatiivset mõju kõigile vaimse tervisega seotud muutujatele linnapiirkondades, samas kui maapiirkondade eakate puhul mõjutab see statistiliselt ainult depressiooniriski ja eluga rahulolu. Kroonilised haigused on mõlemas rühmas suure tähtsusega (v.a linnas registreeritud diagnooside puhul).

Kolmanda uurimisküsimuse fookuses oli keskkonnatingimustega seotud faktorid: roheline ja sinine taristu 500m raadiuses. Koguelanikkonna mudelite puhul vähendab vaimse tervise diagnoose rohetaristu mõõdetuna kõrghaljastuse pindala kaudu elukohaümbruses. Sama kehtib ka hilises tööeas ja vanemaealiste rühmade mudelite kohta. Erinevate asulatüüpide eristamise järel jääb aga keskmiselt väiksem kõrghaljastuse pindala oluliseks vaid linnaelanikele. Samas iseloomustab linna tüüpi asustust aga üllatuslikult sinise infrastruktuuri (veealade) negatiivne mõju depressiooniriskile, ent maapiirkondades on see vastupidine. See võib olla tingitud muutujate arvutamise alustest. Samuti on leitud, et maapiirkondades on keskmine ja keskmisest suurem kõrghaljastusega kaetus olulne eluga rahulolu suurendamisel. Kokkuvõttes võib öelda, et otseselt inimese elukohaümbruses mõõdtud keskkonnatunnused omavad teiste muutujate rühmadega võrreldes suhteliselt väikest mõju vaimsele tervisele.

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Annex 1

Descriptive statistics variables

Name of the variable	Groups	Modified data	Source	Description
Mental health disorders	Dependent variables	0-absence 1-presence	Register data (any registered mental health disorders from 2016 to 2020 and in 2021), questionary in all three waves (in 1st – B6, in 2nd – B6, in 3rd – B7): "Have you been diagnosed with a mental disorder (such as depression, anxiety or alcoholism)?" (1-no, 2-yes, 3-Don't know, 4- Prefer not to answer)	Merged registered and self-reported data. Registered data combined as if presence of disorders appears in one of the times, then it is "1-presence", else "0-absence". Self-reported data merged as if "1-no" and "3-Don't know", else "0-absence" and if "2-yes", else "1-presence".
Self-rated health condition		0-good 1-bad	Questionary in all three waves (in 1st – C4, in 2nd – C1, in 3rd – C3): "How would you assess your current state of health?". Answers are presented as 1-5 range (1-very good, 2-good, 3-average, 4-poor, 5-very poor)	In the dataset I use answers from each wave were already preprocessed as 0/1 way (bad/good), where to 0 were belonged answers 4 and 5, and to 1 - answers from 1 to 3. From my side I used pmax() function for merging these results. After, I mirrored the output and factored.
Life satisfaction		0-satisfied 1-not satisfied	Questionary in all three waves (in 1st-B1, in 2nd – B1, in 3rd – B2): "Please rate your satisfaction with following aspects of your life: Life in general". Answers are presented as 1-4 range (1-very satisfied, 2-quite satisfied, 3- not particularly satisfied, 4- not satisfied at all)	In the dataset I use answers from each wave were already preprocessed as 0/1 way (not satisfied/satisfied), where to 0 were belonged answers 3 and 4, and to 1 -answers 1 and 2. From my side I used pmin() function for merging these results. After, I mirrored the output and factored.
Depression risk		0- absence 1- presence	Questionary screening in all three waves (in 1st- B13-B20, in 2nd-B7-B14, in 3rd-B8-B15): "Carefully read the following list of problems and complaints that people	In the dataset I use answers from each wave were already preprocessed as 0/1 way (absence/presence), where to 0 were belonged answers in sum of

			sometimes experience. Please indicate how much each one has bothered you”. Answers are presented as 1-5 range (1- not at all, 2-rarely, 3-sometimes, 4-often, 5-constantly). Each number of answer represents as score.	score less than 9, and to 1 -answers sum score more than 9. From my side I used pmax() function for merging these results. Factored.
Age	General social-economic factors	1- 15-35 years 2- 36-55 years 3- 56-75 years 4- 76+ years	Questionary in all three waves (in 1st, 2nd, 3rd is A2):” Date of birth”. Answers are presented as “DD.MM.YYYY” format	Age variable was grouped for four major cohorts: 15-35, 36-55, 56-75 and 76+. Factored them.
Gender		1- Male 2- Female	Questionary in all three waves (in 1st, 2nd, 3rd is A1):” Sex”. Answers are presented as 1-Male, 2-Female	I proved if gender has been changed in first- second and first-third waves via cross table tool. These tests revealed that no gender reassignment was performed. Factored them.
Education		0- higher, 1-secondary 2-basic	Questionary in all three waves (in 1st- A6, in 2nd-A3[ab] , in 3rd-A4): “What is the highest level of education you have completed?”. Answers are presented as 1-8 levels (1-primary, 2-basic, 3-basic with vocational training, 4-secondary,5-vocational secondary, 6-higher vocational,7-Undergraduate degree (Bachelor’s), 8-Postgraduate degree (Master’s, PhD)	In the dataset I use answers from each wave were already preprocessed as basic (1,2 levels), secondary and vocational(3,4,5,6 levels) and higher (7,8 levels). From my side I used pman() function for merging these results. Factored.
Working status	Lifestyle habits and social connections	0- not working 1- working	Questionary in all three waves (in 1st- A7, in 2nd-A4[a] , in 3rd-A5): “Which of the following is the most accurate description of your current employment status?”. Answers are presented as: 1-I am studying or doing an unpaid internship,	Here I use example of study De Vries et al.(2016), when they use only those, who are having paid jobs. Based on presented in question answers, all answers 2 and 3 are related to status “working” and the rest are to “not working”. Then while merging I used

			2-I am employed/working as a contractor, 3-I am an entrepreneur, 4-I am registered as unemployed, 5-I am unemployed and not actively seeking employment, 6-I am an old-age pensioner, 7-I have been declared incapacitated for work, 8-I am on parental leave, 9-I am a homemaker, 10-I am in military service, 11-I am the caregiver to a close relative, 12-other.	ifelse() function to reveal the last working status. Then I factored this variable.
Living alone		0- not living alone 1- living alone	Questionary in all three waves (in 1st-A12, in 2nd-A10, in 3rd-A12): “How many people live in your household?”. Answers are presented as: 1-I live alone, 2-There are ….people in addition to me. Plus, question “What is your current marital status?” (in 1st- A5, in 2nd-A3[a], in 3rd-A3). Answers are pre-modified as 1-single, 2-married (including cohabitation and steady relationship without live together), 3-divorced (separated and widowed).	After modifying three-wave responses (pmax() function for live alone question and ifelse() function for marital status question for seeing the last status and after simplifying to single(1,3)/not single(2)), merged two variables into one for saving more possible responses. Factored them.
Pets		0- absence 1- presence	Questionary in second waves (A26): “Do you have any pets?”. Answers are presented as:1-No, 2-Cat(s), 3-Dog(s), 4-Fish, 5-Rodents (e.g. rabbit, hamster, guinea pig, rat), 6-Other.	Optimized as absence/presence variable, where answer “absence” belongs to “1-No” and “presence” – to the rest from the dataset, thus I did not lose participants in logistic repression models while adding this variable. Factored them.

Movements		0- < 15 minutes 1- 15-30 minutes 2- 30-60 minutes 3- > 60 minutes	Questionary in second wave (C4): "How many minutes do you walk or ride a bicycle on a regular day?". Answers are presented as: 1-Less than 15 minutes a day, 2-15–30 minutes a day, 3-30–60 minutes a day, 4-More than 60 minutes a day.	Used as it is in dataset without any changes, only factored them.
Sleeping hours		0- < 7 hours 1- 7-9 hours 2- > 9 hours	Questionary in all three waves (in 1st-C18, in 2nd-C18, in 3rd-C18): "How many hours a day have you slept in the past three (3) months?". Answers are presented in free form as: …hours and ….minutes on a week day.	Optimized as from 0 to 6 (incuding) = 0, from 7 to 9 (including) = 1, more than 9 = 2. Then I used pmax() function to see maximum in all three waves answers.
Social media using		0- not using 1- using	Questionary in second wave (C29): "How many hours on a regular day do you use electronic devices (computer, tablet, smartphone, etc.) for non-work communication?". Answers are presented as: 1)Not at all, 2)Less than one hour a day, 3)1–2 hours a day, 4)2–4 hours a day, 5)4–6 hours a day, 6)More than 6 hours a day. Plus, question "Do you use social media?" (C30) with answers 1)No, 2)Yes.	First, I optimized question C29 as no/yes vision, where no belongs to "1)not at al" and yes to all the rest. Secondly, I used ifelse() function, which worked as if "no" answer in both questions, then it is "not using", else "using". Factored them.
Satisfaction with friends		0- not satisfied 1- satisfied	Questionary in all three waves as a part of questions about well-being, self-feelings and mental health (in 1st- B4, in 2nd-B4, in 3rd-B4): "Satisfaction with friendship". Answers are presented as 1-4 range: 1-Very satisfied, 2- Quite satisfied, 3-Not particularly satisfied, 4-Not satisfied at all.	Firstly, I optimized answers to not satisfied/ satisfied way, where 1 and 2 answers are related to "1-satisfied" and 3 and 4 – "0-not satisfied". After I modified all three way responses in one with pmin() function for seeing the least value. Factored them.

Chronic diseases	Psychological profile and risk factors	0- absence 1- presence	Questionary in first and third waves (in 1sr-C5, in 3rd-C4): "Do you have any longstanding (chronic) illness or health problem?". Answers are presented as: 1-No, 2-Yes.	To merge them, I used pmax() function to reveal the maximum respondents with chronic diseases. Factored them.
Post-traumatic stress disorder (PTSD)		0- absence 1- presence	Questionary in all three waves, PTSD checklist (Weathers et al., 1993) (in 1st-B55a-B55d, in 2nd-B49a-B49d, in 3rd-B84-B87): 1)"Repeated, disturbing memories, thoughts or images of a stressful experience", 2) "Feeling very upset when something reminded you of a stressful experience", 3)"Avoiding activities or situations because they reminded you of a stressful experience", 4) Being watchful or easily startled". Answers are presented as 1-5 range: 1-Not at all, 2-Rarely, 3-Sometimes, 4-Often, 5-Constantly.	Firstly, each variable has been optimized to 0/1 way (absence/presence), where answers from 1 to 3 were related to 0 and 4-5 to 1. Then, in each wave of survey PTSD checklist I used pmax() function for collecting the most 1 responses. Finally, I used pmax(0 function for responses from all three waves. Factored them.
Type of settlement	Environment	1- urban 2- rural	Statistic Estonia	Used as it is in dataset without any changes
Tree cover		0- low 1- medium-low 2- medium-high 3- high	Estonian Topographical Database of the Land Board (ETAK) as square meters in 500-meter buffer radius.	Used summary() function, based on which I divided variable in 4 even range categories: 1- <21067 sq.m, 2-21067-79126 sq.m, 3- 79126-202811, 4- >212811. Factored them.
Water body		0- absence 1- presence	Estonian Topographical Database of the Land Board (ETAK) as square meters in 500-meter buffer radius.	If variable contained value more than 0, then it marked as 1, else 0. While merging used pmax() for revealing presence of any of water bodies in 500-metres radius.

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