New metrics for noise exposure related to mental health

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Executive Summary

In epidemiological studies focusing on mental health, well-being, and cognitive development, noise exposure is often addressed in a rather imprecise manner. Historically, the lack of affordable and flexible noise monitoring devices necessitated reliance on computational noise models. However, the choice of noise model and its underlying assumptions can lead to significant discrepancies in calculated exposure levels. Three key limitations in current practices can be identified:

1. **Façade Noise Levels and Sleep Disturbance**: Noise levels are typically calculated for the most exposed façade, neglecting the possibility that a dwelling may have a quieter side where the bedroom—crucial for sleep, an identified mediator for many studied effects—may be located. Furthermore, for assessing sleep disturbance, indoor noise levels are more relevant. Given modern building codes emphasizing energy efficiency, open windows during sleep are no longer standard. Unfortunately, conventional noise models perform poorly in accounting for shielded façades and courtyard acoustics, which can lead to underestimations of exposure in such areas.
2. **Simplistic Noise Indicators**: The most commonly used indicators, such as façade L_{den} and L_{night}, rely on A-weighted equivalent sound levels, which are straightforward to calculate. While these indicators show high spatial correlation with more sophisticated metrics, they lack the validity needed for nuanced analyses. As a result, researchers often forego more complex calculation models despite their higher accuracy in certain contexts.
3. **Limited Source Representation**: Noise exposure calculations frequently focus on specific sources (e.g., road traffic) or subsets thereof (e.g., traffic on major roads), excluding other contributors. However, this limitation is partially offset by the fact that specific sources produce characteristic spectro-temporal sound patterns, which can aid in identifying associations with health outcomes.

In the Equal-Life project, the aforementioned shortcomings were addressed by integrating direct measurements and introducing conceptually robust noise indicators, alongside methods for their efficient calculation.

To analyse the complete sound environment—both outside the bedroom window and inside the children's rooms—data from measurements conducted in Gothenburg and the Ghent area were utilized. A wide range of noise indicators proposed in the literature were calculated for each location at 15-minute intervals. Clustering this extensive dataset revealed that specific combinations of noise indicators are particularly effective in identifying distinct "disturbances." These clusters highlighted either unique disturbed sound environments specific to individual measurement sites or common patterns across multiple locations, such as the morning rush hour. Notably, the largest cluster, representing an undisturbed urban living sound environment, frequently occurred at night but persisted for extended periods during the day in many areas.

Indoor sound climate analysis based on the Gothenburg measurements revealed that indoor noise levels were less influenced by outdoor sound events than anticipated. This was determined by analysing the number of indoor sound peaks attributable to outdoor sources, as well as clustering indoor sound environments and correlating each cluster with outdoor measurements. Interestingly, only a limited number of indoor sound environment classes showed strong associations with outdoor noise indicators.

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Currently, it is not feasible to efficiently calculate the contribution of all sound sources to detailed spectro-temporal exposure patterns at any location across Europe. As a result, the calculation models in this study focused on road traffic noise. Indicators for road traffic noise were selected based on three criteria: validity, applicability, and transparency, as well as their relevance to expected pathways affecting mental health and cognitive development—namely, sleep, stress, and restoration. For sleep, the focus was on accurately predicting indoor sleep-disturbing sound events. A novel indicator was introduced, synthesizing insights from laboratory and home sleep studies. Regarding stress, it was hypothesized that the home environment—particularly during the evening hours—serves as a critical space for restoration after a stressful day for both parents and children. Consequently, evening median noise levels were identified as a relevant metric.

Calculating noise events and median levels, which exclude single transient events, requires precise estimates of local traffic dynamics, including both direct exposure and background noise. To address this, experience from the QSIDE project, which focused on quiet side noise estimation, was integrated into the model. However, despite simplifying assumptions, these models remain too resource-intensive in terms of labour and computational power to be efficiently deployed at scale across Europe. To overcome this limitation, a machine learning-based surrogate model was developed. This approach, combined with simplified traffic intensity estimates and OpenStreetMap data, enables the resulting software to estimate traffic noise indicators at any location in Europe with significantly improved efficiency.

The relevance of the proposed indicators and the associated calculation model was assessed through direct correlations with selected outcomes from the ABCD and Alpine cohorts, as well as the preschool children in-depth study. These analyses revealed a small but statistically significant Spearman correlation, suggesting the potential utility of these indicators. However, the proposed indicators also correlated with L_{den} and L_{night} values previously calculated for these cohorts and with proxies such as the distance to the nearest main road.

These relationships were further explored using a knowledge graph that integrated findings from previous studies and other components of the Equal-Life project. Additionally, insights from a prior Shapley analysis of the surrogate model (D3.5) supported these observations. The analysis highlighted that the proposed sleep disturbance indicator for different age groups, calculated at the least exposed façade, and the evening median exposure indicators were strongly associated with the presence of major roads within a few hundred meters. Sleep disturbance at the most exposed façade, in contrast, was linked to the length of nearby roads and traditionally calculated L_{den} values.

In summary, there is sufficient direct and indirect evidence to support the relevance of the sound environment—when characterized using innovative indicators—for mental health, well-being, and cognitive development. This warrants continued use of the sleep disturbance index at both the least and most exposed façades of dwellings, as well as median or 90th percentile noise levels at these façades.

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1. Introduction

1.1. Context

It has long been debated whether indicators for noise that are based on equivalent level and standard diurnal patterns suggested by the environmental noise directive (END, EC 2002/49/EC) and widely used in WHO reviews, namely L_{night} and L_{den}, are sufficient to assess all possible effects of environmental sound on health and well-being. For Equal-Life in particular, making indicators more specific for children and young people related to their different diurnal activity pattern and specific sensitivities might be useful. In relation to mental health and well-being, Equal-Life focuses on several potential pathways: sleep, stress and restoration, and coping. In this report we focus on sleep and restoration. The importance of sleep for mental health, wellbeing, and cognitive development is well established (see D1.1 for theoretical considerations). For stress and restoration, a slightly unconventional [1]point of view is taken: stress (both parental and child) has many different causes that are out of control of those involved in creating livable neighborhoods. Yet guaranteeing a place and time for restoration could be a target of urban planning. Providing green and blue space is studied in several other deliverables of Equal-Life, so here we focus in particular on guaranteeing restorative time during time spend at home in the evening.

Sound level measurements at home provide a wealth of information not only on the sound as disturbance but also about the presence of nature, humans, recreation, industry, etc. In 2024 sound recognition embedded in the measurement devices (the so-called edge) could reveal all these details. However the current report will use as the finest spectro-temporal resolution one-third octave bands and 125 msec time sampling as more refined recognition was not available at the time of the measurement and privacy regulation has not been adapted to accommodate automatic sound recognition in monitoring. The main innovation in processing sound measurements for Equal-Life consists in clustering sound environments based on the multitude of indicators that can be calculated from these measurements. The software for calculating indicators as well as for clustering them is made available (see Section 6).

Modelling of the contribution of specific sources – here road traffic – to the overall sound environment in Europe is mostly done based on CNOSSOS. This model is developed as a tool for strategic noise mapping and targets the standard indicators L_{den} and L_{night}. The propagation part of this model allows to obtain more refined spectro-temporal characteristics, yet for the strategic mapping purposes of the END, its application is restricted by the input data and sound power calculation. This model was first extended to include contributions of individual vehicles and therefore allow calculation of a wealth of new indicators. It was also extended with the QSIDE model for scattering into shielded areas. Such a modelling effort however requires huge computational power, hence a hybrid surrogate model based

[1] Traditionally, environmental noise at home is considered an environmental stressor rather than a factor that prohibits restoration at home.

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on open source data was created that can be used anywhere in Europe to get an estimate of the exposures relevant for mental health and wellbeing.

Validation of the new indicators is limited in this report. Further validation could be found in WP1 and WP7 deliverables.

1.2. Organisation of the report

The report starts by identifying new indicators based on theoretical considerations. This is related to the work already presented in D3.5 and conference publications [97][98][99][99][101]. Some parts are repeated here for the convenience of the reader (Section 2).

The second part of the report introduces techniques for extracting indicators from measurements and clustering them to typical sound environments. The latter is in line with the exposome concept that combines multiple aspects of the living environment of the child. Both outdoor and indoor measurements are considered (Section 3).

The third part of the report extends the use of new indicators to the broader cohorts. Here the surrogate model plays a crucial role and the focus is on traffic noise. Proof of concept for the model and the proposed indicators is given on the ABCD and the Alpine cohort (Section 4).

While combining the multitude of indicators for mental health and wellbeing into the exposome concept, evidence from Equal-Life's own results from in-depth studies and cohort studies have to be combined with prior knowledge considering the overlap between indicators and their relevance for the studied outcomes. To this end, a graph-based methodology is proposed in Section 5 and applied to environmental sound indicators.

A final Section briefly discusses the open source software.

2. New noise indicators for mental health assessment

2.1. The need for new indicators

In general, studies that have investigated the impact of noise on mental health in the past thirty years were based on a methodology that consists of cross-referencing average noise levels obtained from modelling, with the results of standardised tests such as the Strength and Difficulties Questionnaire (SDQ). A recent review [1] 2022) showed that noise exposure, assessed by energetic indicators, has significant associations with non-auditory health effects: psychophysiological, cognitive development, mental health and sleep effects. Percentile and event-based indicators provided significant associations to cognitive performance tasks and well-being dimension aspects. If an overall effect is observed [7], there is no real consensus between studies: some studies tend to show that the effects are not established [1][2][83][84], while others highlight an effect [85][86][87][88][89][90][91][92][5][6][2]. This

[2] More elaborate investigation of the state-of-the-art can be found in WP1 deliverables and publications.

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lack of consensus may be due to the variability of exposures, as some studies focus on road or air traffic noise exposure situations, some at home and others at school. Further, the variability in the age groups studied may also explain differences in the outcomes.

But it is also likely that the acoustic indicators selected itself, which consist of an average of noise levels over long periods, mask some of the effects. Indeed, unlike other pollutants that are active in the definition of the exposome, noise is a non-cumulative quantity: it is not necessarily only the dose of noise received that counts, the temporal distribution of noise levels possibly plays a role. An overview of possible improvements can be found in [93][94]. Some studies have shown for example the advantage of introducing the temporal noise dimension via and additional noise metric: the Intermittency Ratio when assessing annoyance [9], a more transparent indicator reflecting the importance of noticing a sound [95]. Amongst the temporal dimensions, the access to restorative periods of calm, the number and magnitude of noise peaks, can be of interest. Sleep disturbance is also a dimension in noise exposure that should be targeted, as [7] states that "further research on residential childhood (nighttime) traffic noise exposure is needed to determine if the risk of conduct disorders is indeed increased by transportation noise". In addition, there is much to be gained by understanding which dimensions in noise are responsible for the effects to better target noise mitigation measures: the dose, the absence of quiet periods, noise peaks, certain sound frequencies?

There is therefore a need to refine the proposed acoustic indicators to better characterise the links with children's mental health. However, acoustic impact studies are often limited to analyses based on modelled L_{den} levels, as this is the indicator used in the noise modelling required by the European Noise Directive for the production of strategic noise maps, and standard methodologies do not provide access to other indicators. In addition, it is very difficult – not feasible until recently – to use measurement data for cohorts of several hundred individuals.

Fortunately, recent developments offer new insights:

- Numerous acoustic indicators have been proposed to characterize noise environments, some of which have been tested in sound pleasantness studies. In addition, the impact of noise dynamics on annoyance and night-time awakenings has been demonstrated [18][19].
- Recently, noise prediction models have made it possible to estimate so-called dynamic indicators, either through costly modelling based on dynamic road traffic modelling [20][21][22][23][96], or statistically through the development of machine learning models [26].

The question of which indicators should be used to study the links between noise and mental health therefore needs to be re-examined.

2.2. Criteria towards the definition of noise indicators

Noise indicators can be used for a variety of purpose: to characterize the sound environment, to describe health effects, to support decision-making, or to communicate with the community. Depending on the

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objectives sought, the selection criteria to be met may vary. In addition, the different temporal dynamics that characterize sound environments need to be taken into account.

The computation of long-term indicators

In noise, several time scales are intertwined. On a fifteen minutes timescale, the acoustic environment is relatively stable [10]; in other words, the indicators that describe it vary little from one quarter of an hour to the next. However, even on this time scale, the acoustic environment has its own dynamics, in that it varies from one second to the next (or from one 125 ms time frame to the next). The role of acoustic indicators calculated on the short term, for instance every 15 minutes, is to capture this dynamic, which encompass mean sound levels, the temporal distribution of noise levels, background noise, the number and intensity of sound events, the spectral content.

Consequently, over the course of a day, ideally 96 different 15-min sound environments (or 24 different one-hour sound environments) should be characterized by these indicators. Then at the 24-hour time scale, calculating statistics on these 15 min-calculated indicators (maximum, minimum, median, arithmetic mean, percentiles, etc.) serves to highlight, within a day, the arithmetic mean of noise peaks, a percentile on background noise, and so on. The way in which short-term information is aggregated must make sense in terms of the sequences of daily mobility/activity (time at home for instance), and the processes (cognitive or otherwise) leading to a health effect, if the objective is to characterize this effect. If, for example, the aim is to highlight periods of restoration, one can assume that percentiles showing the absence of noisy periods will be of interest. Sub-periods of the day may also be considered, if one wishes to target certain effects of noise, or to highlight certain characteristics of the sound environment (hours relating to sleep, for example).

It is these aggregated indicators that can be related to effects. It should be noted that certain indicators, by their design, are already defined for 24-hour periods or for some given subperiods. This is the case, for instance, with the Sleep Disturbance Index (see 2.3), the Absence of Restorative periods ARP (2.4), or estimates on the number of awakenings.

Finally, it should be noted that sound environments exhibit a high degree of repeatability from one day to the next. It is therefore usual to show indicators for a typical day only. However, it is also possible to consider statistics at an annual scale by conducting annual statistics on the indicators calculated over a 24-hour period. This can, for example, help emphasize calm periods during weekends or holidays, which are likely to be beneficial from a mental health perspective. However, if the input data for the calculations are modelled, this would mean having access to noise modelling every day, which is costly.

Criteria for indicators selection.

The qualification of acoustic indicators can be based on the following three criteria: “validity”, “practical applicability”, “transparency” (see Figure 1). These three dimensions have been discussed in the past [13]. The selection of indicators should be considered in light of these three dimensions. If the primary objective is the characterization of effects, then the "validity" criterion should take precedence.

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However, merely seeking associations requires relying on indicators that can be calculated, thus the "practical applicability" criterion intersects with the "validity" criterion. Finally, in any process of communicating the associations found, it is in the interest of the indicators to fulfil the "transparency" criterion, meaning that the selected indicators should be easy to understand.

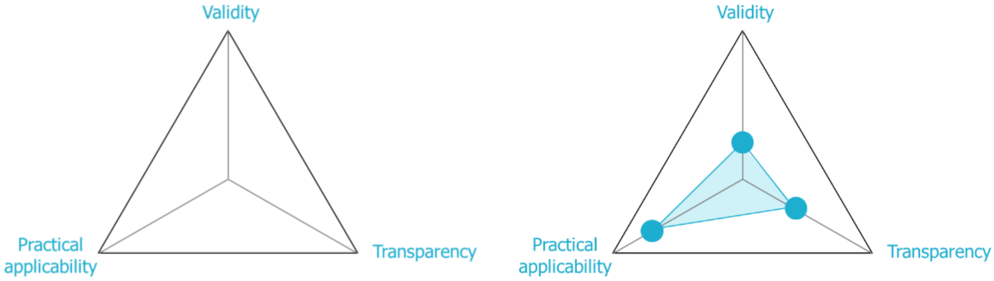

Figure 1 The three main considerations when selecting an indicator; the right picture positions the commonly used L_{Aeq} in this three-dimensional framework.

Selection between noise indicators.

The literature has proposed hundreds of acoustic indicators, with many capable of being rapidly generated, including percentile-based or threshold-based measures of sound events, various spectral values, and more. The nested temporal structures discussed earlier further contribute to the potential proliferation of indicators. However, defining the exposome requires reliance on a carefully selected, limited set of indicators. Research in environmental acoustics consistently highlights strong correlations between different indicators, underscoring the need for dimensionality reduction techniques. Statistical methods such as Principal Component Analysis (PCA) [10][24][25] have been proposed to address this challenge by reducing the complexity and redundancy among indicators. PCA and any other dimension reduction methods such as UMAP used in this report, have the disadvantage that they rely on the data and thus are not universal. However, they can be a good pathway to defining weighted combinations. This is preferred over selecting one representative of each dimension or cluster.

The suggestions below are a combination of the indicators developed as a results of the insights gained in WP1 and the original scope of WP3 in the proposal. Sleep, stress and coping, and mental restoration were identified as potentially important pathways connecting early-life exposome to mental health in the Equal-Life proposal. Hence indicators for these pathways are of main concern here.

2.3. Sleep disturbance index

The neighbourhood physical environment is an important determinant of children's sleep quality and sleep duration. Studies on transportation noise have shown well-known direct short-term effects on sleep, annoyance, and cognition in both, adults and children. The long-term effects on children and adolescents are less investigated, although some evidence points to effects of impaired sleep on cognitive, mental and physical health outcomes (adiposity). However, these studies have inherent shortcomings. The hitherto used exposure characterisation is very crude (average sound levels) and have not considered the role of the soundscape and the wider interaction with the neighbouring built

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environment. Moreover, existing studies have methodological shortcomings, as analyses related to the potential mediating role of sleep impairment on health outcomes were not seriously considered.

Therefore, in the framework of Equal-Life, we initiated an attempt to improve on the prediction of sleep disturbance and potential long-term health effects in children and adolescents with an improved exposure characterisation. The development of this sleep disturbance indicator is a first step.

Figure 2 gives an overview of the different steps involved in calculating the indicator, either based on measurements or on simulations.

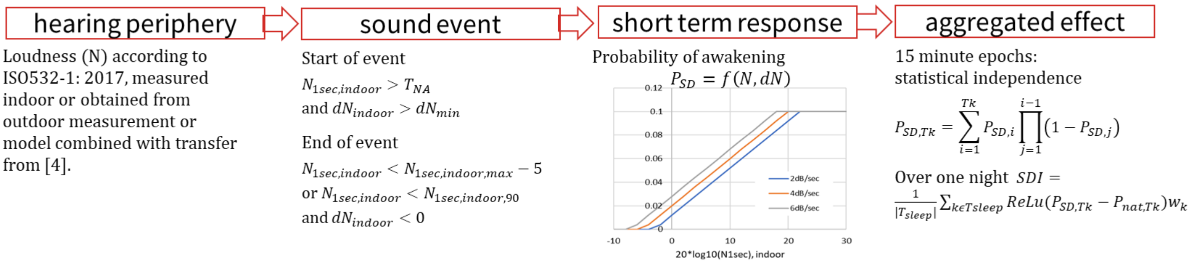

Figure 2 overview of the model used to estimate the sleep disturbance index as an indicator for night-time exposure with potential impact on mental wellbeing and cognitive development

The indicator for sleep disturbance is grounded in laboratory and field results on sleep disturbance by sound events. Hence, the definition of an event is considered first.

The start of a sound event is detected when the indoor loudness exceeds a given threshold, $N_{1sec,indoor} > T_{NA}$ and at the same time loudness in increasing, dN>0. Energetic masking is implicitly included in the calculation of loudness and hence an additional criterion based on relative level like in the calculation of the intermittency ratio is avoided [30]. The event is thought to continue until the N_{1sec} drops 5 dB below its maximum level or when the level drops below the 15-minute 90 percentile value of loudness, N_{90}.

Once an event is detected, the probability of sleep disturbance P_{SD} is calculated. Sleep disturbance can be detected via noise induced cardiac[2][31], changes in sleep stages [32], etc. For the purpose of constructing the indicator, all these outcomes are pooled and the main trends with respect to exposure are extracted: (1) probability of sleep disturbance shows an S-like curve with a threshold around 35 dBA (1-second average) and a saturation point between 60 and 75 dBA; (2) the type of sound plays a role and recognition may play a role, yet the strongest evidence is found for an increase in probability of sleep disturbance with rise time of the sound envelope [33][34]; (3) spectral content may be important but as most studies consider A-weighted levels rather than loudness, this evidence is inconclusive [33][35][36]. Based on the above $P_{SD} = f(N, dN)$ is proposed. The pattern of subsequent noise events may be important for determining sleep disturbance and Markov-style models have been proposed to account for this [37]. When the indicator is calculated based on measurements or a traffic microsimulation [38], this approach could allow for observing the effect of platooning or traffic lights, but as most simulations will treat vehicle passages as a random, Poisson process, preference is given to treating sleep disturbing events as independent and hence:

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$$P_{SD,Tk} = \sum_{i=1}^{Tk} P_{SD,i} \prod_{j=1}^{i-1} \left(1 - P_{SD,j}\right)$$

where |Tk| is the time duration of sleep epochs, which is set to 10 minutes, inspired by [39].

In children, loudness perception itself may be deviant from loudness perception in adults, yet there is little direct evidence on this, neither from EEG based studies nor from behavioural research. Yet it is known that hearing threshold peaks at 6 to 8kHz in young children rather than at 500 Hz to 4kHz in adults. Moreover pure-tone hearing threshold is higher in young children [40].

There is some evidence that the effect threshold for sleep disturbance may increase with decreasing age although there are some differences depending on the outcome where EEG based sleep stages show a stronger dependence than cardiovascular response [41][42].

Considering the above and in absence of further evidence, an increase in effect threshold of 10 dB for the age range [0y,3y] and of 5 dB for the age range [3y,6y] is used as a working hypothesis.

There exists a complex interplay between the diurnal pattern of exposure and the sensitivity to sleep disturbance. To account for the changing sensitivity over the night, a weighting w_k is introduced in the calculation of the nightly accumulated sleep disturbance index (SDI) where k refers to the sleep time interval. This weight is linearly increasing from 5:00 until 7:00 from 1 to 2 to account for the lack of bedtime that will allow to catch up on deep sleep after being woken by an early morning noise event. The instantaneous probability of noise related sleep disturbance is expected to be relevant if it exceeds a natural sleep disruption probability, $P_{nat,Tk}$, which is kept independent on the time of the night T_k and fixed at 0.1 in the current implementation of the model.

$$SDI = \frac{1}{|T_{sleep}|} \sum_{k \epsilon Tsleep} ReLu(P_{SD,Tk} - P_{nat,Tk}) w_k$$

Children sleep longer and usually during earlier hours of the night when traffic noise is still high. In the age dependent definition of the SDI, this is accounted for by adjusting the duration of the night to 14 hours for age range [0y,3y], 12 hours for [3y,6y], 10.5 hours for [6y,12y], 9 hours for [12y,18y].

Sleep patterns may change with age making children of different ages more vulnerable to sound events that occur at different times during the night.

2.4. Absence of restorative periods

The literature review of WP1 [102] showed the importance of the interplay between stress and restoration. Restorative periods can moderate the effect of everyday stress related to social and physical exposome. These restorative periods can be found in or near the house, or at a reachable distance. But obviously, they can also be important in school environments.

There is a large bulk of literature showing that visual nature (as a separate cue) is stress reducing for people [46][47], but the same holds for natural sounds (as a separate cue) [48]. Although one mostly

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refers to (visual) natural green (garden, green view, indoor plants, park, street green, bluespace) when talking about human stress relief, sound may strengthen or weaken the effect (see discussion in [49]).

In general, one can expect that a garden, a park, street green and bluespace embed or attract natural sounds either by design or because the (bio-diverse) natural biotopes attract vocalising species (birds, insects, amphibians, mammals). This will however only happen if traffic noise it not too intense which could prevent the natural habitat to be not suitable [50] and the natural sounds should be audible to the human visitor.

Likewise, an indoor space can only be restorative if intruding sounds from outside do not prohibit social sounds to be primarily audible. Note that indoor sound sources such as heating, ventilation also play a role and these are hard to quantify.

In soundscape research, it has been argued that single loud events that could result in relatively high L_{Aeq}, do not necessarily prevent a (natural) environment from being restorative. Moreover, animals may also adapt to focus vocalisations in the quiet periods in between events, in addition to pitch changes, song length adaptation and intensity increases [51][52]. Hence a statistical level may be more appropriate to characterise the suitability of a place to be restorative. In D5.3 it was shown that statistical levels L_{A1} to L_{A10} cluster with L_{Aeq} in urban measurements (1 year of data for 25 locations in Paris) which is mainly due to the construction of the L_{Aeq} making it very sensitive to sound events. Thus high values for these statistical levels would, like high values of L_{Aeq}, not necessarily prohibit restoration. Hence, we opted for $L_{A50,traffic}$ as an indicator for disturbance of restorative places. This choice corresponds to the value selected by many previous studies.

Spatially, the home micro-environment for restoration is defined as the dwelling and any space immediately connected to it, a garden, balcony, the street. The absence of tranquillity in this micro-environment is considered a negative exposome factor, although vision through the window could compensate high sound exposure levels to some extent, at least when looking at long-term self-reported noise annoyance [53][54]. The importance of a quiet side has been convincingly shown in relation to noise annoyance in the past [55][56][57].

There is very little evidence for the beneficial effect of restorative spaces – in a classical definition of parks and gardens – on mental health and cognitive development of young children, mainly because of the lack of research [58]. Purely hypothetically, one could see a number of possible reasons for observing a lesser effect of restorative spaces for young children: (1) The stress level caused by other stressors may be lower (although some studies might indicate the contrary) and hence the need for restoration may be limited; (2) sleep may be the most important factor to consolidate the neural development; (3) the spatial horizon of young children may be limited and restoration in children may occur in a different way. Mainly because of the latter, restoration at the home micro-environment may be most important. One could also assume that a secondary effect occurs due to elevated stress levels in parents.

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In simulations, one will only be able to quantify the absence of restorative space due to easy-to-model sound sources such as traffic. Thus, a model relating this factor to mental health should be capable to take unidirectional decisions and assess the possibility of a restorative space in the home micro-environment. Here, we model L_{A50} immediately around the house and consider the lowest value to be indicative. Below a threshold of 50 dBA it is assumed that a (green) space can still be restorative. Hence the absence of restorative periods is defined as:

$$ARP = \frac{1}{20}\sum_{16:00}^{21:00} ReLu\left(\min_{home} L_{A50,15min} - 50\right),$$

Where the sum runs over the evening hours, the ReLu function truncates negative values and keeps the linear trend above zero, and the minimum is taken over all facades of the home.

Initial tests with this indicator showed that it was not very successful. There might be several reasons for this. For example, the hard threshold makes this indicator zero in many locations which negatively influences regression statistics. Moreover the 50 dBA hard threshold could be too high. Therefore other, more transparent indicators were also included (Table 1).

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2.5. Overview of diurnal indicators

It is now a matter of aggregating the "short term indicators" over the 24h or shorter periods, to highlight the listed possible noise dimensions: noise dose, restorativeness, sleep disturbance, and noise peaks (Table 1).

Table 1 Overview of possible long term indicators based on calculated or measured 15-minute indicators We define typical daily periods: day, [16:00-21:00], [21:00-07:00]. E indicates that the indicator could be applied for road traffic noise using the Equal-Life surrogate model (this is related to earlier decisions made for constructing this model), the dots indicate how well the indicator performs on each of these dimensions and criteria.

			Noise assessment dimensions				Criteria		
Indicators	**Definition**	**Rationale**	**Noise dose**	**Restorativeness**	**Sleep disturbance**	**Noise peaks**	**Validity[3]**	**Practical applicability**	**Transparency**
LAeq,24h	*Energetic average of the 24 values of LAeq,1h (resp. 96 values of LAeq,15mn)*	*The simplest indicator to capture daily noise dose*	•••	•			•	••• E	•••
N,24h	*Arithmetical average of the 24 values of ISO-loudness N*	*Partly counters the critique on A-weighted noise levels are not precise for estimating perceived loudness.*	•••	•			•	••• E	••

[3] This is only a first intuitive assessment of the validity of the indicator. Further sections will evaluate validity based on evidence.

ARP	Sum of LA50,15mn values (minus 50, with a floor value at 0), over the [16:00-21:00] period at the least exposed facade. See Section 2.4 $ARP = \frac{1}{20}\sum_{16:00}^{21:00} ReLu\left(\min_{home} L_{A50,15min} - 50\right)$		•	•••			••	• E	••
$LA90_{[16:00\text{-}21:00]}$	Evening restorativeness potential for children and young adults: Arithmetical average of the LA90 values in the [16:00-21:00] period at home	*High continuous noise in the evening will prevent restorativeness*	•	••			••	•• E	•••
$LA50_{[16:00\text{-}21:00]}$	Evening restorativeness potential for children and young adults : Arithmetical average of the LA50 values in the [16:00-21:00] period at home	*High median noise levels in the evening will prevent restorativeness*	•	••			••	•• E	•••
$LAeq_{[16:00\text{-}21:00]}$	Energetic average of the 5 values of LAeq,1h (resp. 20 values of LAeq,15mn) in the [16:00-21:00] period	*High noise levels in the evening will prevent restorativeness*	••	••			••	••• E	•••
$EN70_{[16:00\text{-}21:00]}$	Arithmetical average of EN70 (number of events above 70 dB) values in the [16:00-21:00] period	*A high number of noise events in the evening will prevent restorativeness*	•	••		•	•	••	•••
$ET70_{[16:00\text{-}21:00]}$	Arithmetical average of ET70 (time above 70 dB) values in the [16:00-21:00] period	*This indicator possibly underlines intermittent noise (vehicles pass-byes for*		••		••	•	••	•••

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		instance) which will prevent restorativeness							
NPE	*Noise Peaks Evening:* Weighted average of all the thresholds indicators, calculated over the [16:00-21:00] period. A specific weight is given to each time period and each threshold value. $NPE = \sum_{t=16}^{t=21} \sum_{thresh=65}^{thresh=80} \alpha(t)\beta(thresh)\, ET_{thesh,t}$ With $\alpha(t)$ a weight for the time period, $\beta(thresh)$ a weight for the threshold value. At first, one proposes α(t) = (t-11)/5 between 16:00 and 21:00. Other weighting can be discussed. At first, one proposes $\beta = 1$ for each threshold (this is equivalent to considering a weight of 1 to events above 65dB, 2 to events above 70dB, 3 to events above 75 dB, 4 to events above 80dB, since an event above 80 dB is counted in each of the for cited ET values.	*This indicators describes the presence of noise events in the evening period.*		••		••	•	••	•••
EPE	*Noise Peaks Emergence Evening:* Weighted average of all emergence indicators, calculated over the [16:00-21:00] period. A specific	*This indicators describes the presence of noise events in the evening period*		••		••	•	•• E	••

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	weight is given to each time period and each threshold value. $EPE = \sum_{t=16}^{t=21} \sum_{thresh=5}^{thresh=10} \alpha(t)\beta(thresh)\ ET_{L50+thresh,t}$ With $\alpha(t)$ a weight for the time period, $\beta(thresh)$ a weight for the threshold value. The weights are chosen as α(t) = (t-11)/5 between 16:00 and 21:00 which makes the weights vary between 1 and 2. The weight $\beta(3) = 1$ and $\beta(10) = 1$ while all other thresholds are not considered.	*measured as emergence above the 15-minute LA50.*							
$LA05_{[20:00\text{-}22:00]}$	Maximal value of the LA05 values in the [20:00-22:00] period	*A significant proportion of noisy levels during peripheral periods of the children night is likely to shorten sleep duration*	•		••	•	•	•	••
$LA05_{[05:00\text{-}07:00]}$	Maximal value of the LA05 values in the [05:00-07:00] period	*A significant proportion of noisy levels during peripheral periods of the children night is likely to shorten sleep duration*	•		••	•	•	•	••
SDI	Indicator proposed during Equal-Life, based on the probability of awakening for each 15-minute epoch of the night, summed over the children sleep duration. See Section 2.3				•••		•••	• E	•

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$ET_{[21:00-07:00]}$	Arithmetical average of the ET70 in the [21:00-07:00] period	*Highlights the number of noise peaks during the sleep period*			••		••	•	••
$ET_{[01:00-05:00]}$	Arithmetical average of the ET70 in the [01:00-05:00] period	*Highlights the number of noise peaks during the deep sleep period*			••		••	•	••
NPN	*Noise Peaks at Night:* Weighted average of all the thresholds indicators, calculated over the [21:00-07:00] period. A specific weight is given to each time period and each threshold value. $NPN = \sum_{t=21}^{t=6} \sum_{thresh=65}^{thresh=80} \alpha(t)\beta(thresh)\ ET_{thesh,t}$ With $\alpha(t)$ a weight for the time period, $\beta(thresh)$ a weight for the threshold value. At first, one proposes α(t) = (t-19)/2 between 21:00 and 23:00, α(t) = 2 between 23:00 and 05:00, α(t) = (9-t)/2 between 05:00 and 07:00. Other weighting can be discussed. At first, one proposes $\beta = 1$ for each threshold (this is equivalent to considering a weight of 1 to events above 65dB, 2 to events above 70dB, 3 to events above 75 dB, 4 to events above 80dB, since an event	*More complete than the ET indicators, since it considers all the thresholds and different time steps. In that sense it is not far from relying on probability of awakenings*			••	••	••	•	••

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	above 80 dB is counted in each of the for cited ET values.								
Lnight,children	Energetic average of the 10 values of LAeq,1h (resp. 40 values of LAeq,15mn) in the [21:00-07:00] period	*Lnight is often seen as a good descriptor of sleep disturbance*	••		•		••	••• E	•••
Lden,age	The evening (restorative period) and night start earlier for young children hence age-dependent D,E,N periods are defined	*Lden is a well known indicator used all over Europe. A slight increase in validity might be observed by accounting for the time of the day when children of different ages are usually at home.*					••	••• E	••
Nden	Same as above but for loudness (accounting for spectral weighting more accurately than A-weighting)						••	•• E	•

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3. Indicators derived from measurements

3.1. Towards new indicators via clustering of outdoor measurements

When there is an opportunity to assess the living environment via (noise) measurements, the question naturally arises how to aggregate the measurements to relevant long-term indicators while preserving as much as the information as possible.

3.1.1. Dataset

In Equal-Life two new measurement datasets were collected in the context of the in-depth studies in The Ghent area and in Gothenburg. Both measurement campaigns have in common that the measurements were conducted just outside the bedroom window of the child and that the raw data consisted of 1/3 octave bands acquired with a sampling rate of 8 times per second (which is becoming a de facto standard). This strong similarity allowed us to pool the data from both in-depth studies in the analysis below.

Linking the raw data to long-term effects is best done in multiple steps. Here we advocate that a 15-minute time interval would be a useful intermittent step as discussed above, and in line with the literature [10]. Today, powerful artificial intelligence tools are available that would allow us to identify the sounds that contribute to the 15-minute outdoor sound environments. However, at the conceptualisation of Equal-Life this possibility was not foreseen and hence we rely on the classical 15-minute indicators described above. These indicators derived from the literature in environmental acoustics accurately describe sound environments, with the aim of capturing their effects on human health. The pooled dataset is thus translated to 113050 15-minute intervals collected at 145 locations (which represents a total of more than 1177 days of data).

3.1.2. Methodology

The 15-minute intervals are clustered using a powerful combination of *UMAP* for creating a reduced 8-dimensional embedding of the 150-dimensional data and *hdbscan* for labelling the clusters that emerge in the reduced space based on data density [61][62]. Hdbscan has the advantage that it can ignore data point that are difficult to cluster because they are e.g. very far from other datapoints or e.g. on the border between two clusters. Prior to mapping, the dataset is rescaled to map all indicators to a range around 0 using a sklearn StandardScaler. Parameters for UMAP were n_neighbors=30, min_dist=0.0, n_components=8, random_state=42; parameters for hdbscan were min_samples=20, min_cluster_size=500. Note that these clusters implicitly include exposome components beyond noise as they for example can identify the presence of animal vocalisations and hence the presence of biodiverse green.

Once the clusters of 15-minute sound environments are obtained, diurnal patterns can be further analysed. Once more, clustering of the measurement locations based on the diurnal pattern of cluster membership can shed some light on how urban environments develop over the day. Once more, UMAP and hdbscan are used.

3.1.3. Results

Clustering of 15-minute sound environments based on the above mentioned 150 indicators resulted in 31 clusters. Figure 3 shows the embeddings in 8 dimensions obtained with UMAP, highlighting the second-most populated cluster.

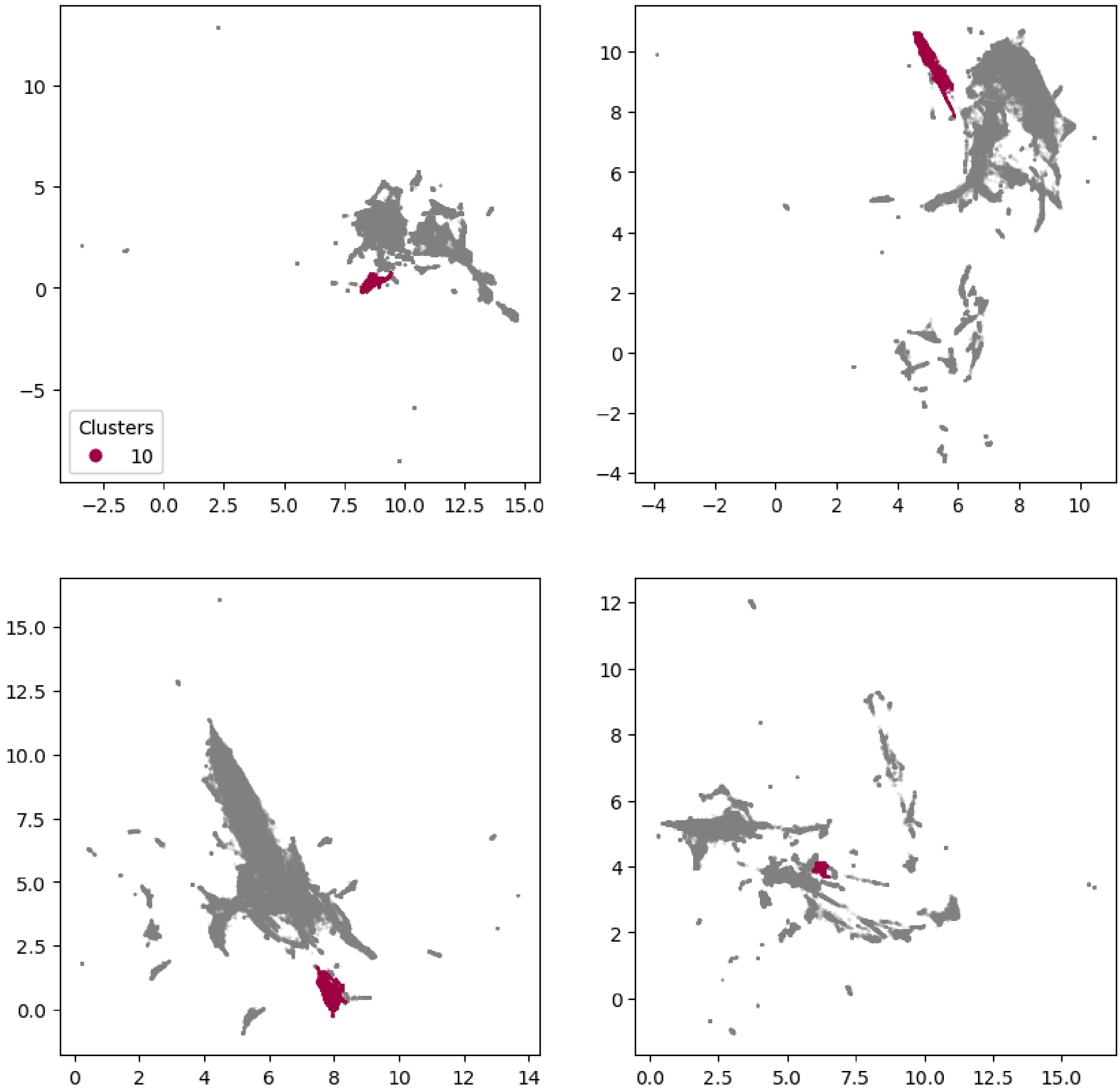

Figure 3 clustering of 15-minute sound environments based on UMAP, shown in 8 dimensions plotted two by two (upper left=dimensions 1 &2, upper right= dimensions 3&4, lower left= dimensions 5&6, lower right = dimensions 7&8). The second most populated cluster obtained with hdbscan is highlighted.

The number of 15-minute intervals in each cluster is very different depending on the cluster. E.g. cluster 14 contains 59000 15-minute observations, cluster 10 has over 5800 and all other clusters contain less than 2500 elements.

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To explore the meaning of each of the sound environment clusters, a heatmap is constructed relating each cluster to all the 15-minute indicator. In view of the skewness of the distributions, we opted for plotting the median value of each indicator calculated over all members of the cluster. The stars indicate whether the inter-quartile interval on the indicator values over the cluster is below 0.2 and gives an indication on whether the indicator takes a value that is consistent over the cluster (Figure 4).

This analysis of the clusters reveals that the most populated cluster (14) has low noise levels with few events. Low frequencies are moderately present and sharpness indicators are medium. This cluster that is found often and at many locations, seems to indicate a quiet environment.

The second most populated cluster (10) has slightly elevated statistical levels with high number and has more tonal components in the 1250 Hz third octave band. As the most populated cluster it has systematically below average event counts and event duration when events are identified against a fixed threshold. Emergence is low but not systematically because of the elevated continuous sound. Sharpness is below average in general as well as statistical. These observations suggest the presence of a ventilation, air conditioning, or other mechanical system close by. The probability of sleep disturbance remains low. A traffic noise model will not be able to distinguish this from the most populated cluster as it is unaware of such sources.

The third most populated cluster (29) has a clearly higher sharpness S01 statistic indication short, high pitch events. This shortness of events is also recognized in the event count above LA10 and the absence of longer, loud events. In combination with an investigation of the time of occurrence, we conclude that this corresponds to a typical urban environment with added bird sound, e.g. a morning chorus. A slightly higher probability of sleep disturbance is observed, especially for the slightly more sensitive 6 to 12 year olds. Yet one should keep in mind that this analysis does not take into account the hour of the day yet and thus PSD may be high when most children have already woken up or left the home. Also here, traffic noise models will not be able to distinguish this cluster.

Now let us turn to some of the louder clusters.

Cluster 13 is mainly observed at one location. The high peaks exceeding various thresholds in combination with a broad spectrum indicate the presence of important traffic infrastructure, rail in combination with road traffic. Cluster 6 is very similar but has lower event counts and less variations in them and combines this with surprisingly high levels at high frequencies. Cluster 2 is characterised by higher emergence counts and a higher spectral canter or gravity.

Secondly, the importance of indicators in distinguishing the different sound environments is considered. Median values of levels and statistical levels differ between clusters, but they do seem to take a consistent value as interquartile intervals are large. This might be due to the variation in absolute levels caused by shielding and reflection near the bedroom window which the clustering approach seems to be able to ignore. The parameters related to sudden increase in level (DLAxx) also vary between clusters, but the interquartile interval between 15-minute intervals remains large. Note that the average value

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has no effect whatsoever as the average increase and decrease compensate. Spectral information summarised in the centre of gravity of the spectrum, seems to be consistently low in some of the clusters The most surprising observation nevertheless relates to tonality. Low frequency tonality has no effect on the clustering, yet many smaller clusters seem to be formed based on a higher-than-average tonality in specific frequency bands above 500 Hz. This might be due to the presence of cooling and ventilation units near the bedroom windows, which are quite often at the side of the house shielded from traffic and street sounds. Loudness and sharpness show similar trends as other level indicators. From the composite indicators, the probability of sleep disturbance has the smallest spread within some of the (smaller) clusters.

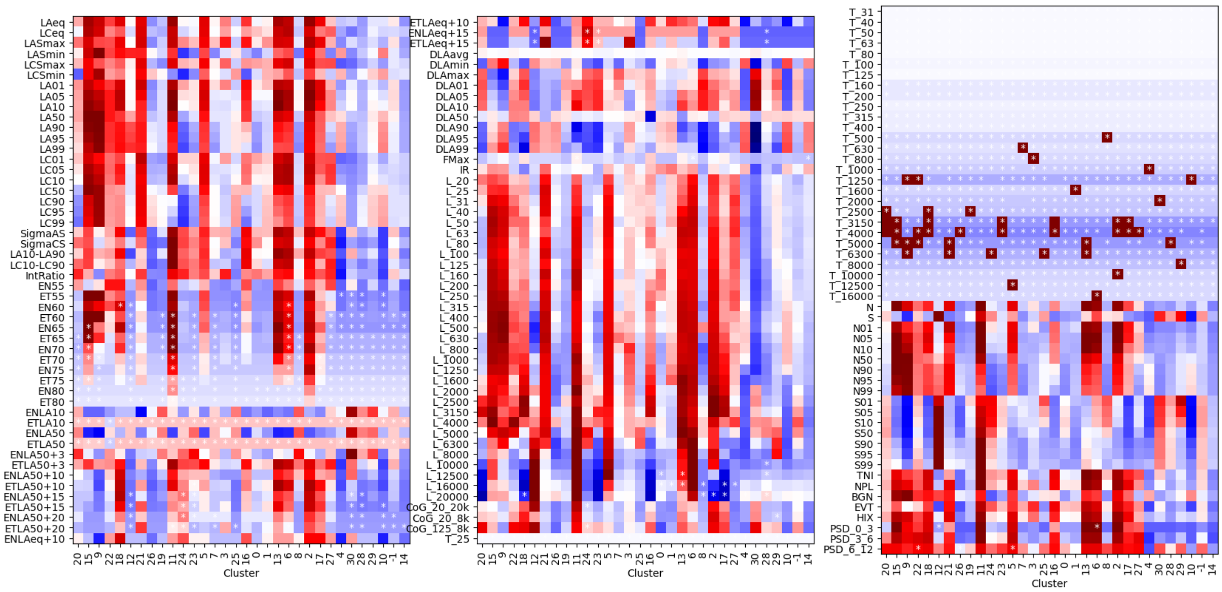

Figure 4 Heat map of the median value of each indicator in the clusters obtained purely based on measurement data; stars indicate where the interquartile interval over all observations in this class is below 0.2 giving an indication of the consistency of values over the 15-minute intervals belonging to this cluster (second is a new clustering, ordered by number of measurements in the cluster.

Figure 5 illustrates in which measurement locations the clusters are found. The most popular sound environment clusters, 14 and 10, are found at many locations. They also occur at all hours of the day (Figure 6). But also, some of the less populated ones such as 8, 29, and 30 are quite generally encountered and typically occur at certain hours of the day (e.g. early morning). But there are also clusters that are very specific for a single location or a couple of locations, e.g. 11, 13, 15, 16, 24. Except for the last one, these are all very loud situations, with slightly different characteristics. Node 24 seems to be unique in its extremely low background.

All in all, the clustering based on 15-minute noise indicators does not seem to differentiate between different flavours of quietness but creates more variations while characterising highly exposed areas. This identification of unique situations may be due to the abundance of indicators focussing on noise

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and noise events. These unique situations may be relevant for mental health but will most likely be very difficult to predict.

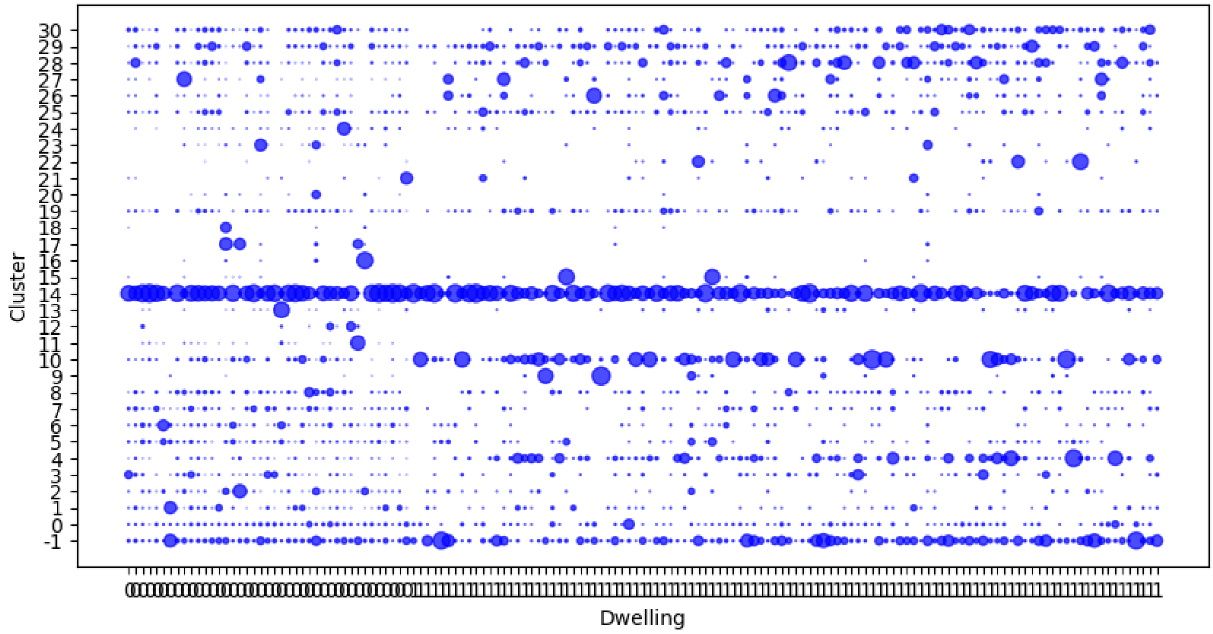

Figure 5 distribution of occurrence of the clusters at each measurement location. The size of the circle indicates the probability of a 15 minute epoch at that location to belong to this cluster . Dwelling numbers have been replaced by 0 for the Ghent dataset and 1 for the Gothenburg dataset.

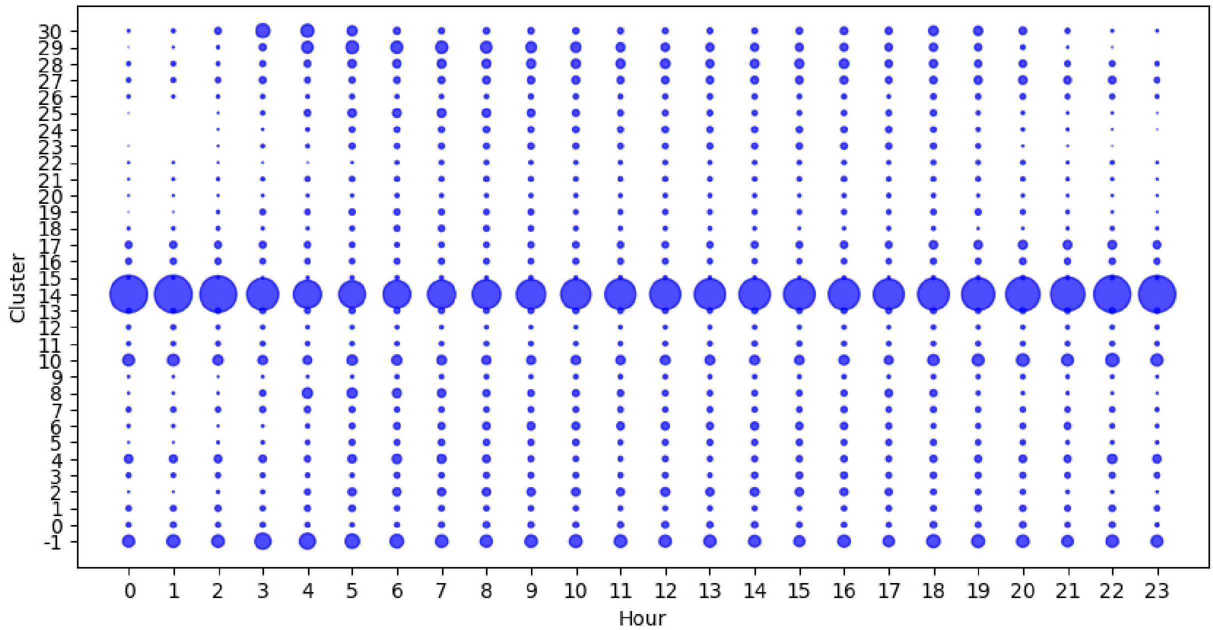

Figure 6 distribution of occurrence of the clusters over the hours of the day. The size of the circle indicates the number of occurrences. Time is in UTC, local time is obtained by adding 1 or 2 hours depending on daylight saving.

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3.1.4. Relevance of clusters – cognitive development

To illustrate the relevance of bedroom window sound exposure clusters for mental health and cognitive development, their relationship with the outcomes of the in pre-school children depth-study (D1.4).

In the Belgian sample, children aged 5-6 years, residing at the measurement sites, underwent cognitive assessments. The selection of cognitive outcomes was based on understanding early developmental indicators and the susceptibility of cognitive functions to physical and social exposures. A comprehensive cognitive test battery, as outlined in Table 2, was utilized. Additionally, parents participated in surveys to assess their children's mental health, well-being, and exposure to social and physical factors. Standard parent questionnaires were utilized, including the SDQ (Strengths and Difficulties Questionnaire) [63] and the KIDSCREEN-27 [64] parent questionnaire, both known for their psychometric quality and extensive use in EU studies focusing on children's well-being and health. The assessment of social exposures encompassed various factors such as family socioeconomic status, home language and literacy, parental stress, single-parent family status, and neighbourhood cohesion and safety. Additionally, physical exposures were examined, analysing the built environment, housing and neighbourhood quality, environmental noise and air pollution. The results from both the cognitive test-battery and parent questionnaires were utilized to cluster the children for further analysis.

Table 2. Cognitive development test utilized with the 5-6 year old in depth study (D1.3).

Domain	Construct	Dimension	Measurement Instrument
Domain-general cognitive functions	Executive Functions Attention Control	Selective attention	IDS-2 Subtest 3: In 2 minutes, items with 2 specified features have to be crossed out on an answer sheet with many similar items.
		Selective attention	IDS-2 Subtest 15: Word Fluency. As many words as possible from a specified semantic category have to be generated within 90 seconds.
		Shared Attention	IDS-2 Subtest 16: Within 2 minutes, specified parrots have to be crossed out while generating category members.
		Inhibition	IDS-2 Subtest 17: The child is asked to name as fast as possible the correct color of animals painted in grey or in a wrong color.
	Intelligence Screening	Nonverbal reasoning	IDS-2 Subtest 6: Matrices with one missing element are presented. The child has to select and mark the element that fits into the pattern.

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Language abilities and precursors of literacy	Phonological awareness		IDS-2 Subtest 26 Part I • Clapping syllables • Identification of rhyme words • Isolation of initial phonemes in words • Isolation of final phonemes in words • Segmentation of words into speech sounds
			IDS-2 Subtest 26 Part II • Letter Knowledge • Vowel length classification

Here, a clustering of children based on their score in the IDS cognitive development test is used to illustrate the applicability of the exposure clustering. Cognitive test were used for this purpose because they did not involve questioning the parents (in contrast to SDQ and KIDSCREEN) and thus are less likely to be influenced by the neighbourhood assessment by the parents. Clustering is based on a dimension reduction using UMAP (two dimensions) followed by HDBSCAN to label the clusters. This resulted in five distinct clusters loading on the IDS sub-tests as shown in Figure 7.

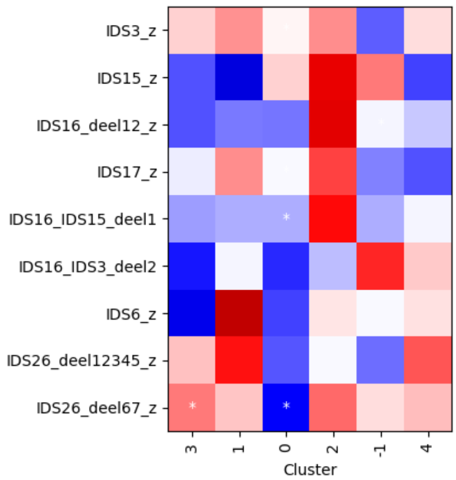

Figure 7 Clustering of the children by IDS score (after z-scoring for age based on norm data); The label "-1" is given to children that do not fall in any of the clusters. Blue indicates a low score, red a high score compared to the mean over all clusters.

Figure 8 shows the membership for each of the exposome clusters of the group of children belonging to each of the clusters based on the IDS test. Children belonging to cognitive cluster 3 seem less likely to experience the exposure cluster 14 sound environment which was identified as being tranquil and eventless. This might affect their sleep. Children in this cluster score lower on attention related tests and general intelligence tests, but not on language abilities. Reversely, when looking at cognitive development cluster 2 that contain children that score very well on almost all subtasks of IDS, but in particular on the attention related tasks, it can be observed that their sound environment often belongs

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to cluster 14, also during the day, but this is also the case for other IDS clusters. In contrast typical morning sound clusters do not occur.

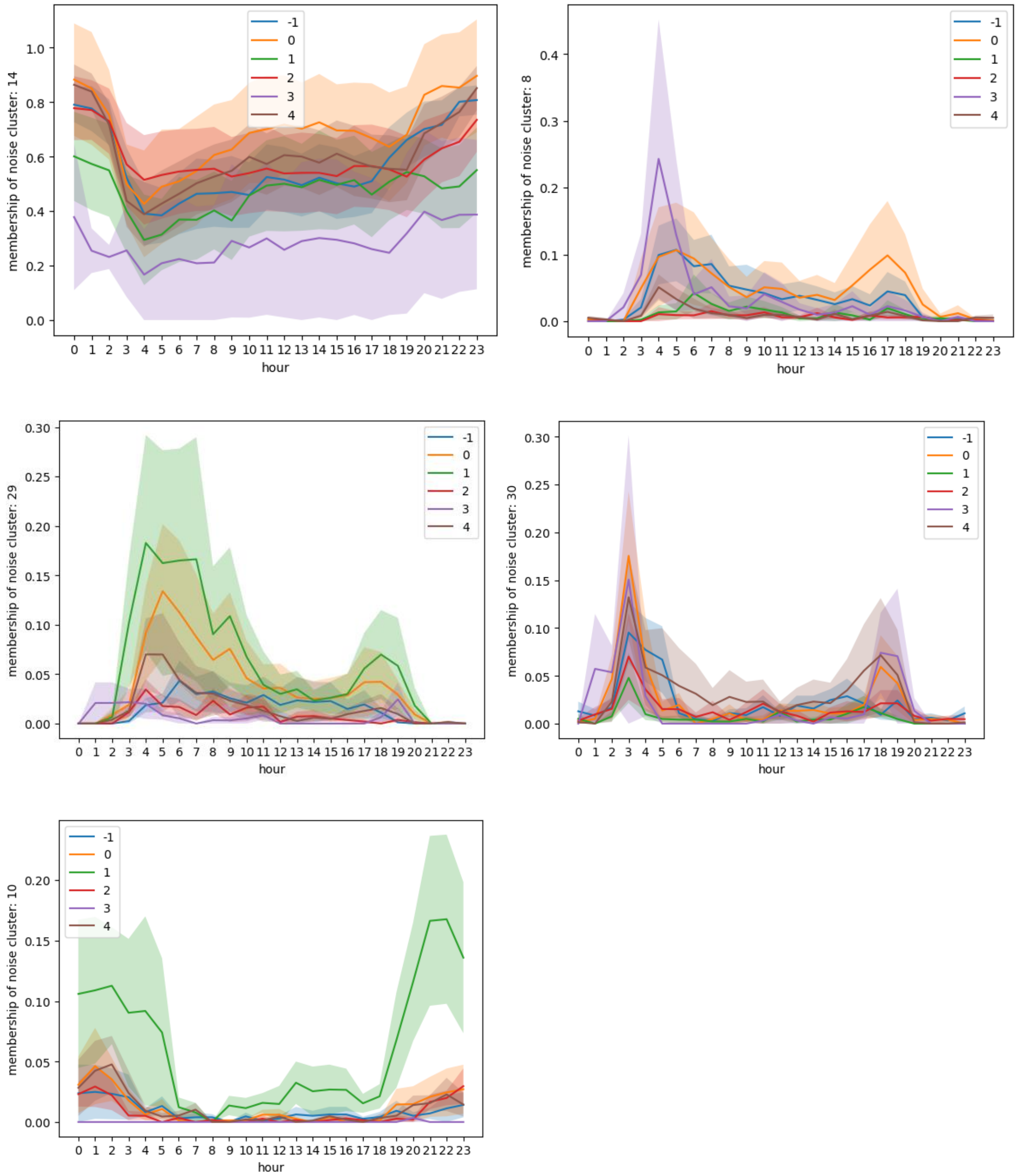

Figure 8. Membership of the sound exposure cluster over the hours of the day (UCT, two hours need to be added to obtain the local time) for each of the five groups of children clustered on the basis of the IDS test.

Although this analysis lacks statistical power when it comes to showing without doubth that there is a significant effect of bedroom window noise exposure cluster, it indicates that using clustering of sound

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exposure indicators to a more general exposome component for sound could make sense. Further information on the pre-school children in-depth study can be found in D1.3.

3.2. Towards new indicators via clustering of indoor measurements

A similar approach can be followed for indoor measurements.

3.2.1. Dataset

In the Gothenburg in-dept study, noise measurements were conducted inside the child's bedroom during night (4 consecutive nights) at the same time as the outdoor measurements discussed above. The raw data consists of 1/3 octave band spectra analysed and stored every 125 msec. Unfortunately, some recorders did not store these detailed data, hence only 80 measurement locations could be retained in the analysis. Nevertheless, this represents the largest available database of simultaneous indoor and outdoor noise level measurements. Details on the measurements and equipment used can be found in D1.3.

3.2.2. Methodology

The same indicators were calculated in 15-minute intervals as was done for the outdoor measurements with the exception of SDI where the assumed sound insulation of the building was omitted. The 15-minute intervals are clustered are again clustered via a 3-step method: scaling, dimension reduction, clustering using the same algorithms and parameter settings as above.

3.2.3. Results

Clustering of 15-minute sound environments based on the above mentioned 150 indicators resulted in 24 clusters. Figure 9 shows the embeddings in 8 dimensions obtained with UMAP (n_neighbors=100, min_dist=0.0), highlighting the second-most populated cluster. It can be observed that many small clusters emerge, in particular visible in the higher dimensions. These are related to individual homes, which indicates the higher diversity in indoor soundscapes compared to outdoor soundscapes.

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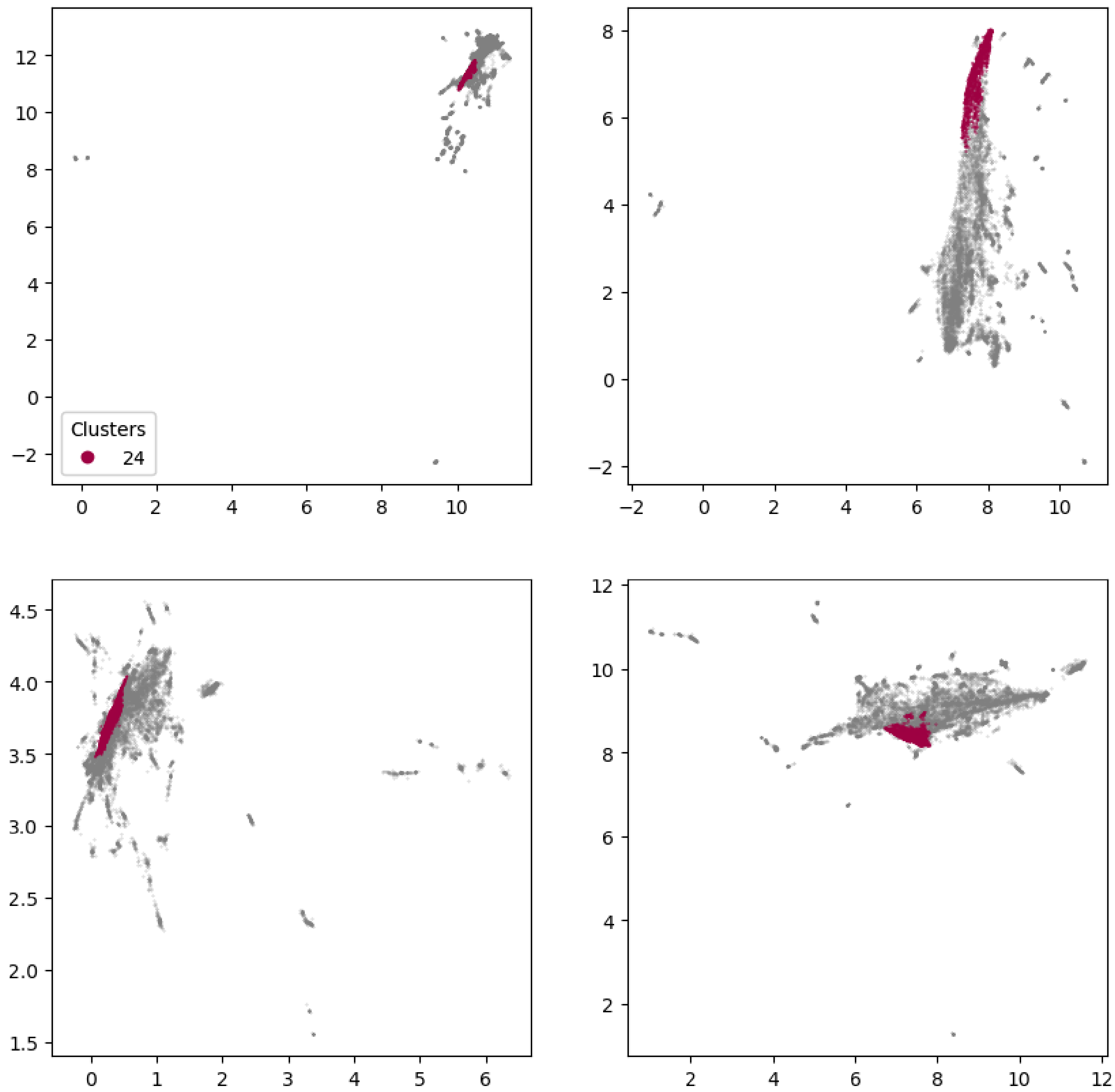

Figure 9 clustering of 15-minute sound environments based on UMAP, shown in 8 dimensions plotted two by two. The second most populated cluster obtained with hdbscan is highlighted. Upper left: first two reduced dimensions, upper right: third and fourth dimension; lower left: fifth and sixth dimension; lower right: seventh and eight dimension.

The loading of different clusters on 15-minute noise indicators is shown in Figure 10. Most of the indoor environments do not belong to a specific cluster (cluster -1). The most populated cluster (cluster 21) shows consistently lower levels, lower event numbers, and lower probability of sleep disturbance. The second most populated class has the highest noise levels including peaks and probability of sleep disturbance. It is attributed to indoor sound such as voices, music, television, probably generated before the child actually goes to sleep (see later for temporal analysis). The third most popular cluster (7) is characterised by low noise levels including low PSD, but still rather high sharpness. The fourth most

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populated class is also characterised by low noise levels but does not show the sharpness of the previous one.

Note that high noise peaks EN55 – EN80 are not influencing the clustering nor are tonalities at high frequency, which is probably consistent with these features being very rare indoors.

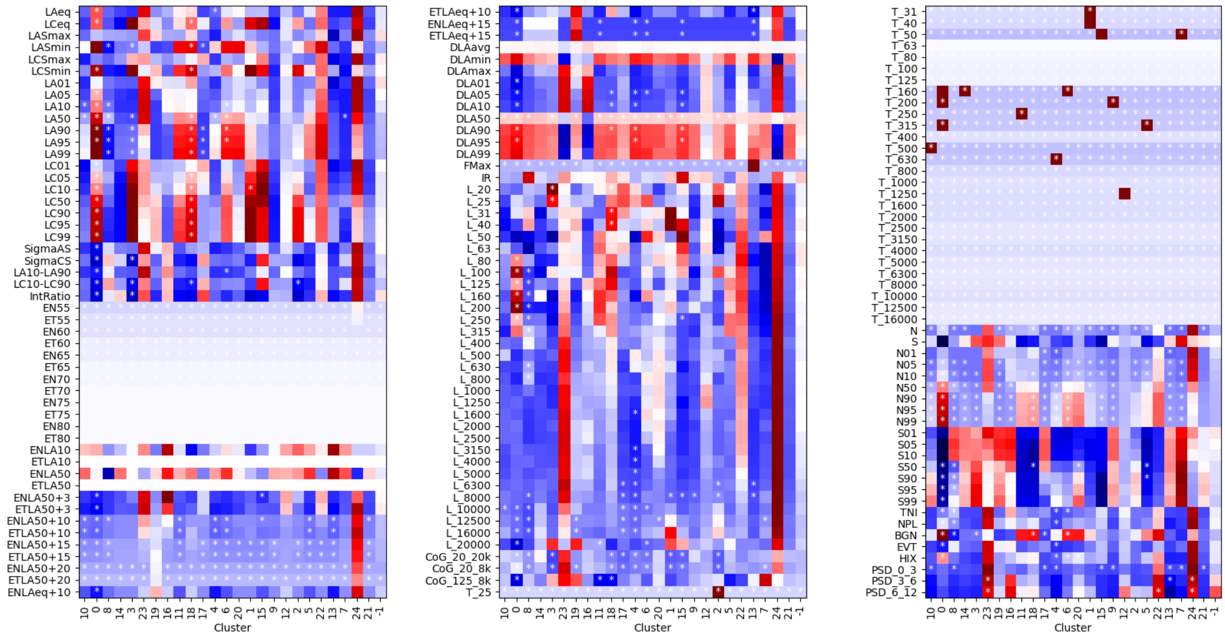

Figure 10 Heat map of the median value of each indicator in the clusters obtained purely based on measurement data; stars indicate where the interquartile interval over all observations in this class is below 0.2 giving an indication of the consistency of values over the 15-minute intervals belonging to this cluster, ordered by number of measurements in the cluster.

Analysis of where the sound environment clusters occur (Figure 11) shows that the tranquil situation (21) occurs almost everywhere as does the second-most popular loud cluster (24). The cluster characterised by low levels but high sharpness (7) occurs at a few locations. It could be attributed to presence and use of an active ventilation system.

The distribution of the 15-minute sound environment belonging to a specific cluster (Figure 12) confirms that the second most populated cluster (24) occurs at the beginning of the night where the suspected sources are present, but also that these speech and music sounds often occur until late at night.

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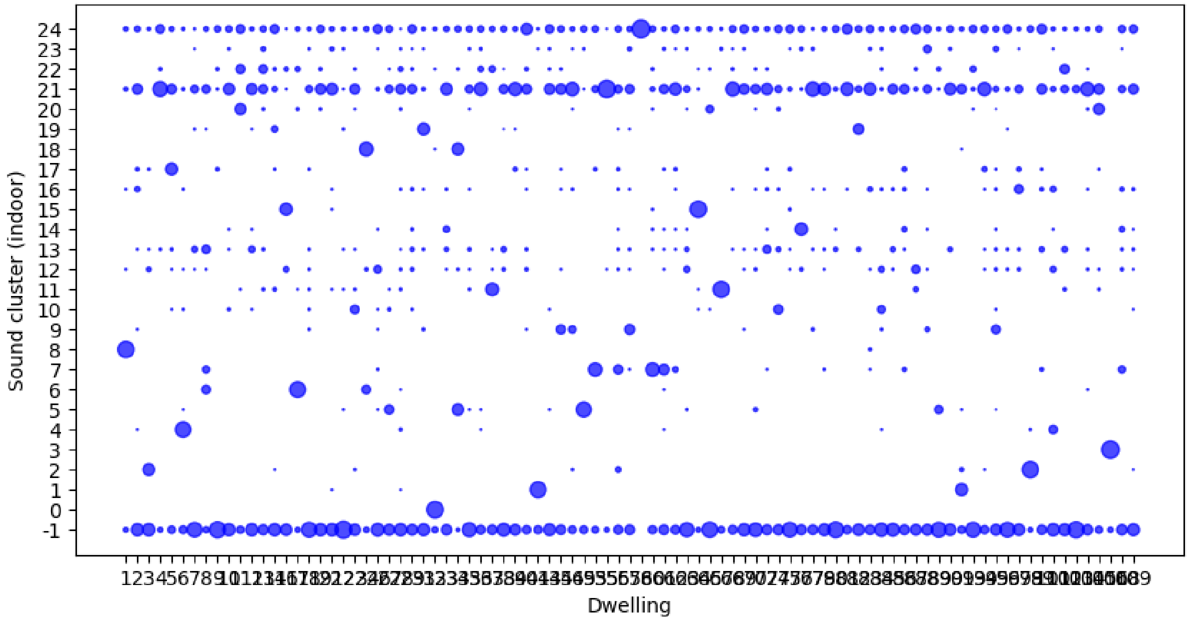

Figure 11 distribution of occurrence of the clusters at each measurement location. The size of the circle indicates the probability of occurrence normalised by Dwelling.

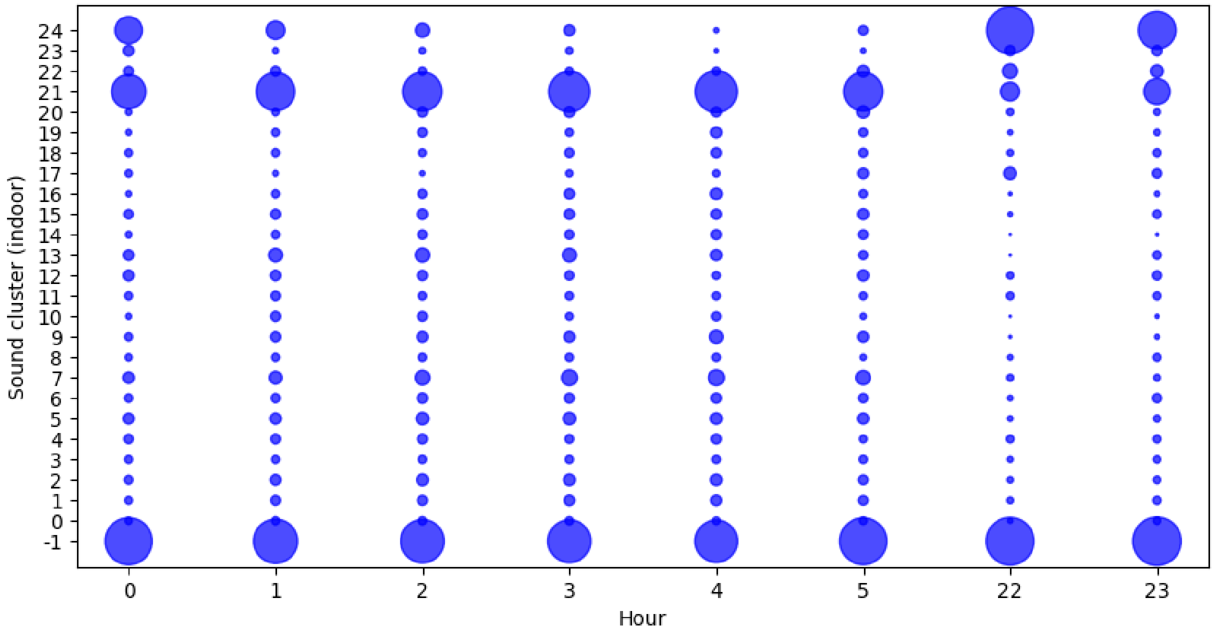

Figure 12 distribution of occurrence of the clusters over the hours of the night. The size of the circle indicates the number of occurrences. Time is in local time at Gothenburg.

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Indoor-outdoor comparison

Comparison of the cluster of the 15-minute outdoor measurement to the cluster of the indoor measurement for the corresponding 15-minute interval (Figure 13) in general does not reveal a strong one-to-one mapping of indoor and outdoor sound environments. Considering the indoor cluster representing a tranquil environment (21), it can be seen that it is found often in combination with outdoor cluster 14, which is by far the most populated cluster identified as a quiet outdoor environment before. But it can also be seen that the indoor tranquil cluster occurs in combination with different outdoor clusters such as cluster 4 which is also tranquil but has less sharp events or cluster 10 which has even less sharp events. In the same line, the loud cluster 24 that was expected to contain evening indoor sound sources such as voices, music, etc., also occurs together with most outdoor sound environments. Similarly, indoor cluster 7 which was assumed to contain cooling or air conditioning noise co-occurs with several outdoor clusters.

Of particular interest is indoor noise cluster 22 which is characterised by continuous rather high noise levels with a relatively low frequency spectrum and a high PSD. It is found in combination with outdoor clusters 5, 6, 15, 9, which are clusters corresponding to loud environments with high PSD but with somewhat different temporal structure, probably all related to traffic.

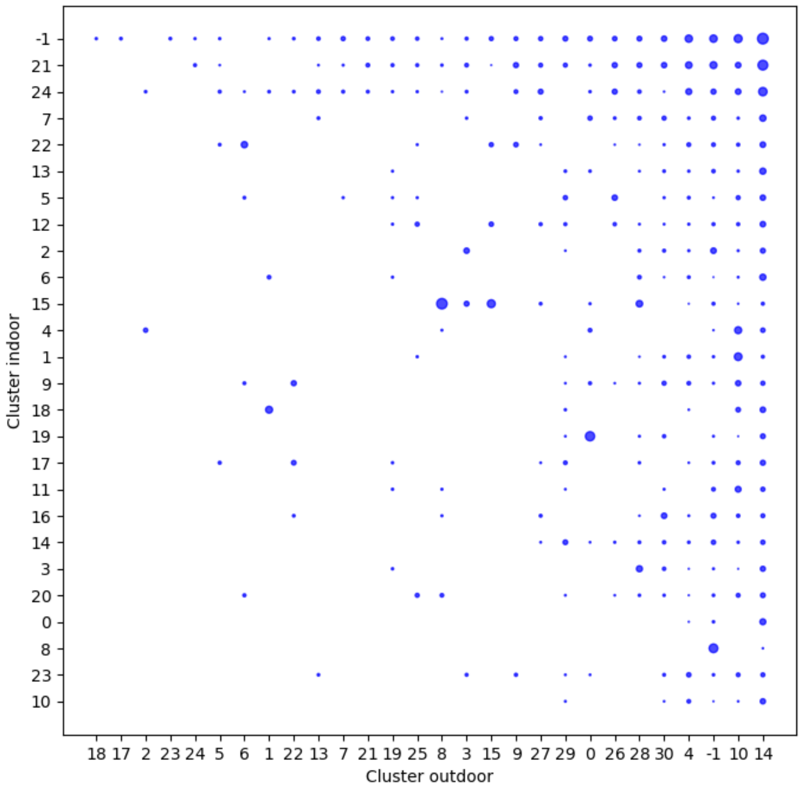

Figure 13 distribution of co-occurrence of clusters based on indoor and outdoor measurements. Size of the circles is proportional to the number of co-occurrent 15-minute intervals normalised by the square root of the total number of occurrences of the two classes that are combined. Clusters are ordered by number of elements with the largest clusters on the right and the top.

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Although clustering of outdoor noise environment seems to be poorly related to indoor nighttime noise clustering, outdoor noise indicators might still be useful to estimate indoor noise clusters. Hence a heatmap of median values of outdoor noise indicators for each indoor noise cluster has been calculated (normalisation is done with respect to all coupled measurements using StandardScaler) and displayed in Figure 14. The difference in outdoor indicators between the most [populated clusters 21 and 24 vanished, which is consistent with this difference being mainly caused by indoor sound. The small difference tends towards less quiet environments where the indoor sound occurs, which could be related to lifestyle differences between neighbourhoods. The indoor sound cluster 7 that had high sharpness probably due to ventilation also has some sharpness outside, indicating that this sound source might also affect the outdoor measurement. The indoor cluster 22, which has already been identified as possibly governed by outdoor (traffic) sound, shows clearly different outdoor indicators such as equivalent levels, statistical levels, and PSD. Cluster 13 like cluster 7 has high indoor sharpness, but this difference is less pronounced in the outdoor indicators which is consistent with an indoor source being responsible for the difference.

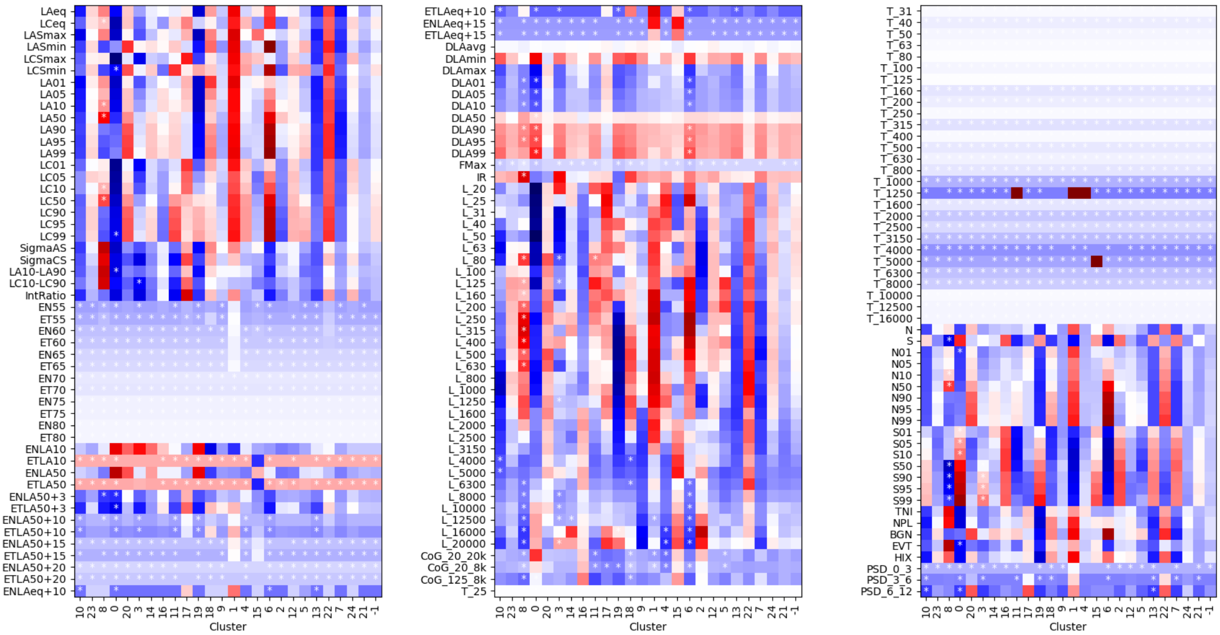

Figure 14 Heat map of the median value of each outdoor indicator in the indoor noise clusters obtained purely based on measurement data; stars indicate where the interquartile interval over all observations in this class is below 0.2 giving an indication of the consistency of values over the 15-minute intervals belonging to this cluster, ordered by number of measurements in the cluster.

All in all, it can be concluded that both clustering of outdoor sound environments and considering single indicators measured outside are insufficient for describing indoor sound environments for most bedrooms (of 18 year olds). From the 11285 combined indoor-outdoor 15-minute measurements, 4002 (35%) cannot clearly be clustered because they either fall between clusters or are very unique, 3682 (32%, clusters 21 and 24) cannot be explained by outdoor sound, 540 (4.7%, clusters 7 and 13) are probably related to ventilation and air conditioning, mainly inside the room, but also noticeable outside

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the bedroom window. Contrary, 216 (1.9%, cluster 22) 15-minute measurement epochs could be linked to distinct outdoor sources, probably traffic. For the remaining 26% of 15-minute interval indoor noise clusters, differences in outdoor indicators seem to hint that outdoor sound environments have an influence while outdoor sound clusters are less convincing. However, these clusters often occur at only a few locations and hence conclusions may be influenced by accidental correlations of outdoor environment and indoor sources.

3.3. Outdoor to indoor

3.3.1. From outdoor to indoor sound levels

Deliverable 3.7 focuses specifically on building sound insulation. In view of the indoor and outdoor clustering of sound environments with exposome in mind performed above, it is worth investigating in a more classical way how outdoor sound affects indoor sound levels on the same dataset.

Indoor levels of noise (and other environmental pollutants) are partly caused by outdoor sources. For some indicators related to sleep disturbance / sleep quality, disturbance of learning in a school environment, and partly even for restoration, the indoor micro-environment is more relevant than the outdoor micro-environment. Without having access to the dwelling or a description of the dwelling by the inhabitant, estimating the state of the indoor environment is rather tedious. What's more, measurements inside buildings, which are fairly rare, do not a priori give any indication of whether the noise levels measured are linked to activity inside the building, or to noise coming from outside. Finally, the acoustic performance of buildings can vary considerably depending on the year of construction, the materials used, etc., and it is therefore very imprecise to rely on standard attenuation values.

Successfully establishing building attenuation values from joint outdoor/indoor measurements is therefore of crucial interest. In this section, the Equal-Life measurement campaign in Gothenburg, which contains simultaneous measurements indoor and outdoor, is analysed, in order to propose a methodological framework to answer these concerns.

3.3.2. Analyse of the Gothenburg dataset

In cases where indoor micro-environments are impacted by numerous noises originating from housing units, determining the contribution from the outdoors to indoor sound levels can be tedious. However, these outdoor noises are responsible for a significant proportion of health effects and impacts on mental health, as they correspond to sources of endured noise (aircraft noise, road traffic noise, human activities in the street, etc.). Moreover, the relationships established between noise exposure and annoyance are based on road traffic, railway or aircraft noise at the facades of residences. It is therefore essential to know how to distinguish between outdoor noise and indoor noise in noise measured inside homes. This section proposes an in-situ method for determining housing attenuation values in 1/3 octave bands, aiming to determine acoustic indicators beyond simple L_{Aeq}, both for indoor and outdoor contributions. The idea is therefore ultimately to decompose the indoor Lf,125ms time series into an outdoor contribution and an indoor contribution.

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Description of the dataset

108 locations were chosen in the Gothenburg region, with simultaneous measurements carried out inside homes and on building facades over a period of 4 days. For practical reasons, 10 noise sensors were moved from one home to another, so that the measurements were not taken simultaneously in all 108 locations. The measurements were taken in 1/3 octave bands from 6.3 Hz to 20 kHz, with a temporal resolution of 125 ms. They were limited to measurements between 9 p.m. and 8 a.m., in order to focus on night time exposure, that are associated with periods of restorative activity and potential sleep disturbance. The sites are relatively quiet, partly because of the night-time periods selected. In detail, the L_{Aeq} calculated over the whole measurement campaign duration at the 108 sites ranged from 37.1 dB(A) for the quietest location to 65.8 dB(A) for the loudest one, with an average of 46.6 dB(A). This makes it essential but tedious to be able to distinguish between indoor and outdoor contributions to the indoor sound micro-environment.

The proposed method relies on a detailed analysis of noise level attenuations by juxtaposing the time series of outdoor and indoor $L_{Aeq,1s}$. Indeed, in the case of relatively low outdoor noise levels, this method allows for the extraction of outdoor noise contribution while eliminating noise generated inside buildings. However, this requires ensuring that there is no temporal misalignment between the time series. A preliminary analysis thus involved temporally aligning the time series to ensure that outdoor noise peaks corresponded to indoor noise peaks on a second-by-second scale. An autocorrelation function was applied to the 108 data points with the *ccf* function of R, per hour data packet, to point and correct for any potential temporal drifts. 36% of hourly frames exhibit a temporal misalignment of less than 5 seconds, 27% of less than 1 second. It is noteworthy that for hourly frames with significant temporal misalignment, this is often associated with time series exhibiting low correlation and very low levels of both outdoor and indoor noise. As a result, they most likely correspond to time slots and locations where outdoor noise is very low and has a limited impact on indoor noise. For the subsequent stages of the study, the temporally aligned data is utilized. Furthermore, to prevent very small misalignments, such as 125 ms, from disrupting the association, sliding averages are used, as explained below.

Description of the method

Figure 15 illustrates the time series of $L_{Aeq,125ms}$ for outdoor and indoor measurements for nodes 1036 and node 1001. The figure for node 1036 clearly demonstrates that each outdoor noise peak is associated with an indoor peak. The indoor time series exhibits additional peaks, which are necessarily related to events occurring indoor. For node 1001, the outdoor noise contains significantly fewer peaks, and indoor noise is higher; so it would be necessary here to focus on the loudest peak to estimate the attenuation. The objective will therefore be to automate the search for the attenuation value by selecting the relevant elements in the time series.

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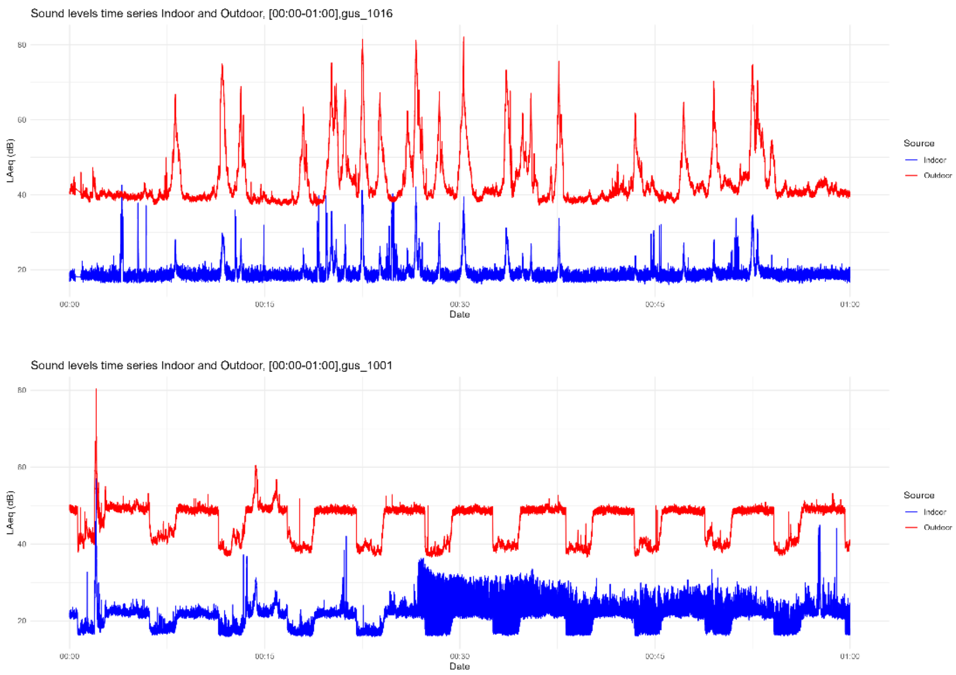

Figure 15 Illustration of LAeq,1s time series indoor and outdoor. Top: node 1036. Bottom: node 1001

The proposed method involves, once the time series are aligned, first selecting the data points where the difference in sound level between the outdoor and indoor is large enough to indicate that the indoor noise originates from the outdoor. This process is conducted for each one-third octave band, as noise peaks outdoors do not necessarily occur at the same frequencies. For example, brake noise, horn noise, or aircraft noise each have distinct frequency content. Therefore, since the goal is to determine attenuation by frequency band, it is necessary to select the emerging time periods by frequency band. Thus, for each 1/3 octave band *f* between 20 Hz and 20 kHz, the 125 ms data points are selected where the difference in sound levels between outdoor and indoor $L_{f,outdoor,125ms}$ - $L_{f,indoor,125ms}$ exceeds 20 dB(A). This ensures that the $L_{f,indoor,125ms}$ sound level most likely corresponds to a contribution originating from the outdoor environment. Then, only the noisiest 28880 125ms time-frames (which makes 30 minutes) are kept, which correspond approximately to 1% of the dataset. That way, the method retains for each 1/3 octave band *f* the most prominent noise peaks indoors that originate from the outside. Tests on the variability of the attenuation calculated at this value of 1% have shown that it is a good compromise, and that the determined attenuation values vary little for thresholds in this order of magnitude. The assumption made is that the attenuation of noise by the building is not dependent on the outdoor noise level, and that therefore identifying emerging outdoor noise peaks is sufficient to determine the attenuation. In practice, it is possible that distant, weaker noises correspond to a different attenuation because the directivity of the sound source is not the same, which may involve different physical phenomena, for example if the sound wave passes through both the window and walls with a different directivity. In practice, verifying this would require an extremely low noise level inside the dwellings, which is outside the scope of this study. However, the hypothesis adopted here, consisting of focusing on high outdoor levels in order to determine in situ attenuation, is in line with the regulatory method,

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which determines attenuation on the basis of controlled laboratory studies, using a powerful standard noise source.

Finally, once the subset of selected data is constituted at the 1/3 octave band *f* for each of the 108 locations, the attenuation A(*f*) is determined as the acoustic mean of the a $L_{f,outdoor,125ms}$ - $L_{f,indoor,125ms}$ values on the subset of selected data. Note that for each 125 ms period, the sliding value of $L_{Aeq,10s}(t)$ replaces $L_{Aeq,125ms}(t)$ to avoid issues caused by small temporal misalignments. Considering measurement points separated by 3 meters, the sound propagation delay between the two points—approximately 10 ms—can be neglected. This substitution has a very minor impact on the calculated attenuation values when alignment is perfect, as noise peaks typically have slower dynamics and L_{Aeq} gives greater weight to higher levels. However, it prevents aberrant results in cases where the time series are slightly misaligned.

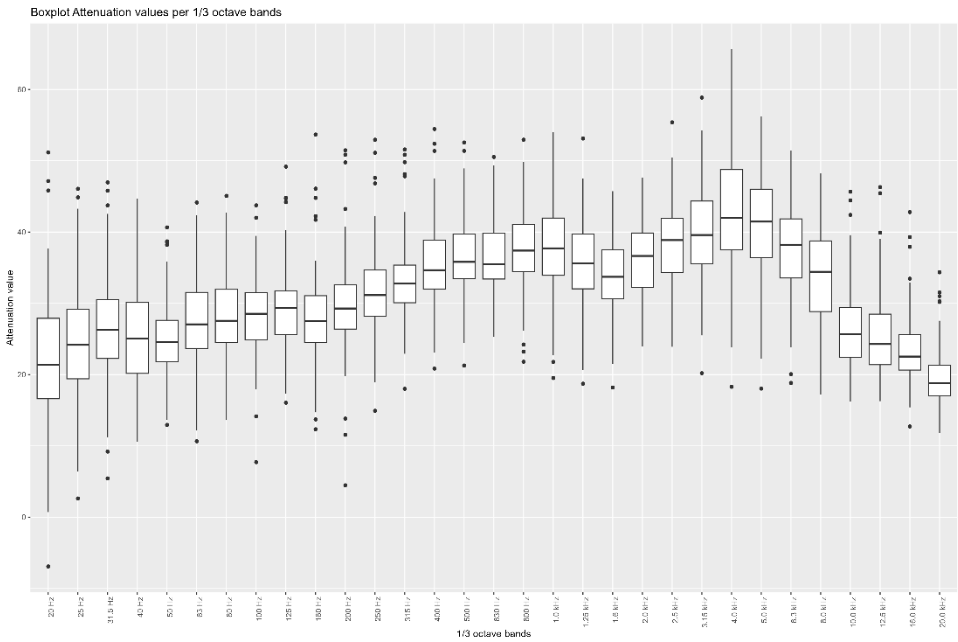

Figure 16 Boxplot of the attenuation values determined per 1/3 octave band, over the 108 nodes

Figure 16 shows the boxplots of attenuation values per one-third octave band between 20 Hz and 20 kHz, determined for the 108 points. The attenuation curve shows a typical pattern up to 4 kHz, increasing with frequency, after which it becomes less realistic: the curve would logically continue to increase (mass law), yet a decrease is observed. This is due to outdoor levels not being high enough to provide a reliable estimate of attenuation at higher frequencies (such low levels are impossible to measure accurately and are lost in the indoor background noise). We can hypothesize attenuation values above 40 dB for frequencies above 4 kHz; however, this has no impact on the indoor values determined, precisely because of the low outdoor levels at these higher frequencies.

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Figure 17 shows the histogram of attenuation values determined in L_{Aeq}. These values are obtained by applying frequency-specific attenuation, assuming pink noise outdoors. The median of the attenuation values is 36.0 dB, with interquartile ranges of 33.1 dB and 40.0 dB.

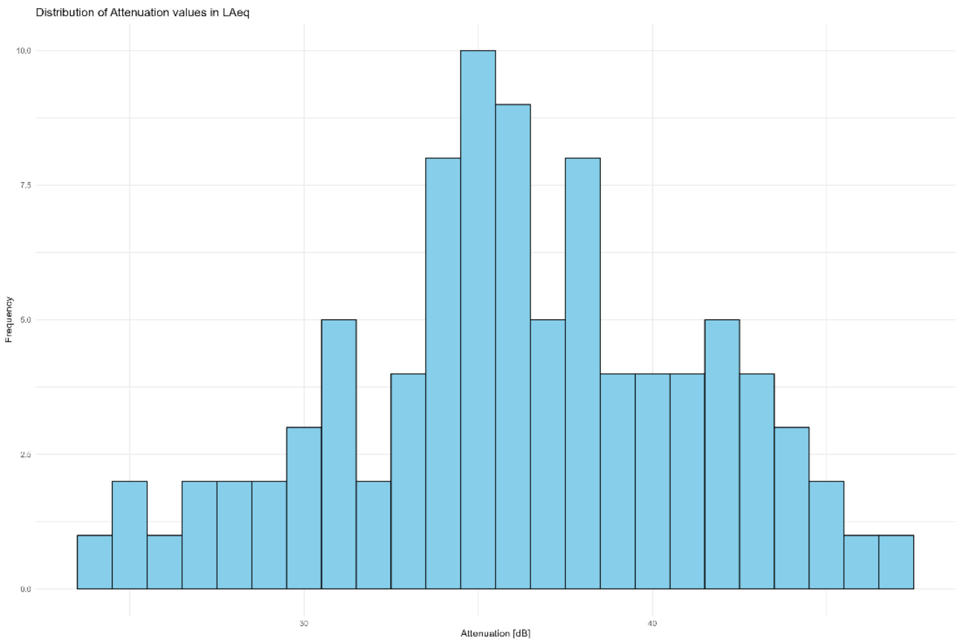

Figure 17 Distribution of the Attenuation values calculated.

Once the attenuation value A(*f*) is determined for a given location, it is possible to calculate the contribution to $L_{f,indoor,125ms}$ from the corresponding $L_{f,outdoor,125ms}$ simply by subtracting the attenuation value A(*f*). This results, for each 1/3 octave band *f* in two indoor time series, $L_{f,indoor,125ms}$ and $L_{f,indoor\_from\_outdoor,125ms,}$ the latter describing the outdoor contribution to the indoor level. A third time series, $L_{f,indoor\_from\_indoor,125ms,}$ represents the acoustic difference between these two latter ones and describes the indoor contribution to indoor sound levels. From these three time-series, typical acoustic indicators, but discriminating between indoor and outdoor contributions, can be calculated. D3.7 gives a few alternatives for handling brut sound insulation.

Results

To illustrate the possibilities offered by the discrimination of indoor and outdoor contributions to residential noise, various common acoustic indicators have been calculated every 1h in addition to $L_{Aeq,1h}$: statistical indicators, representing each hour sound levels from L_{Amin} to L_{Amax}, passing through various fractile indices: L_{A95} for the level exceeded 95% of the time, L_{A90} for the level exceeded 90% of the time, L_{A50} for the median sound level, L_{A10}, L_{A5} and L_{A1} for sound levels exceeded respectively 10%, 5% and 1% of the time. Figure 18, Figure 19, and Figure 20 depict the boxplots, for each hour of the day, calculated over the 108 locations, for L_{Aeq}, L_{A10} and L_{Amax}, respectively.

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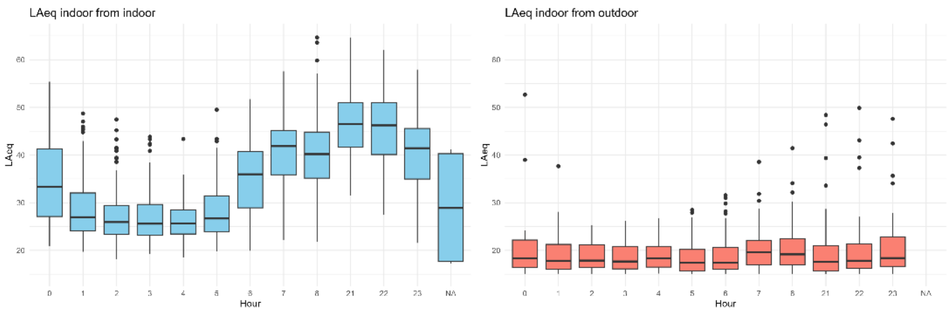

Figure 18 $L_{Aeq,indoor}$ values, for both indoor and outdoor contributions, calculated over the 108 locations.

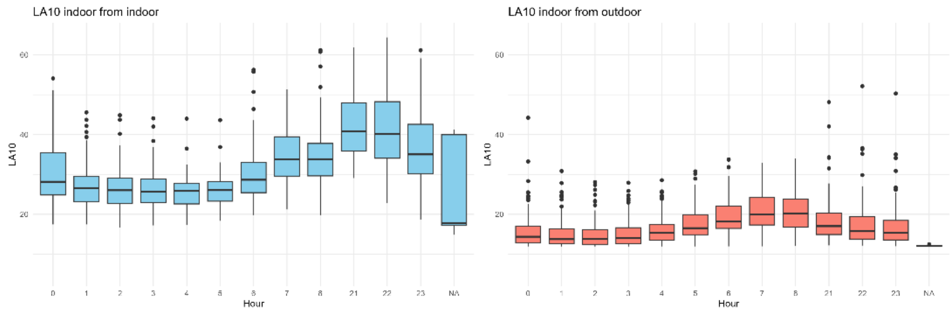

Figure 19 $L_{A10,indoor\ values}$, for both indoor and outdoor contributions, calculated over the 108 locations.

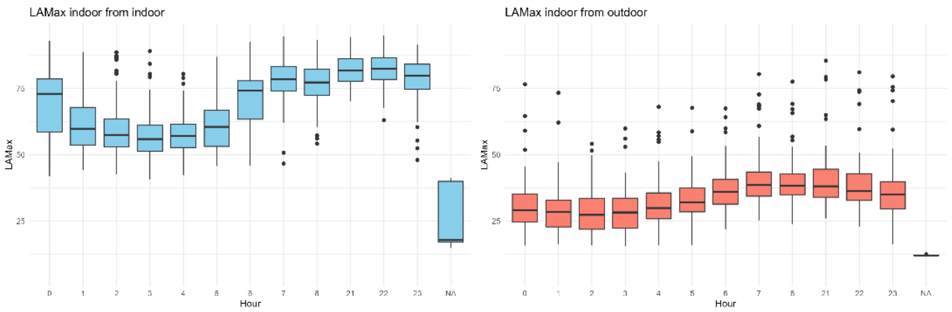

Figure 20 $L_{Amax,indoor}$ values, for both indoor and outdoor contributions, calculated over the 108 locations.

Discussion

Determining the contribution of outdoor noise to the noise measured indoors is challenging, especially in a nighttime noise context where outdoor noise levels are relatively low. In this section, an ad-hoc method is proposed, which has the advantage of determining various indoor acoustic indicators, aiming to improve associations with health effects and mental health. However, several limitations are identified:

- It would be interesting to confront the method with diverse datasets, involving daytime measurements. Indeed, the contrasts between outdoor sound levels and indoor sound levels are more significant during the day, which would simplify the determination of the sought attenuation value.

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- In the analyzed dataset, the indoor contribution to indoor sound levels seems quite high, suggesting that the attenuation values might be underestimated. This could be verified with daytime data containing more pronounced noise peaks, to see if the attenuation is higher or not.
- Finally, the assumption is made here that attenuation is independent of outdoor sound level. It is possible that maximum levels are more or less attenuated than the rest. The physics of sound propagation tends to suggest that maximum levels are more attenuated than others. In the example of road traffic, maximum levels are attenuated more strongly than low levels as one moves away from a sound source, and this compression of noise dynamics is well-known in the literature (a vehicle is considered a point source whereas traffic flow is considered a linear source). However, other factors may contradict this for certain outdoor/indoor exposure cases, depending on the directivity of the source, the geometric configuration of the housing and its windows, etc. To test this, one would need to rely on a dataset with highly varied outdoor sound levels and exceptionally low indoor levels, which is beyond the scope of this study and the usual real exposure situations encountered.

3.3.3. Analyse of Ghent dataset

The first dataset consists of 72 unique living rooms along an inner ring road 2x2 lanes with traffic lights in the city of Ghent. The non-normalised sound insulation ($L_{p,out}$-$L_{p,in}$) is obtained from a measurements in front of the front door facing the road (façade level) and measurement inside near the (closed) window of the living room facing the road. The noise source is the traffic sound naturally occurring during the day. All dwellings are exposed to approximately the same noise level, L_{Aeq}=65-70 dBA. During pre-processing only data are retained where the traffic noise is well above any background hum that may exist in the house. More details regarding the context of these measurements can be found in [54]. This dataset illustrates that significant differences can be found in brut sound insulations even for dwellings in a similar environment in the same city. Figure 21 shows the median and interquartile interval of the measurements.

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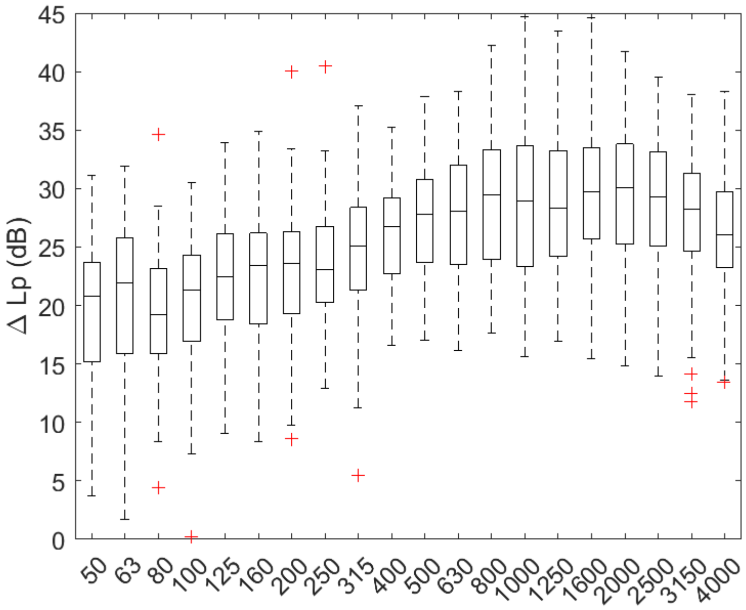

Figure 21 median, interquartile interval, and range of sound pressure level difference between indoor and outdoor levels for 72 dwellings near an inner road.

3.4. Comparing insulation between Gothenburg and Ghent

The "on-field" attenuation measurements proposed for Gothenburg can be compared to those estimated from the Ghent dataset. Both methods show, unsurprisingly, an increase in attenuation with frequency, which aligns well with the literature. While low-frequency attenuations are around 20 dB at 50 Hz in both case studies, they differ significantly at higher frequencies: approximately 30 dB at 1 kHz in the Ghent dataset and nearly 40 dB in the Gothenburg study. These differences could have several underlying causes:

- **Structural origin**: It is possible that the buildings in the Gothenburg case study have superior acoustic quality, as Sweden's colder climate demands better thermal insulation, which often enhances acoustic insulation as well.
- **Experimental origin**: In the Ghent experiment, indoor measurement points were positioned just behind the windows, while in the Swedish experiment, they were placed near the bed in the bedroom. This positioning could add a few dB of attenuation since the sound field might not be entirely homogeneous within the room.
- **Methodological origin**: The methodology used to determine "on-field" acoustic attenuation for the Gothenburg case study may tend to overestimate attenuation slightly. Since outdoor levels were relatively low, filtering was necessary to retain only time frames with sufficiently high exterior noise levels. Efforts were made to address any potential temporal misalignments, as a mismatch could cause an outdoor noise

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peak to not coincide with an indoor level increase, suggesting a misleadingly high attenuation. However, a few inconsistencies may still remain for certain measurement points.

Among these three hypotheses, the first—structural differences—is likely the most plausible explanation

4. Modelled road traffic noise indicators tested on cohorts

4.1. Road traffic noise indicator modelling

The surrogate model for advanced noise indicators (D3.5) allows to calculate 15-minute indicators: LAeq, LA50, LA90, LA10-LA90, IntRatio, ETLA50+3, ETLA50+10, CoG_125-8k, N, N50, N90, S05, S10, PSD_0_3, PSD_3_6, PSD_6_12, and PSD_12_18, for every 15 minute epoch of the day, based on open data on roads and buildings and traffic intensities on these roads. Detailed definitions of these indicators can be found in D3.5 as well.

The surrogate model for advanced noise indicators takes the traffic intensity on all roads near the observation point as input, but deduces vehicle speed distributions. If traffic information is available or is part of a mitigation, it can be used as input for the model. To improve local traffic information, the Equal-Life model proposed in D3.2 could be used. Nevertheless, unless otherwise stated below, the traffic intensities obtained from the simple model based on Open StreetMap road category and edge betweenness of the road segment (D3.5) was used.

Based on the analysis in Table 1 and the availability of 15-minute indicators, the diurnal indicators of Table 3 have been included in the analysis. The first six indicators have been calculated for all cohorts, the others only for selected cohorts. All of these indicators are calculated for the most “m” and the least “l” exposed façade of the dwelling. It should nevertheless be noted that the model does not consider individual dwellings but the building where the dwelling is a part of and that only 4 calculation points are used to characterize the building exposure.

Table 3 Overview of the diurnal indicators calculated for the validation on cohorts

	Brief description	reference
SDI_0_3	sleep disturbance index, 0-3 year olds	Section 2.3
SDI_3_6	sleep disturbance index, 3-6 year olds	Section 2.3
SDI_6_12	sleep disturbance index, 6-12 year olds	Section 2.3
SDI_12_18	sleep disturbance index, 12-18 year olds	Section 2.3
Lnight	Lnight (European)	Environmental noise directive
ARP	absence of restorative period	Section 2.4
LAeq	24-hour equivalent level	Table 1
LA90_ev	90-percentile of A-weighted level during evening	Table 1
N90_ev	90-percentile of loudness during evening	Table 1
LA50_ev	median of A-weighted level during evening	Table 1

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N50_ev	median of loudness during evening	Table 1
LAeq_ev	equivalent level during the evening	Table 1
Len_3_12	evening-night weighted for 3-12 year olds	Table 1
Len_12_18	evening-night weighted for 12-18 year olds	Table 1
EPE	noise peak emergence during evening	Table 1

4.2. ABCD

Spearman's correlation is calculated between SDQ subscales and calculated proposed new noise indicators for road traffic noise (Table 4). Indicators related to night exposure and sleep disturbance calculated at the least exposed façade in general correlate with the emotion, hyperactivity, peer problems and prosocial subscales but not with the conduct subscale. There is no difference between L_{night} and SDI for the 6 to 12 years and 12 to 18 age range, but these indicators are highly correlated (r=0.93). SDI for the younger age range only is correlated to hyperactivity. These indicators are characterized by a higher threshold for disturbance by events and a definition of the night that starts earlier in the evening.

Indicators related to restorative periods at the most exposed façade only correlate with the peer problems subscale. The relevant indicators seem L_{A90} and L_{A50}, as expected. The more drastic indicator ARP that classifies the most exposed façade on the basis of L_{A50} reaching a threshold has a much lower correlation as does the event counting indicator EPE.

Indicators for restorative periods at the least exposed façade seem to be much more correlated with SDQ subscales, in particular the hyperactivity and peer problems subscales, but also emotion and prosocial subscales show some correlation with these noise indicators. L_{Aeq} and $L_{Aeq,evening}$ have the highest correlation with the aforementioned subscales. Statistical levels during the evening correlate with the hyperactivity and peer problems subscales. The new indicator Len, comparable to L_{den} but with evening and night adapted for children in the age range 3 to 12 years and in the age range 12 to 18 years obtained at the least exposed façade seems to have a slightly stronger relationship with pro-social behavior than other indicators.

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*Table 4 Spearman's correlation between elements of the SDQ scale and various road traffic noise exposure indicators under test. All correlations are very weak but because of the size of the ABCD dataset (n~4000) some are statistically significant at p<0.05 (**bold**). Spearman's correlation above 0.05 are highlighted.*

	emotion	conduct	hyper	peer	prosocial	Total SDQ
SDI_0_3l	0.018	0.008	**0.047**	0.035	-0.032	**0.044**
SDI_3_6l	**0.042**	0.012	0.051	0.039	-0.039	0.055
SDI_6_12l	**0.046**	0.017	0.054	**0.044**	**-0.041**	0.059
SDI_12_18l	**0.045**	0.019	0.054	**0.042**	**-0.043**	0.059
Lnightl	**0.048**	0.015	0.052	0.053	**-0.047**	0.062
SDI_0_3m	0.009	0.009	0.035	0.030	-0.020	0.029
SDI_3_6m	0.011	0.002	0.030	0.031	-0.020	0.026
SDI_6_12m	0.013	0.007	0.037	0.035	-0.031	0.033
SDI_12_18m	0.013	0.007	0.037	0.036	-0.032	0.034
Lnightm	0.012	0.003	0.029	0.031	-0.026	0.026
ARP	-0.019	0.011	-0.007	0.004	-0.016	-0.005
LAeqm	0.006	0.000	0.031	0.027	-0.024	0.023
LA90_evm	0.010	0.007	0.015	0.054	-0.032	0.027
N90_evm	0.005	0.011	0.003	0.052	-0.030	0.021
LA50_evm	0.026	0.000	0.013	**0.042**	**-0.041**	0.027
N50_evm	0.024	0.002	0.011	0.033	-0.038	0.023
LAeq_evm	0.007	0.001	0.033	0.026	-0.025	0.024
Len_3_12m	0.007	0.004	0.037	0.030	-0.025	0.029
Len_12_18m	0.007	0.005	0.039	0.031	-0.026	0.031
EPEm	-0.001	-0.019	0.002	-0.007	0.023	-0.011
LAeql	**0.049**	0.015	0.057	0.061	-0.039	0.067
LA90_evl	0.013	0.007	0.022	0.052	-0.028	0.032
N90_evl	0.019	0.013	0.009	**0.040**	-0.027	0.026
LA50_evl	0.024	0.003	0.024	0.051	-0.032	0.035
N50_evl	0.027	0.001	0.013	0.037	-0.031	0.026
LAeq_evl	**0.049**	0.015	0.058	0.063	-0.037	0.067
Len_3_12l	**0.048**	0.015	0.051	0.062	**-0.043**	0.064
Len_12_18l	**0.047**	0.015	**0.050**	0.062	**-0.044**	0.063
EPEl	0.004	-0.007	0.006	-0.020	0.014	-0.003

Spearman's correlation is also calculated for indicators for attention from the Amsterdam Neuropsychological Tasks (ANT): Baseline Speed (BS) and Response Organization Objects (ROO) on school children aged 5-6 years and results are shown in . BS is reported as the reaction time to a changing visual stimulus and is expected to indicate arousal of attention. ROO is expected to measure response organisation, inhibition prepotent responses and attentional flexibility. Tested children click left and right button depending on the location of an object with respect to a central cross and the objects colour, the latter being used to trigger compatible and

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incompatible responses. The strongest correlation, albeit still small, is now found between the mean value of the ROO and median values of noise levels during the evening. The difference between correlations with the noise indicator at the most or the least exposed façade is limited. A-weighted levels and loudness give similar correlations.

*Table 5 Spearman's correlation between elements of the attention variables and various road traffic noise exposure indicators under test. All correlations are very weak but because of the size of the ABCD dataset (n~4000) some are statistically significant (**bold**). Spearman's correlation above 0.05 are highlighted.*

	Baseline Speed		Response Organization Objects	
	mean	stdev	mean	stdev
SDI_0_3l	0.019	0.015	0.001	0.004
SDI_3_6l	0.029	0.021	-0.004	-0.008
SDI_6_12l	**0.042**	0.035	0.019	0.018
SDI_12_18l	**0.042**	0.034	0.020	0.018
Lnightl	**0.046**	**0.038**	0.027	0.023
SDI_0_3m	**0.040**	**0.038**	0.031	0.027
SDI_3_6m	**0.040**	**0.039**	0.031	0.028
SDI_6_12m	**0.045**	**0.040**	0.035	0.030
SDI_12_18m	**0.044**	**0.039**	0.034	0.029
Lnightm	**0.044**	0.035	0.031	0.030
ARP	0.010	0.018	-0.010	0.001
LAeqm	**0.044**	**0.038**	0.031	0.031
LA90_evm	0.022	0.021	**0.039**	0.021
N90_evm	0.011	0.007	0.030	0.016
LA50_evm	**0.041**	0.029	**0.057**	**0.042**
N50_evm	**0.042**	0.026	**0.059**	**0.044**
LAeq_evm	**0.044**	**0.039**	0.031	0.031
Len_3_12m	**0.046**	**0.040**	0.036	0.033
Len_12_18m	**0.046**	**0.041**	**0.038**	0.034
EPEm	0.005	0.002	-0.027	-0.006
LAeql	**0.041**	**0.041**	0.023	0.022
LA90_evl	0.027	0.031	**0.054**	0.032
N90_evl	0.025	0.018	**0.040**	0.020
LA50_evl	0.033	0.031	**0.063**	**0.043**
N50_evl	0.031	0.022	**0.061**	0.035
LAeq_evl	**0.040**	**0.041**	0.021	0.021
Len_3_12l	**0.044**	**0.043**	**0.038**	0.031
Len_12_18l	**0.045**	**0.043**	**0.042**	0.033
EPEl	-0.004	-0.022	**-0.043**	-0.017

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Discussion

The difference between the effect of indicators on SDQ subscales when assessed at the least and most exposed façade jumps out, yet both correlations are rather low. This could be explained by a purely acoustic effect, that is, (1) children sleeping at the least exposed façade benefit when this is quiet and (2) the availability of a least exposed façade where the noise level has long tranquil periods is beneficial for avoiding hyperactivity, or even reduce peer problems.

However, these "noise" indicators may also be indicators for broader discrimination between exposome situations. While the levels at the most exposed façade are not particularly different depending on the type of house or the general building density, the level at the least exposed façade is. Open suburban areas may not show the low levels at the least exposed façade that could be found in closed inner city building blocks. These living conditions may be very different both from a physical and from a social exposome point of view leading to differences in the SDQ subscales.

Considering the SDQ subscales, hyperactivity and peer problems seem to have the strongest relationship with the traffic noise indicators. More specifically SDQ-hyperactivity relates slightly more on the sleep disturbance indicators while SDQ-peer problems relate slightly more to evening noise levels as well. Intuitively this makes sense, but to get a more objective evaluation, these findings are related below to the outcomes on cohorts in D7.2.

The cohort analysis uses SDQ-prosocial as an outcome. In D7.2, Table 8 shows that sleep_qlt (sleep quality), NO2, NDVI_gr_100 (normalised difference vegetation index during the greenest season within a 500 m buffer around residence), peer_prob (peer problems reported by the mother) and emo_prob (emotional problems reported by the mother) are the most important factors in the random forest analysis. No noise-related indicators appear among the most important indicators. However, one should keep in mind that peer_probl and emo_prob are SDQ subscales. Hence the effect of noise might indirectly be included via these variables and therefore a small effect could indeed be expected.

The TDS of SDQ is used in D7.2 for ABCD (Table 10 in D7.2). The top variables in the random forest analysis include dep_m (Mothers' score subscale DASS21 depression), diet_sdrink (child daily number of sweet drinks), stress_ch (sum score life events weighted for duration of suffering), oa_assist (Number of old-age social assistance recipients per 1000 inhabitants), diet_fruit (child mean daily fruit intake), MSAVI_500 (Average 5-year moving average of Modified Soil Adjusted Vegetation Index during all seasons within a 500 m buffer around residence), diet_vegeta (child mean daily vegetable intake), int_close_300 (The mean street intersection closeness scores of every street segment within 300m from each geo-coordinate.), diet_snack (child daily number of snacks), m_w_15_20 (Number of men and women 15-20 years). Amongst these only two variables, MSAVI_500 and int_close_300 refer to the local environment, which could be indirectly measured with the extensive list of noise indicators given above. Noise-related indicators (the detailed indicators mentioned above were not yet in the analysis of D7.2) do not appear among the most important indicators, but average street betweenness and nearest street betweenness appear in the 17th and 19th position.

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Attention-related indicators BS and ROO may be influenced by noise events during the evening and night and restorative periods in the evening respectively. One could hypothesise that sleep disturbance is a mediator for BS, essentially a reaction time. On the other hand, sleep related indicators do not influence ROO as much as the median level in the evening, hence a wake restorative period.

The cohort analysis in Table 7 of D7.2 shows that the average street betweenness scores of every street segment within 300m from each geo-coordinate (avg_betw_300) is the most important physical exposome indicator together with the slope within 300m (slope) in the random forest analysis. Avg_betw_300 is an important input to the noise indicator model as it reflects the expected traffic intensity on the street. Amongst the top 10 most important indicators, some differences can be observed between BS and ROO. For BS, the top 10 contains streets_lenght_500 (total length (m) of street sections within 500 m buffer from residence) and int_close_300 (The mean street intersection closeness scores of every street segment within 300m), while for ROO, int_close_100 (The mean street intersection closeness scores of every street segment within 100m), mj_road_distance (Euclidean distance (m) between residence and the closest major road) and road_distance (Euclidean distance to the closest road) can be found. The latter may indicate the presence of streets with more and more continuous traffic, which may indeed lead to higher L50. Hence there is some consistency between the random forest analysis and the correlations with the advanced indicators that are found here.

Finally, we cannot exclude methodological issues. All indicators are calculated based on distance to streets, edge betweenness, and building intensity. This might not be accurate enough to predict e.g. the event-related indicators at the most exposed façade. Some data such as new houses may be missing in the building database, some streets may be wrongly categorised. All these limitations of calculated indicators may have affected the outcome. E.g. inaccurate traffic intensity and composition will have a stronger effect on the prediction of indicators at the most exposed façade that include event indicators. Similarly, the absence of important sound sources like rail and air traffic in the model may result in event-related indicators not popping up.

4.3. Alpine

The Alpine cohort was mainly used to compare calculation methods for noise indicators.

Details on the cohort and the in-depth study on sleep can be found in D7.2 and D1.2. Here we focus on the kindl_mental, kindl_prosocial, and kindl_hedonic subscales because these data were gathered with approximately 1500 children while the in-depth variables were only available for 156 children.

As the equivalent levels caused by rail and road traffic were calculated with multiple models, these have been compared first. Three models are investigated:

Model 1: *sources*: traffic data obtained from local authorities; *propagation parameters*: dwellings, noise barrier, terrain obtained from local authorities; *propagation model*: Harmonoise 2.5D [4]; *approximate setup time*: months; *approximate run time*: weeks.

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Model 2: *sources*: open street map (OSM) with traffic estimate based on betweenness; *propagation parameters*: dwellings from OSM; *propagation model*: Equal-Life surrogate model (D5.3); *approximate setup time*: hours; *approximate run time*: one day.

Model 3: *sources*: open street map (OSM) with traffic estimate based on betweenness; *propagation parameters*: dwellings from OSM; *propagation model*: Equal-Life surrogate model (D5.3, improved model 6); *approximate setup time*: hours; *approximate run time*: one day.

Table 6 shows the Spearman's correlation coefficient between the selected outcome variables and the L_{night} calculated using the above models. Although correlations are extremely small, the size of the dataset makes some of them significant. Firstly, we explore the interrelationship between the outcome variables kindl and reported sleep quality, which is considered as a pathway in Equal-Life. The correlation between sleep and kindl-mental is high and positive while it is negative for kind-prosocial and kindl-hedonic.

In general, L_{night} correlates weakly with sleep problems but this relationship is statistically significant except for L_{night} highway. The latter might indicate that noise events are important for sleep disturbance. Comparing both models it can be seen that the Equal-Life surrogate model gives roughly the same results as the classical model which requires orders of magnitude more setup time and calculation time. Spearman's correlation between the results of both models are in the order of magnitude of 0.48 for the most and 0.46 for the least exposed façade, which reveals that the models do not calculate exactly the same quantity but that both capture the essential features for predicting sleep problems.

*Table 6 Spearman's correlation between elements of the KINDL scale, sleep quality and L_{night} calculated using the different models for different sources. All correlations are very weak but because of the size of the Alpine dataset (n~1500) some are statistically significant at $p<0.05$ (**bold**). Spearman's correlation above 0.05 are highlighted.*

	mental	prosocial	hedonic	sleep problems
mental	-	**-0.450**	**-0.406**	**0.381**
prosocial	**-0.450**	-	**0.724**	**-0.279**
hedonic	**-0.406**	**0.724**	-	**-0.275**
sleep problems	**0.381**	**-0.279**	**-0.275**	-
Model 1				
L_{night} highway	0.043	-0.028	-0.038	0.028
L_{night} main road	0.031	0.003	-0.010	**0.066**
L_{night} rail	0.036	-0.015	-0.011	**0.064**
L_{night} total	0.046	-0.026	-0.030	**0.081**
Model 2				
L_{night} road least	0.018	0.017	0.020	**0.082**
L_{night} road most	0.051	0.009	0.009	**0.056**
Model 3				
L_{night} road least	0.026	0.024	-0.006	**0.075**
L_{night} road most	0.051	0.023	0.014	**0.079**

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To further investigate the potential relevance of different indicators, Spearman's correlation between elements of the kindl well-being scale and sleep problems at the one hand and various proposed indicators at the other is calculated and presented in Table 7. The elements of the kindl scale correlate significantly with sleep problems. Noise indicators focussing on the night: SDI, L_{night}, Len (an Lden with time intervals according to the child's age), and L_{Aeq} (24hours) correlate significantly with sleep problems. Indicators for noise during the evening also correlate but this is probably due to the fact that they correlate strongly with L_{Aeq} and L_{night}: for the equivalent levels correlation is close to perfect, for statistical levels it is between 0.5 and 0.6.

The only indicator that correlates significantly with any of the kindl subscale values is ARP, an indicator based on the value of L50 above a given threshold, designed as an indicator for the absence of restorative periods during the night.

*Table 7 Spearman's correlation between elements of the KINDL scale, sleep quality and several noise indicators calculated using model 3. All correlations are very weak but because of the size of the Alpine dataset (n~1500) some are statistically significant at p<0.05 (**bold**). Spearman's correlation above 0.05 are highlighted.*

	mental	prosocial	hedonic	sleep problems
mental	**-**	**-0.444**	**-0.408**	**0.390**
prosocial	**-0.444**	**-**	**0.725**	**-0.270**
hedonic	**-0.408**	**0.725**	**-**	**-0.278**
sleep problems	**0.390**	**-0.270**	**-0.278**	**-**
SDI_0_3l	0.050	0.038	0.006	**0.064**
SDI_3_6l	0.042	0.029	-0.002	**0.084**
SDI_6_12l	0.035	0.026	-0.004	**0.091**
SDI_12_18l	0.039	0.030	0.000	**0.091**
Lnightl	0.026	0.024	-0.006	**0.075**
SDI_0_3m	0.040	0.028	0.012	**0.077**
SDI_3_6m	0.032	0.030	0.016	**0.073**
SDI_6_12m	0.028	0.030	0.012	**0.072**
SDI_12_18m	0.028	0.031	0.012	**0.068**
Lnightm	0.051	0.023	0.014	**0.080**
ARP	**0.093**	0.001	-0.027	0.013
LAeqm	0.054	0.015	0.010	**0.083**
LA90_evm	0.020	-0.006	-0.006	0.048
N90_evm	0.017	-0.002	-0.004	0.046
LA50_evm	0.012	0.015	0.001	0.048
N50_evm	0.008	0.020	0.004	0.047
LAeq_evm	0.056	0.010	0.006	**0.084**
Len_3_12m	0.037	0.020	0.012	**0.081**
Len_12_18m	0.036	0.022	0.013	**0.079**
EPEm	0.025	0.017	0.017	-0.017
LAeql	0.030	0.023	-0.006	**0.079**

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LA90_evl	0.001	0.022	-0.007	0.044
N90_evl	-0.002	0.026	-0.001	0.050
LA50_evl	0.004	0.034	-0.003	0.059
N50_evl	0.002	0.035	-0.003	0.058
LAeq_evl	0.034	0.020	-0.009	**0.082**
Len_3_12l	0.020	0.030	0.001	**0.069**
Len_12_18l	0.017	0.033	0.002	**0.067**
EPEl	0.033	0.002	0.002	-0.015

Discussion

L_{night} does not show any significant Spearman's correlation with any of the components of the kindl wellbeing scale. This holds for traffic noise as a whole (calculation model 1) and road traffic noise (calculation models 1, 2, and 3). Reported sleep problems are not specifically related to noise in the questionnaire. Thus, in contrast to the results of questionnaires specifically asking for sleep and noise, the variance explained by L_{night} is expected to be lower: Spearman's correlation for road traffic noise is between 0.06 and 0.08 for all models considered. A few interesting observations can be made: (1) highway L_{night} shows much less correlation than the same indicators calculated for the main road and rail traffic. This could indicate that noise peaks are more relevant than the steady noise of the highway. However, one should keep in mind the specific situation of this Alpine area where the highway impact is limited to the main valley. In this study area, night time railway activity cannot be neglected compared to road traffic contributions to sleep disturbance.

Comparing models shows that for road traffic noise the L_{night} calculated with the extensive model and with the surrogate models gives roughly the same correlations. This indicates that the main contributions to the dynamic noise are indeed captured by the surrogate model. Model 3 which is based on the 6th variant of the trained surrogate model (see D3.5) gives more similar correlations for the most and least exposed façade than model 2. These observations are in line with the results reported in [65]. There a linear regression coefficient of the order of 0.1 is found for the relationship between L_{night} and sleep problems. Moreover, using structural equation modelling it is shown that 0.03 of the effect occurs through the perceived neighbourhood quality indicator. Most of the effect also persists when the availability of green and a garden is taken into account.

From the new indicators, all nighttime indicators correlate significantly with sleep problems. Even with the more balanced model 3 indicators calculated at the least exposed façade slightly outperform those calculated at the most exposed façade. This trend is generally observed, but we should caution the reader that this may also be due to a inaccuracies in the modelling. L_{Aeq} during the evening or even over the whole day show a very similar correlation with sleep problems as the nighttime indicators. This is probably due to the very strong correlation between both sets of indicators caused by the underlying traffic situation in this area. On the contrary, statistical levels correlate less. These are determined by continuous traffic such as the traffic on the highway and it was already established above that highway noise contributes less to sleep problems.

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Surprisingly, the only indicator that correlates significantly with any of the kindl subscales is ARP. In addition equivalent levels show some effect on the mental health subscale.

5. Combining all available knowledge

5.1. Methodology for selecting indicators for exposome assessment

The Equal-Life project aims at relating mental health, cognitive development, and well-being of children and young people to the exposome, including both physical and social components. In this deliverable, the focus is on a specific group of indicators for the sound environment within the broader definition of exposome. The selection of suitable indicators and concepts can nevertheless follow the same methodology as the general definition of (physical) exposome. Ideally it is based on both prior knowledge from the systematic literature review (WP1) and relationships observed in the cohort studies (D7.3) and in-depth research (D1.3).

As discussed in Section 2.2, indicators should fulfil multiple requirements. To assess the validity of indicators, proof of a significant relationship with specific effects such as ADHD, internalizing/externalizing problems, selective attention should be found. Each indicator is also representative for a concept or dimension that is believed to affect the outcomes. These various relationships are shown in Figure 22.

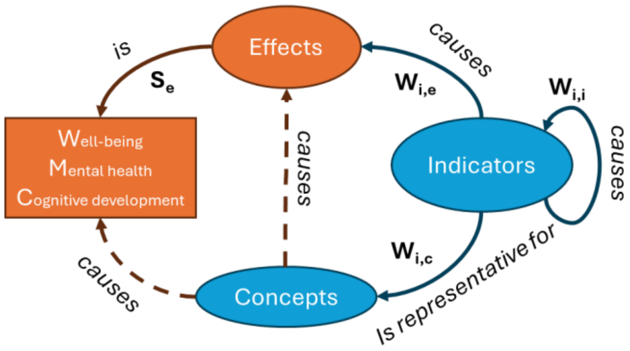

Figure 22. Well-being, Mental health, and Cognitive development of children is affected by the exposome over early life. This exposome can be defined by a number of concepts. These concepts are measured via precisely defined indicators that have a degree of representativeness for the concepts. WM&C are also made operational via a set of defined and measurable effects which contribute to WM&C with a certain severity. The weights in the graph are extracted from evidence-based expert judgement. Relationships represented by dashed lines are deducted from these weights whenever possible needed.

The methodology starts by condensing knowledge on indicators and indicator-effect relationships in a database (excel sheets) containing (1) the indicators for physical and social exposure that have been used, either pre-existing in some of the cohort studies, calculated within the Equal-Life project, or simply drawn from literature; (2) the relationships between these indicators and between these indicators and outcomes. The indicator sheet has additional information on:

- the concept that it is an indicator for (e.g. air pollution);

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- how representative the indicator is for this concept, rated between 0=not at all and 1=extremely based on expert opinions; this is $W_{i,c}$
- how the indicator is obtained (calculated/measured);
- and whether the indicator relies solely on open data available in the EU.

The latter aspect is important to allow to produce tools that are directly applicable in the whole EU avoiding the huge effort to collect local data.

Additional information entered for each relationship in the relationships sheet includes:

- the source of evidence for proposing this relationship;
- the strength rated on a [0,1] scale, 1 indicating that the relationship is extremely important;
- the confidence of belief in this relationship rated on a [0,1] scale, 1 indicating absolute certainty; this confidence can come from cohort studies, in-depth studies or literature when the relationship is between an exposome indicator and an outcome and from the calculation process or from literature when it is between exposome indicators.

Relationships come in two forms, relationships between indicators and effects, with strength measures as $W_{i,e}$ and relationships between indicators with strength measures as $W_{i,i}$. The quantification of relationships can be guided by the data (e.g. correlations over a single cohort) but will require human expert knowledge. Once all relationships have been quantified, this knowledge can be represented in a knowledge graph. Centrality of a node in this graph is then used to measure the importance of the indicator.

5.1. Correlation and overlap between indicators

To estimate the overlap between indicators and associated weights, as $W_{i,I}$ one can partly rely on the correlation (Pearson or Spearman) between indicators over a certain dataset. Yet in addition theoretical considerations as well as in depth knowledge on the construction of the indicators needs to be used. Moreover, some indicators are only available in some datasets (cohorts).

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	SDI_0_3l	SDI_3_6l	SDI_6_12l	SDI_12_18l	ARP	Lnightl	SDI_0_3m	SDI_3_6m	SDI_6_12m	SDI_12_18m	Lnightm	LAeqm	LA90_evm	N90_evm	LA50_evm	N50_evm	LAeq_evm	Len_3_12m	Len_12_18 m	EPEm	LAeql	LA90_evl	N90_evl	LA50_evl	N50_evl	LAeq_evl	Len_3_12l	Len_12_18l	EPEl
SDI_0_3l	1.00	0.89	0.74	0.75	0.46	0.64	0.32	0.33	0.32	0.32	0.32	0.34	0.27	0.36	0.29	0.37	0.35	0.37	0.37	0.02	0.62	0.24	0.32	0.34	0.47	0.61	0.59	0.58	0.13
SDI_3_6l	0.89	1.00	0.93	0.93	0.35	0.81	0.39	0.43	0.44	0.44	0.42	0.44	0.40	0.48	0.43	0.49	0.44	0.48	0.48	-0.02	0.78	0.37	0.44	0.48	0.61	0.77	0.76	0.75	0.09
SDI_6_12l	0.74	0.93	1.00	1.00	0.27	0.91	0.48	0.56	0.59	0.59	0.54	0.54	0.50	0.52	0.58	0.60	0.54	0.58	0.59	-0.03	0.87	0.46	0.49	0.61	0.69	0.86	0.86	0.86	0.04
SDI_12_18l	0.75	0.93	1.00	1.00	0.27	0.90	0.49	0.57	0.60	0.60	0.55	0.54	0.49	0.51	0.57	0.59	0.54	0.58	0.59	-0.02	0.86	0.45	0.48	0.60	0.68	0.84	0.85	0.84	0.04
ARP	0.46	0.35	0.27	0.27	1.00	0.20	0.15	0.15	0.13	0.14	0.15	0.18	0.23	0.38	0.20	0.31	0.19	0.22	0.22	-0.13	0.21	0.25	0.45	0.25	0.44	0.21	0.23	0.24	-0.08
Lnightl	0.64	0.81	0.91	0.90	0.20	1.00	0.39	0.48	0.53	0.52	0.48	0.47	0.51	0.48	0.57	0.53	0.47	0.52	0.53	-0.06	0.97	0.49	0.48	0.63	0.64	0.96	0.96	0.95	0.01
SDI_0_3m	0.32	0.39	0.48	0.49	0.15	0.39	1.00	0.95	0.86	0.87	0.88	0.86	0.42	0.44	0.63	0.73	0.85	0.86	0.86	0.23	0.36	0.25	0.23	0.37	0.39	0.35	0.37	0.38	0.00
SDI_3_6m	0.33	0.43	0.56	0.57	0.15	0.48	0.95	1.00	0.97	0.97	0.94	0.91	0.48	0.47	0.71	0.76	0.90	0.91	0.91	0.23	0.44	0.32	0.29	0.46	0.47	0.44	0.46	0.47	-0.03
SDI_6_12m	0.32	0.44	0.59	0.60	0.13	0.53	0.86	0.97	1.00	1.00	0.93	0.89	0.52	0.49	0.75	0.76	0.88	0.91	0.91	0.20	0.50	0.37	0.33	0.53	0.52	0.49	0.52	0.53	-0.06
SDI_12_18m	0.32	0.44	0.59	0.60	0.14	0.52	0.87	0.97	1.00	1.00	0.92	0.88	0.52	0.48	0.75	0.76	0.87	0.90	0.90	0.20	0.49	0.37	0.33	0.53	0.52	0.48	0.51	0.52	-0.06
Lnightm	0.32	0.42	0.54	0.55	0.15	0.48	0.88	0.94	0.93	0.92	1.00	0.98	0.44	0.44	0.64	0.69	0.96	0.96	0.95	0.31	0.46	0.27	0.25	0.42	0.42	0.45	0.47	0.47	0.02
LAeqm	0.34	0.44	0.54	0.54	0.18	0.47	0.86	0.91	0.89	0.88	0.98	1.00	0.46	0.50	0.64	0.71	1.00	0.99	0.98	0.29	0.45	0.28	0.28	0.41	0.44	0.45	0.47	0.47	0.01
LA90_evm	0.27	0.40	0.50	0.49	0.23	0.51	0.42	0.48	0.52	0.52	0.44	0.46	1.00	0.87	0.90	0.82	0.47	0.57	0.60	-0.55	0.54	0.89	0.80	0.85	0.79	0.54	0.63	0.65	-0.69
N90_evm	0.36	0.48	0.52	0.51	0.38	0.48	0.44	0.47	0.49	0.48	0.44	0.50	0.87	1.00	0.79	0.88	0.51	0.61	0.63	-0.44	0.50	0.72	0.80	0.71	0.77	0.50	0.57	0.58	-0.51
LA50_evm	0.29	0.43	0.58	0.57	0.20	0.57	0.63	0.71	0.75	0.75	0.64	0.64	0.90	0.79	1.00	0.92	0.64	0.73	0.76	-0.36	0.57	0.77	0.70	0.86	0.80	0.57	0.65	0.68	-0.50
N50_evm	0.37	0.49	0.60	0.59	0.31	0.53	0.73	0.76	0.76	0.76	0.69	0.71	0.82	0.88	0.92	1.00	0.71	0.79	0.82	-0.27	0.52	0.65	0.68	0.73	0.76	0.52	0.58	0.60	-0.38
LAeq_evm	0.35	0.44	0.54	0.54	0.19	0.47	0.85	0.90	0.88	0.87	0.96	1.00	0.47	0.51	0.64	0.71	1.00	0.99	0.98	0.28	0.45	0.29	0.28	0.41	0.44	0.45	0.47	0.47	0.00
Len_3_12m	0.37	0.48	0.58	0.58	0.22	0.52	0.86	0.91	0.91	0.90	0.96	0.99	0.57	0.61	0.73	0.79	0.99	1.00	1.00	0.18	0.50	0.39	0.39	0.51	0.53	0.50	0.53	0.53	-0.07
Len_12_18m	0.37	0.48	0.59	0.59	0.22	0.53	0.86	0.91	0.91	0.90	0.95	0.98	0.60	0.63	0.76	0.82	0.98	1.00	1.00	0.15	0.52	0.42	0.42	0.54	0.56	0.51	0.54	0.55	-0.10
EPEm	0.02	-0.02	-0.03	-0.02	-0.13	-0.06	0.23	0.23	0.20	0.20	0.31	0.29	-0.55	-0.44	-0.36	-0.27	0.28	0.18	0.15	1.00	-0.09	-0.67	-0.62	-0.51	-0.47	-0.09	-0.17	-0.20	0.72
LAeql	0.62	0.78	0.87	0.86	0.21	0.97	0.36	0.44	0.50	0.49	0.46	0.45	0.54	0.50	0.57	0.52	0.45	0.50	0.52	-0.09	1.00	0.53	0.51	0.65	0.66	1.00	0.99	0.98	-0.03
LA90_evl	0.24	0.37	0.46	0.45	0.25	0.49	0.25	0.32	0.37	0.37	0.27	0.28	0.89	0.72	0.77	0.65	0.29	0.39	0.42	-0.67	0.53	1.00	0.88	0.92	0.84	0.54	0.63	0.66	-0.72
N90_evl	0.32	0.44	0.49	0.48	0.45	0.48	0.23	0.29	0.33	0.33	0.25	0.28	0.80	0.80	0.70	0.68	0.28	0.39	0.42	-0.62	0.51	0.88	1.00	0.82	0.90	0.52	0.60	0.62	-0.57
LA50_evl	0.34	0.48	0.61	0.60	0.25	0.63	0.37	0.46	0.53	0.53	0.42	0.41	0.85	0.71	0.86	0.73	0.41	0.51	0.54	-0.51	0.65	0.92	0.82	1.00	0.93	0.65	0.75	0.77	-0.57
N50_evl	0.47	0.61	0.69	0.68	0.44	0.64	0.39	0.47	0.52	0.52	0.42	0.44	0.79	0.77	0.80	0.76	0.44	0.53	0.56	-0.47	0.66	0.84	0.90	0.93	1.00	0.66	0.74	0.76	-0.47
LAeq_evl	0.61	0.77	0.86	0.84	0.21	0.96	0.35	0.44	0.49	0.48	0.45	0.45	0.54	0.50	0.57	0.52	0.45	0.50	0.51	-0.09	1.00	0.54	0.52	0.65	0.66	1.00	0.99	0.98	-0.03
Len_3_12l	0.59	0.76	0.86	0.85	0.23	0.96	0.37	0.46	0.52	0.51	0.47	0.47	0.63	0.57	0.65	0.58	0.47	0.53	0.54	-0.17	0.99	0.63	0.60	0.75	0.74	0.99	1.00	1.00	-0.14
Len_12_18l	0.58	0.75	0.86	0.84	0.24	0.95	0.38	0.47	0.53	0.52	0.47	0.47	0.65	0.58	0.68	0.60	0.47	0.53	0.55	-0.20	0.98	0.66	0.62	0.77	0.76	0.98	1.00	1.00	-0.18
EPEl	0.13	0.09	0.04	0.04	-0.08	0.01	0.00	-0.03	-0.06	-0.06	0.02	0.01	-0.69	-0.51	-0.50	-0.38	0.00	-0.07	-0.10	0.72	-0.03	-0.72	-0.57	-0.57	-0.47	-0.03	-0.14	-0.18	1.00

Table 8 Pearson's cross correlation between the road traffic noise indicators on the ABCD cohort. Orange highlights strong positive correlations, green highlights strong negative correlations.

	SDI_0_3l	SDI_3_6l	SDI_6_12l	SDI_12_18l	ARP	Lnightl	SDI_0_3m	SDI_3_6m	SDI_6_12m	SDI_12_18m	Lnightm	LAeqm	LA90_evm	N90_evm	LA50_evm	N50_evm	LAeq_evm	Len_3_12m	Len_12_18m	EPEm	LAeql	LA90_evl	N90_evl	LA50_evl	N50_evl	LAeq_evl	Len_3_12l	Len_12_18l	EPEl
dist_streets_2018	-0.04	-0.03	0.00	0.00	0.03	0.02	0.04	0.03	0.02	0.03	-0.03	-0.06	0.10	0.07	0.12	0.09	-0.06	-0.02	0.00	-0.07	0.02	0.12	0.11	0.12	0.09	0.02	0.04	0.04	-0.08
length_streets_100_2018	0.01	0.00	-0.04	-0.05	-0.08	-0.05	-0.16	-0.15	-0.15	-0.16	-0.09	-0.07	-0.20	-0.15	-0.24	-0.21	-0.07	-0.11	-0.12	0.06	-0.05	-0.17	-0.17	-0.19	-0.16	-0.05	-0.08	-0.09	0.13
length_streets_300_2018	-0.04	-0.07	-0.10	-0.10	-0.08	-0.15	-0.02	-0.05	-0.07	-0.07	-0.03	-0.01	-0.25	-0.21	-0.24	-0.18	-0.01	-0.06	-0.08	0.10	-0.17	-0.21	-0.23	-0.22	-0.20	-0.17	-0.19	-0.20	0.13
length_streets_500_2018	-0.06	-0.09	-0.11	-0.10	-0.08	-0.17	0.02	0.01	-0.01	-0.01	0.02	0.02	-0.23	-0.22	-0.18	-0.14	0.02	-0.02	-0.04	0.11	-0.20	-0.20	-0.23	-0.19	-0.18	-0.20	-0.21	-0.21	0.09
dist_roads_2018	-0.04	-0.05	-0.11	-0.12	0.05	-0.06	-0.22	-0.25	-0.27	-0.27	-0.24	-0.20	-0.04	0.01	-0.15	-0.12	-0.19	-0.19	-0.19	-0.13	-0.05	-0.04	0.02	-0.12	-0.07	-0.04	-0.05	-0.06	-0.02
length_roads_100_2018	0.08	0.12	0.19	0.20	-0.02	0.13	0.38	0.40	0.40	0.41	0.35	0.31	0.09	0.05	0.22	0.22	0.30	0.30	0.30	0.18	0.10	0.06	0.02	0.13	0.11	0.10	0.11	0.11	0.04
length_roads_300_2018	-0.01	0.01	0.08	0.09	-0.04	0.04	0.15	0.19	0.21	0.22	0.17	0.14	0.06	-0.01	0.15	0.10	0.13	0.13	0.13	0.05	0.04	0.08	0.01	0.14	0.09	0.03	0.05	0.06	-0.06
length_roads_500_2018	-0.02	-0.02	0.01	0.02	-0.03	-0.01	0.10	0.12	0.13	0.13	0.11	0.09	0.10	0.02	0.12	0.07	0.08	0.09	0.09	-0.03	0.00	0.14	0.05	0.15	0.08	0.00	0.03	0.04	-0.13
dist_majorroads_2018	-0.13	-0.19	-0.20	-0.19	-0.08	-0.20	-0.12	-0.15	-0.15	-0.15	-0.13	-0.16	-0.46	-0.36	-0.36	-0.33	-0.16	-0.20	-0.21	0.39	-0.22	-0.46	-0.37	-0.39	-0.37	-0.23	-0.27	-0.28	0.46
length_majorroads_100	0.22	0.23	0.21	0.21	0.25	0.17	0.27	0.27	0.26	0.27	0.25	0.28	0.23	0.36	0.28	0.39	0.29	0.30	0.31	-0.04	0.17	0.14	0.21	0.18	0.26	0.17	0.18	0.18	-0.07
length_majorroads_300	0.21	0.30	0.29	0.27	0.16	0.27	0.14	0.19	0.21	0.21	0.18	0.22	0.36	0.45	0.36	0.40	0.23	0.27	0.28	-0.21	0.29	0.30	0.39	0.33	0.41	0.29	0.31	0.32	-0.22
length_majorroads_500	0.19	0.27	0.26	0.24	0.14	0.25	0.09	0.13	0.15	0.14	0.11	0.16	0.41	0.44	0.36	0.37	0.17	0.21	0.23	-0.32	0.28	0.38	0.44	0.38	0.43	0.29	0.32	0.33	-0.31
built_ESM_300_2015	-0.14	-0.19	-0.20	-0.19	-0.08	-0.28	0.02	0.00	-0.02	-0.02	-0.01	-0.01	-0.23	-0.20	-0.16	-0.12	-0.02	-0.05	-0.07	0.06	-0.29	-0.18	-0.20	-0.17	-0.16	-0.30	-0.29	-0.29	0.03
built_ISA_300_2015	-0.12	-0.18	-0.22	-0.20	-0.05	-0.30	0.04	0.01	-0.03	-0.02	-0.01	0.00	-0.25	-0.19	-0.17	-0.10	0.00	-0.05	-0.06	0.07	-0.32	-0.23	-0.21	-0.21	-0.18	-0.33	-0.32	-0.32	0.02
infrast_100_2018	0.08	0.10	0.11	0.12	0.04	0.07	0.18	0.19	0.19	0.19	0.19	0.19	-0.05	0.02	0.07	0.11	0.18	0.17	0.16	0.17	0.05	-0.11	-0.06	-0.03	0.01	0.04	0.03	0.02	0.14
urbanhigh_500_2018	-0.10	-0.14	-0.16	-0.14	-0.07	-0.23	0.03	0.02	0.00	0.00	0.01	0.01	-0.14	-0.14	-0.11	-0.08	0.01	-0.02	-0.03	0.06	-0.23	-0.10	-0.15	-0.12	-0.13	-0.24	-0.22	-0.22	0.00
urbanlow_500_2018	0.07	0.11	0.13	0.13	-0.03	0.19	-0.02	0.01	0.03	0.02	0.01	0.00	0.09	0.06	0.07	0.03	-0.01	0.02	0.02	0.02	0.20	0.08	0.06	0.11	0.07	0.20	0.19	0.19	0.07
green_urb_500_2018	0.07	0.11	0.14	0.13	0.04	0.17	-0.02	0.01	0.04	0.04	0.03	0.02	0.23	0.17	0.16	0.09	0.02	0.06	0.07	-0.10	0.19	0.24	0.21	0.22	0.17	0.20	0.21	0.21	-0.10
water_500_2018	-0.02	-0.06	-0.09	-0.09	-0.01	-0.05	-0.04	-0.09	-0.12	-0.11	-0.09	-0.08	-0.17	-0.12	-0.14	-0.09	-0.08	-0.10	-0.11	0.05	-0.06	-0.22	-0.15	-0.22	-0.15	-0.07	-0.09	-0.10	0.09
lum_500_2018	0.11	0.15	0.19	0.18	0.01	0.25	-0.01	0.02	0.06	0.05	0.04	0.03	0.19	0.14	0.17	0.10	0.03	0.06	0.07	-0.07	0.26	0.18	0.16	0.22	0.17	0.26	0.26	0.26	-0.02
pop_WP_300_2020	-0.01	-0.02	-0.01	0.00	-0.03	-0.09	0.14	0.15	0.15	0.15	0.14	0.14	0.02	-0.01	0.06	0.07	0.14	0.12	0.12	0.01	-0.10	0.05	-0.01	0.06	0.04	-0.10	-0.08	-0.07	-0.08
ndvi_5yrs_all_300_2011	0.09	0.15	0.19	0.18	0.04	0.25	-0.03	0.01	0.05	0.05	0.03	0.01	0.24	0.17	0.16	0.08	0.02	0.06	0.07	-0.05	0.27	0.25	0.20	0.24	0.17	0.28	0.28	0.28	-0.03
ndvi_5yrs_all_std_300	0.07	0.13	0.18	0.18	0.04	0.23	0.04	0.08	0.11	0.11	0.09	0.08	0.37	0.26	0.28	0.19	0.08	0.12	0.14	-0.23	0.25	0.38	0.31	0.33	0.26	0.25	0.28	0.29	-0.24
ndvi_5yrs_greenest_300	0.09	0.14	0.19	0.18	0.04	0.24	-0.01	0.03	0.07	0.07	0.05	0.03	0.27	0.18	0.19	0.10	0.03	0.08	0.09	-0.07	0.26	0.28	0.22	0.26	0.19	0.27	0.28	0.28	-0.06
ndvi_5yrs_green-est_std_300	0.05	0.11	0.15	0.14	0.02	0.21	0.00	0.03	0.05	0.05	0.04	0.03	0.23	0.18	0.17	0.11	0.03	0.06	0.07	-0.11	0.22	0.23	0.21	0.21	0.18	0.22	0.23	0.23	-0.11
msavi_5yrs_all_300_2011	0.08	0.14	0.18	0.17	0.05	0.24	-0.05	-0.01	0.02	0.02	0.01	-0.01	0.20	0.16	0.13	0.06	-0.01	0.03	0.04	-0.03	0.26	0.21	0.18	0.20	0.15	0.27	0.27	0.27	0.01

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msavi_5yrs_all_std_300	0.10	0.17	0.22	0.21	0.06	0.28	0.00	0.04	0.08	0.07	0.06	0.05	0.32	0.24	0.23	0.15	0.05	0.10	0.11	-0.13	0.29	0.31	0.28	0.29	0.23	0.30	0.31	0.32	-0.12
msavi_5yrs_green-est_300	0.09	0.15	0.19	0.18	0.05	0.25	-0.04	0.00	0.04	0.03	0.02	0.01	0.23	0.18	0.16	0.08	0.01	0.05	0.06	-0.05	0.27	0.24	0.21	0.22	0.17	0.28	0.28	0.28	-0.02
msavi_5yrs_green-est_std_300	0.06	0.11	0.15	0.14	0.04	0.21	0.00	0.04	0.06	0.06	0.05	0.04	0.24	0.19	0.17	0.11	0.04	0.08	0.09	-0.07	0.22	0.23	0.21	0.21	0.17	0.23	0.24	0.24	-0.08
stops_100_2018	0.02	0.05	0.08	0.09	-0.01	0.05	0.16	0.17	0.17	0.17	0.14	0.13	0.00	0.00	0.06	0.07	0.12	0.12	0.12	0.12	0.03	-0.01	-0.02	0.02	0.02	0.03	0.03	0.03	0.06
lines_100_2018	0.17	0.19	0.20	0.21	0.17	0.14	0.29	0.31	0.30	0.31	0.27	0.27	0.16	0.22	0.23	0.29	0.26	0.28	0.28	0.06	0.12	0.11	0.15	0.15	0.19	0.11	0.13	0.13	-0.02
lines_500_2018	0.10	0.12	0.11	0.11	0.11	0.08	0.08	0.10	0.10	0.10	0.08	0.11	0.24	0.24	0.19	0.20	0.12	0.14	0.15	-0.18	0.08	0.24	0.25	0.22	0.24	0.08	0.11	0.12	-0.22
ne_DEM_500	-0.05	-0.09	-0.11	-0.10	0.00	-0.18	0.09	0.06	0.03	0.04	0.04	0.05	0.01	-0.02	0.00	0.04	0.05	0.03	0.03	-0.12	-0.20	0.02	-0.02	-0.03	-0.01	-0.20	-0.18	-0.17	-0.18
treecover_2015_300	0.07	0.11	0.16	0.16	0.03	0.19	0.05	0.10	0.13	0.12	0.12	0.09	0.29	0.18	0.23	0.14	0.09	0.13	0.14	-0.12	0.21	0.31	0.21	0.29	0.20	0.21	0.24	0.24	-0.15
treecover_pxls_2015_300	-0.05	-0.04	-0.04	-0.05	0.00	-0.02	-0.13	-0.14	-0.13	-0.13	-0.15	-0.15	0.05	0.02	-0.01	-0.05	-0.15	-0.13	-0.12	-0.10	0.00	0.07	0.05	0.04	0.01	0.01	0.01	0.01	-0.07
BEV_DICHTH	-0.07	-0.11	-0.13	-0.12	-0.02	-0.20	0.08	0.05	0.03	0.03	0.03	0.04	-0.06	-0.07	-0.04	0.01	0.05	0.02	0.01	-0.05	-0.21	-0.06	-0.08	-0.09	-0.07	-0.21	-0.20	-0.19	-0.07
OAD	-0.07	-0.11	-0.14	-0.13	-0.01	-0.22	0.10	0.08	0.06	0.06	0.06	0.07	-0.04	-0.05	-0.01	0.03	0.07	0.05	0.04	-0.09	-0.24	-0.02	-0.06	-0.05	-0.04	-0.25	-0.22	-0.21	-0.14
STED	-0.05	-0.07	-0.08	-0.08	0.01	-0.07	-0.11	-0.13	-0.13	-0.13	-0.14	-0.14	-0.09	-0.04	-0.08	-0.07	-0.14	-0.13	-0.13	0.02	-0.06	-0.11	-0.04	-0.10	-0.07	-0.06	-0.07	-0.08	0.06
P_HOOG_INK	-0.07	-0.10	-0.11	-0.10	-0.01	-0.11	0.01	-0.01	-0.03	-0.02	-0.03	-0.04	-0.12	-0.10	-0.10	-0.06	-0.04	-0.05	-0.06	0.05	-0.14	-0.12	-0.10	-0.14	-0.11	-0.14	-0.14	-0.14	-0.01
P_NIET_ACT	0.10	0.14	0.15	0.14	0.02	0.13	0.06	0.08	0.10	0.09	0.09	0.10	0.15	0.13	0.12	0.11	0.11	0.12	0.12	-0.03	0.15	0.15	0.13	0.16	0.15	0.15	0.16	0.16	-0.01
P_PENS_ONT	0.12	0.17	0.22	0.22	-0.02	0.24	0.07	0.12	0.14	0.13	0.14	0.13	0.12	0.06	0.12	0.07	0.12	0.13	0.14	0.04	0.24	0.13	0.06	0.16	0.11	0.24	0.24	0.23	0.02
P_UIT_ONTV	0.08	0.11	0.11	0.11	0.01	0.11	0.01	0.03	0.05	0.04	0.05	0.06	0.11	0.08	0.07	0.05	0.07	0.07	0.08	-0.01	0.13	0.10	0.08	0.11	0.09	0.14	0.13	0.13	0.02

Table 9 Pearson's cross correlation between the road traffic noise indicators and a selection of other relevant indicators on the ABCD cohort. Orange highlights strong positive correlations, green highlights strong negative correlations.

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Table 8 shows the correlation between the road traffic noise indicators calculated using the surrogate model proposed in D3.5 over all locations in the ABCD cohort. The proposed sleep disturbance index (SDI) correlates across all age categories and with L_{night} and it does so both for the most exposed as for the least exposed façade. This is not unexpected as all of these indicators or variants on the same underlying idea: road traffic noise events disturb sleep. Similarly, the indicators for restoration in the evening: L_{A90}, L_{A50} and N_{90}, N_{50}, correlate strongly amongst each other by construction, but they correlate slightly less with the sleep disturbance indicators. The same indicators calculated at the least and most exposed façade show some, but lower correlation reflecting the different contributions from close by and distant traffic. The ARP (absence of restorative periods) mostly correlates with the N50 (and N90) at the least exposed façade where its definition is based on. The negative correlation between EPE and L_{A90} and others are explained by the fact that this indicator is based on emergence above background. Also all other correlations that can be observed in Table 8 match expectations.

Table 9 illustrates another interesting overlap between the noise indicators and a selection from the other indicators calculated at the dwelling of the ABCD cohort. For the selection, for each group (e.g. by buffer distance) the most strongly correlating index is retrained.

The first relationship that is clearly illustrated is the driver-pressure relationship: the presence of road traffic causes noise. While interpreting the indicators for the presence of roads, one should keep in mind the difference between streets, roads, and major roads that is explained in deliverable 5.1. The total length of major roads (highways and primary roads) within a certain radius correlates most with background levels, L_{A90}, L_{A50}, etc. and the circle of 500m is still relevant. The length of roads within a short distance from the dwelling correlates most with sleep disturbance indices calculated at the most exposed façade. Noise indicator values at the least exposed façade are not only influenced by the closest road but contain contributions from other roads and thus the correlation is less strong. The negative correlation with the presence of streets at short distances with L_{A90}, L_{A50}, etc. at the one hand and levels at the least exposed façade at the other needs further reflection. We suspect that this reflects typical housing situations: persons living in living neighbourhoods with lots of small streets probably live further away from highways and primary streets that cause the high background levels. These results confirm what was reported in D3.5 whare Shapley analysis was used to understand what drives the traffic noise model.

The correlations between noise indicators and the other indicators in Table 9 reflect the urban morphology and where people live. These might be specific for the region covered by the ABCD cohort. Most correlations can clearly be explained but might not seem trivial for some reasons. For example, high urbanisation correlates negatively with road traffic noise indicators at the least exposed façade due to the increased screening by buildings resulting in quiet backyards. Several indicators for the presence of green within 300m correlate positively with the road traffic noise indicators, especially at the least exposed façade and the background levels. This might be because also green buffers around main roads are counted as green and thus their presence may indicated the presence of traffic noise unscreened by buildings. Such correlations are not to be included in the $W_{i,j}$.

5.2. Relevance for mental health, wellbeing and cognitive development

5.2.1. Potential relevance from in depth analysis

To assess the strength of relationships between indicators and effects on wellbeing, mental health, and cognitive development, based on the in-depth analysis on particular cohorts, significant correlation is used. This does not imply that the noise indicator has a causal relationship with the outcome but simply that this indicator is worth investigating e.g. in other deliverables or future work. For the purpose of indicator relationship analysis and selection, all relationships that are statistically significant in Table 4, Table 5, and Table 7 are included, but the confidence level is set to 0.1, that is very low.

No information from clustering based on measurement and WP1 in depth studies is included.

5.2.2. Potential relevance from cohort studies (WP7)

The random forest analysis of the 7 cohorts is used as a starting point for this section (see D7.2 for details).

Method

A method is proposed for selecting indicators to characterize the impacts on children's mental health. The difficulty lies in the fact that the indicators are tested on 7 different cohorts, of varying sizes, and on different variables, with not all indicators being present in each cohort. Therefore, the aim is to propose a ranking method for the indicators that takes these particularities into account, allowing for the inference of an indicator's results in a cohort where it is absent. It should be noted that this work, by its methodology, goes beyond the scope of the project and could be adapted to other themes. The literature on "inter-championship" rankings is for instance abundant in the field of sports.

More specifically, the input data for this work consists of the ranking of indicators derived from random forests applied to each of the 7 cohorts (ranking and importance indicator). A weight has been assigned to each cohort to account for differences between them (number of samples, percentages of ADHD positives, and number of variables tested). The sample sizes for the 7 cohorts are respectively 138,970 for FAIR, 2,759 for ABCD, 2,306 for PIAMA, 2,641 for BREAHTE, 2,914 for ALSPAC, 1,251 for ALPINE, and 579 for WALNUTs. These sample sizes are normalized between 0 and 1 to define a weight for each cohort. The same normalization is applied to the percentages of ADHD positives and the number of variables in the cohort. The final weights defined for each cohort are calculated as the average of these three weights; they are respectively 0.78 for FAIR, 0.34 for ABCD, 0.46 for PIAMA, 0.30 for BREAHTE, 0.09 for ALSPAC, 0.33 for ALPINE, and 0.54 for WALNUTs.

We have decided to work with the importance indicator (CI, confidence interval) provided by the random forest algorithm for each cohort, as this indicator yields more robust results than the ranking indicator (if two indicators have almost identical importance scores, their difference in ranking is less meaningful than if they are far apart in terms of importance). For the FAIR cohort, the dataset was split in 5 due to limitations on the calculation power and five random forest runs were conducted, and the average of the "Importance" indicator value is retained for each variable. More details on the random

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forest procedure can be found in D7.2. The next step involves assigning importance values to the indicators for the cohorts in which they are not present. On average, the indicators appear in 4.2 out of the 7 cohorts, meaning that approximately 40% of the indicator values are inferred. To accomplish this, we use the kNN algorithm (kNN function from the VIM library in R). The k-Nearest Neighbour algorithm performs imputation based on a variation of the Gower Distance for numerical variables.

The importance values are normalized for each cohort, and the number of neighbours considered is 10 (The results are quite insensitive to the number of neighbours selected, ranging from 5 to 10). The results are presented for the mental health ADHD indicator. This method can easily be extended to a wider variety of indicators by (i) considering the 7 response sets of a new indicator as 7 new cohorts, or (ii) performing an indicator ranking for each new mental health indicator, and then conducting a new ranking of these rankings, either as a simple average of the rankings or as a ranking based on the average importances.

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Results

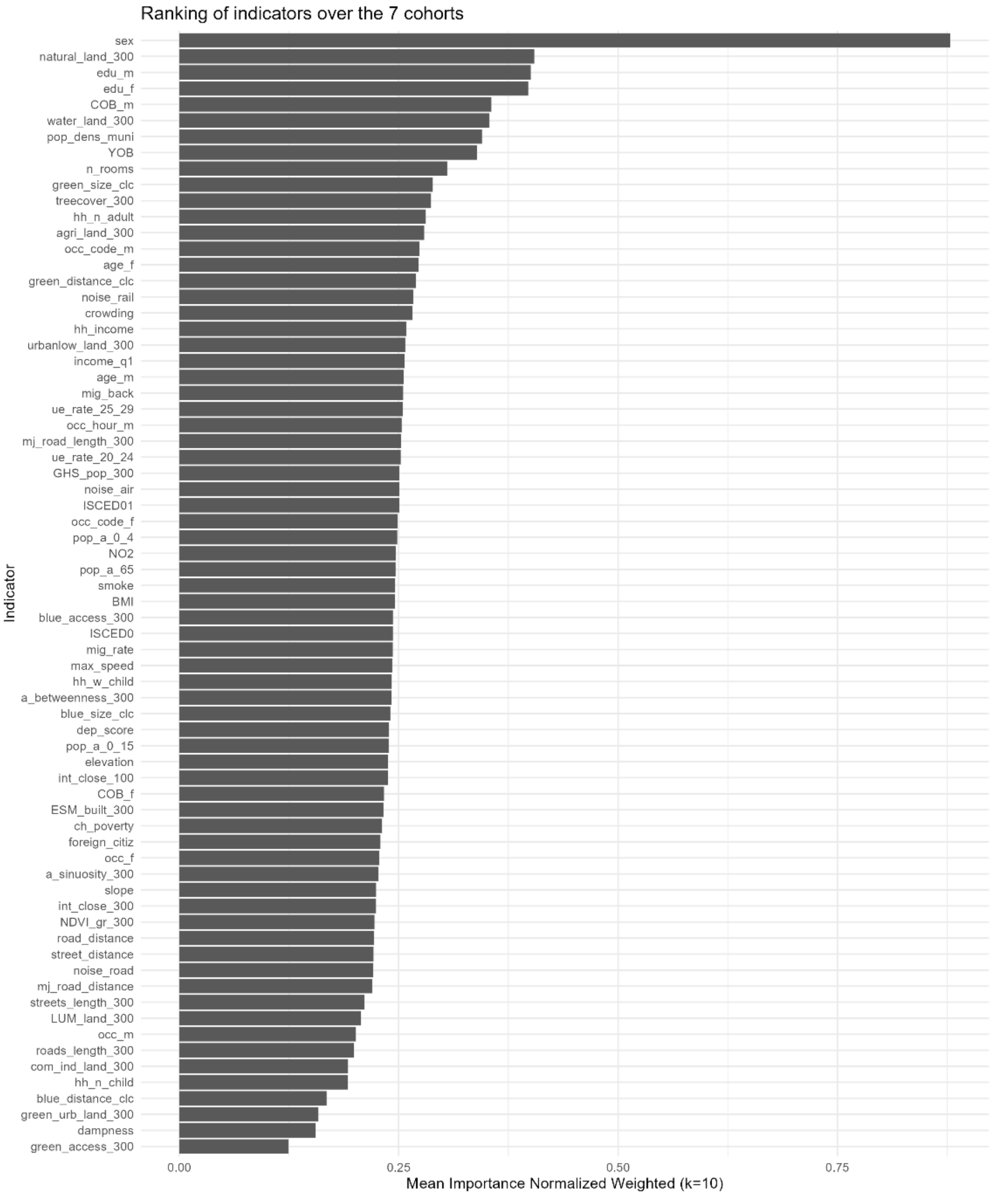

Figure 23 Ranking of importance of indicators across 7 cohorts in a random forest model for ADHD

The ranking of indicators across the seven cohorts places "Sex" as the clear leader, which is unsurprising since this indicator ranks first in four cohorts and second in two. This variable is not very relevant for exposome and was therefore removed from later versions of the analysis reported in D7.2. Following are three other indicators—"Natural_land_300," "edu_m," and "edu_f.

It is notable that, while the average number of cohorts in which the indicators are present is 4.2, this number rises to 5.4 for the top 10 ranked indicators, and even 6.2 for the top 5; The indicator "sex" is for instance tested on the seven cohorts. This is logical, as indicators expected to yield the best results

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based on state-of-the-art knowledge are more likely to be tested across multiple cohorts. However, this also limits the influence of the inference method on the results. The only notable exception is the indicator "n_rooms", which was tested in only one cohort yet ranked 9th across all cohorts (it was ranked 3rd in the single cohort where it was tested, PIAMA), illustrating the "conservative" nature of the inference method. These findings tend to reinforce confidence in the results obtained across all cohorts.

Discussion

The proposed method allows for the selection of indicators tested on different cohorts, while inferring indicator values for cohorts where they have not been tested. This is suitable for this dataset, in which 40% of the indicator values are inferred. However, in cases where the number of inferred indicator values is greater, the results may lose consistency. A limitation of this method is that it does not account for the redundancy of information between indicators. Indeed, the random forest algorithm tends to penalize two correlated indicators, as the importance attributed to each indicator can be lower compared to a situation where only one of them is present. This could be taken into account in the inter-cohort ranking model by using a graph-based approach, defining a strong attractiveness for pairs of highly correlated indicators. This weight can be defined by expert knowledge.

For ADHD, all of the importance ratings in Figure 23 are included in the graph analysis.

5.2.3. Potential relevance from literature

A detailed literature review on studied and known relationships between exposome and wellbeing, mental health, and cognitive development can be found in D1.2.

Already anno 2000, Stansfeld et al. [66] reviewed effects of noise on mental health in children and concluded that evidence was poor and advised amongst others to include detail noise measurements and more targeted populations in future studies. The 2018 WHO review on effects of noise concludes that there is insufficient evidence for including mental health as an outcome [67]. Most studies in the review are however based on calculated L_{night} or L_{den} as exposure indicators.

A more recent review [68] explores the stress-brain path towards mental health and compares these mechanistic findings to epidemiologic research. They conclude that the effects are weak. But the combination of epidemiological evidence with a clear mechanism, gives us confidence in the relationships studied: L_{den} versus anxiety and depression at the one hand and L_{den} and SDQ at the other. The significance of trends tends to be higher for aircraft noise. Unfortunately, also this review does not consider indicators not grounded in an equivalent level. It can nevertheless be observed that aircraft noise is by definition governed by noise events. At high noise exposure levels L_{den}>70 dB, effects on SDQ, cognition, and behaviour problems in preschool children become more significant as shown in a Brazilian study [69]. Calculated intermittency ratio (IR) and number of noise events were added to a study on problem behaviour in adolescents in [70]. However, significant effects were only found for the relationship between L_{den} and SDQ-peer, yet it remains unclear how accurately IR and number of events were calculated and how these were accumulated over day and night.

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Noise exposure can also be assessed via self-reporting. Such studies usually show a consistently higher relative risk for mental health [71]. This could indicate that the calculated noise exposure indicators are not accurately representing the perceived exposure, e.g. because indoor levels are not considered, because the L_{den} indicator is not appropriate, or because the noise model is not precise enough. This would advocate the use of indicators and models that more accurately predict perceived noise exposure. However, there could also be an underlying treat that influences both mental health and environmental noise perception. Indeed, high noise sensitivity was associated with several mental health outcomes in Lim et al. [72]. Reported poor sleep quality (not necessarily induced by noise) might also affect the relationship between noise and mental health outcomes [73].

In the absence of literature directly relating more advanced noise indicators to wellbeing, mental health and cognitive development in children, we can also rely on the pathways studied in Equal-Life: stress and restoration [74], and sleep quality. Thus we explore the use of new metrics for noise exposure that have been related to these pathway variables.

Effects of noise on sleep in children and adolescents have recently been studied extensively [75][76][77][78][79][80][81][82], yet very often exposure in an epidemiologic context is rather low. Most studies rely on calculated traffic L_{den}, L_{dn}, or L_{night}.

Table 10 Summary of evidence from literature included in the graph analysis

relationship	start variable(s)	end variable(s)	strength	belief
L_{den} → SDQ	RES_RT_Lden_ch_t, RES_RW_ Lden_ch_t, RES_AIR_Lden_ch_t	ASQ Total Difficulties Score	0.1	0.2
noise annoyance → mental health	Annoyance interference restoration score	?	0.2	0.1
L_{den} → noise annoyance	RES_RT_Lden_ch_t, RES_RW_ Lden_ch_t, RES_AIR_Lden_ch_t	Annoyance interference restoration score	0.2	0.5
L_{den} → sleep	RES_RT_Lden_ch_t, RES_RW_ Lden_ch_t, RES_AIR_Lden_ch_t	insomnia	0.1	0.3

5.3. Analysis of the graph

The graph analysis software Gephi is used to analyse the connections between indicators and effects. Edges represent relationships between exposome indicators individually and between indicators and effects. These edges are directional for relationships between exposome indicators that relate a driving

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force to a state or a state to an impact[4]. They are also directional if they represent a relationship between an exposome indicator and an effect indicator. Correlations between indicators result in undirectional edges. Figure 24 introduces a first view on the representation. Road traffic noise indicators introduced in this deliverable cluster in the center of the graph due to their multiple correlations. The driving forces, mainly the presence of roads float around this tight cluster. The direct relationship to insomnia, SDQ (Strength and Difficulties Questionnaire), and ROO (Rate of Occurrence of Offense) lead to multiple connections within this cluster. Through the noise indicators used in the cohorts (RES_RT_Lden_ch_t, RES_RT_Lden_mr_t) and presence of roads and major roads, a connection emerges to other effect indicators such as ADHD (Attention Deficit / Hyperactivity Disorder) (Figure 25).

Formally analysing the communities that occur in the knowledge graph shows - not surprisingly - that all indicators for road traffic noise at home belong to the same community but so do the distance to and length of roads and major roads. Eigenvector centrality places all noise indicators central (EC>0.95) except for ARP (EC=0.87) and EPEl and EPEm (EC=0.45 and EC=0.73 respectively). Using a *ForceAtlas* algorithm with *gravity=5* and weigt *influence=10*, where the weight is the strength of the association, sibclasses in the noise indicators can be observed Figure 24. It shows that SDI and Laeq-based indicators for the most and the least exposed façade respectively form sub clusters. Indicators for restorativeness of the home environment also tend to cluster. The latter are also closer to the presence of major roads at some distance, which is completely in line with expectations.

Although the random forest results based on 7 cohorts for predicting ADHD did not include the indicators, indirect evidence of relevance can still be obtained from the graph. The potential relevance of an indicator can be estimated based on a direct relationship between a wellbeing, mental health or cognitive development indicator, but also indirectly because of a proven link to an intermediate indicator. As ADHD is a well-studied diagnose in the cohorts, this variable is first analysed. To this end, ADHD is fixed as an outcome indicator and only indicators that are connected via at most one intermediate indicator are retained. After reorganising the graph using the gravity algorithm, Figure 25 is obtained. Most new noise indicators remain connected via either road traffic Lden (RES_RT_Lden_ch_t, noise_road) or major road length (mj_road_length, …), which indicates their potential relevance for this mental health outcome.

[4] The DPSIR framework is used for this categorization.

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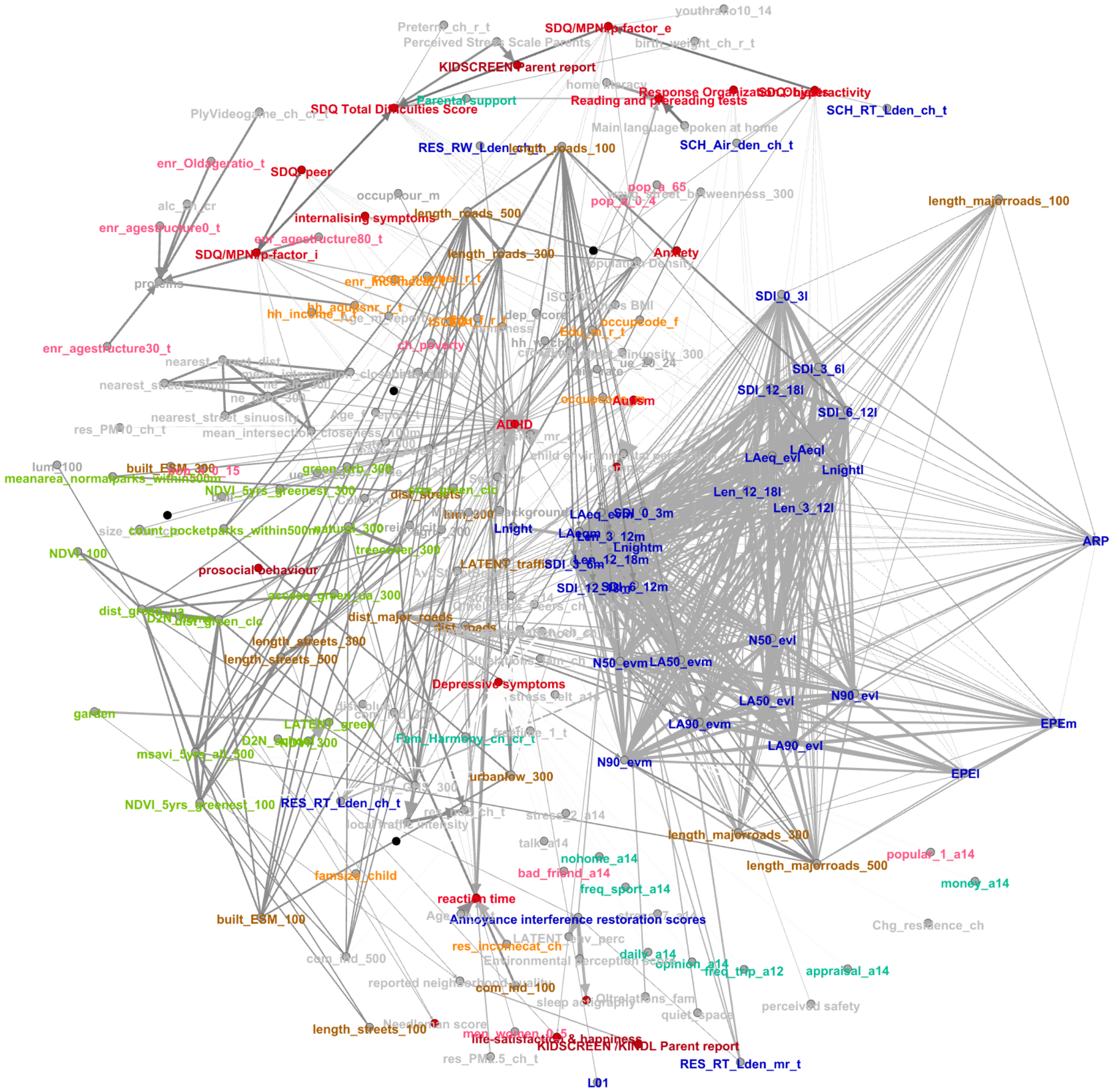

Figure 24 graph representation of the indicators and their connections highlighting noise indicators in blue text and nodes corresponding to effect indicators as red dots.

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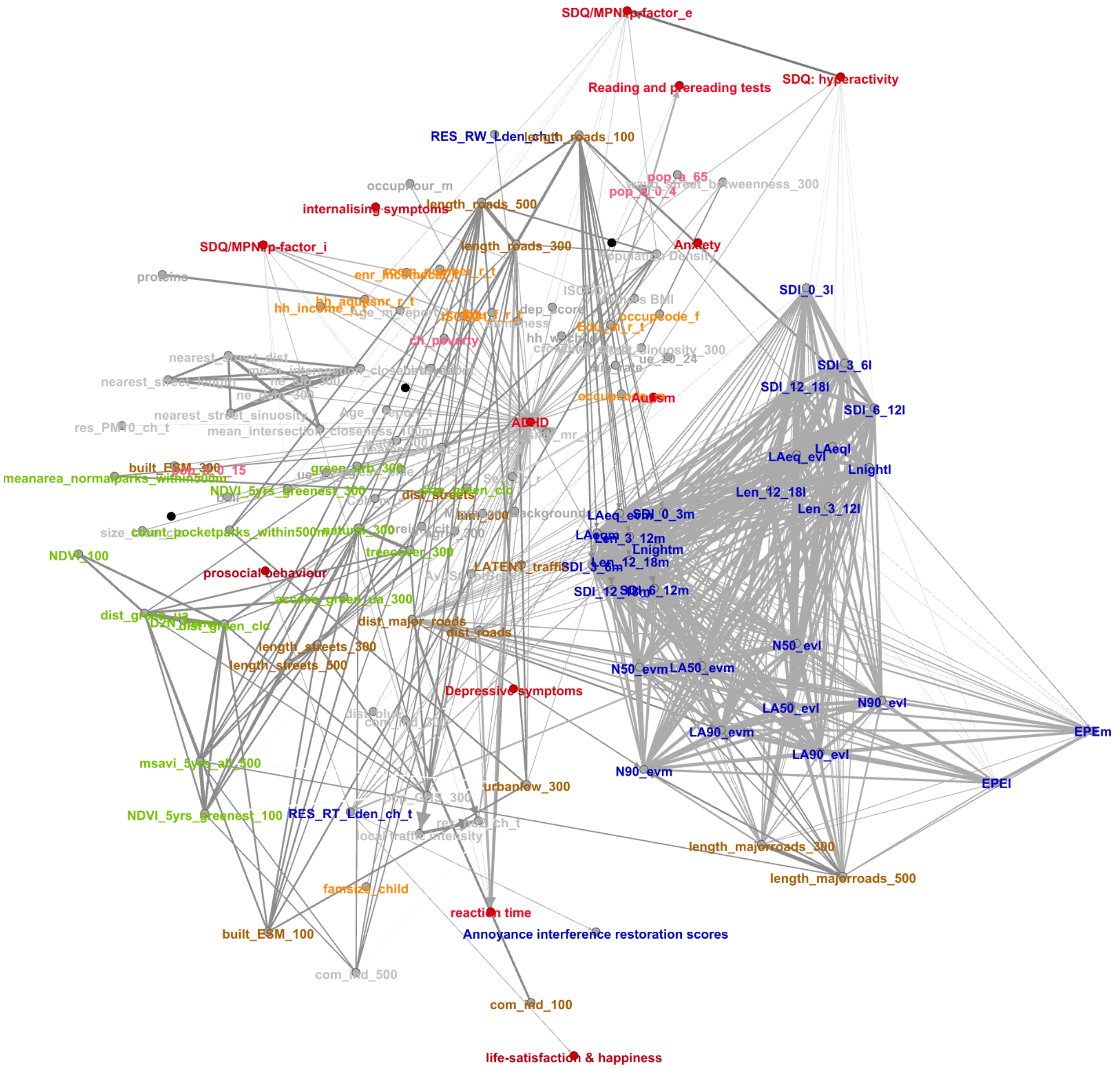

Figure 25 graph representation of the indicators connected to ADHD in second order, that is by direct evidence or by evidence relating the indicator and ADHD to at least one common indicator.

6. Software for calculating new metrics

Two software codes are made available: (1) the surrogate model for calculating advanced road traffic noise indicators in Table 3; (2) the calculation of indicators and clustering based on 1/3 octave band measurements with 125ms resolution.

The code is available on Github: [waves-acoustics/Equal-Life_noise: Horizon 2020 Equal-Life project data-driven and hybrid models for new metrics for noise exposure related to mental health (D3.6)]()

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The surrogate model (1) is purely based on Open Streetmap (OSM) data and can thus be run everywhere in Europe and beyond. The outcome will nevertheless be influenced by the local accuracy of OSM. It is most efficient to run the code for a group of receiver points in a region or large city. Using it for producing maps is sub-optimal as it is assumed that all receivers are connected to a dwelling. CPU-time needed depends largely on the density of buildings and streets around the receiver points. This code has been tested on all cohorts in Equal-Life. Instructions for use can be found in the README file.

The clustering model (2) contains two parts: (a) a python script for calculating a multitude of noise indicators based on the spectral measurements. Some code adaptation is needed to accommodate for the formatting of the measurement file (CSV file, excel file) produced by your measurement equipment. (b) an assignment of your measurement to one of the clusters obtained in this work. This code should be seen as a step in future research as the relevance of the clusters on large datasets has not been established due to the lack of broad noise measurement campaigns combined with wellbeing, mental health, and cognitive development assessment.

7. Overall conclusion and outlook

This deliverable addressed the challenge of characterizing environmental sound at home in a manner relevant to the mental health, well-being, and cognitive development of children—the primary focus of Equal-Life. Evaluating the relevance of novel sound environment indicators remains complex; traditional metrics such as L_{den} and L_{night} have been widely used due to their *transparency* and *practical applicability*, and much of the existing evidence, where available, pertains to these indicators. However, our findings demonstrate that more specifically tailored indicators, designed with pathways and a priori hypotheses regarding noise effects, may exhibit stronger predictive value for certain outcomes, including SDQ, KINDL, cognitive development, and attention, thus leading to indicators with higher *validity*. In this report, simple correlation analyses were conducted to explore these relationships, with more sophisticated analyses deferred to relevant work packages. Notably, the findings suggest that specific noise indicators may hold greater relevance for particular subcomponents of scales like SDQ and KINDL.

Cluster analysis of sound measurements taken at the bedroom windows of children during in-depth studies in WP1—5-7-year-olds in the preschool study in Ghent and 18-year-olds in the sleep study in Gothenburg—revealed that the majority of 15-minute epochs could be categorized as representing a tranquil urban sound climate. The remaining clusters were either common across locations, often tied to specific times of the day, or identified as distinctly disturbing location. A similar cluster analysis of indoor measurements (bedrooms of 18-year-olds) indicated that the indoor sound climate is minimally influenced by the outdoor sound environment, with only a small proportion of indoor clusters showing a relationship to outdoor noise indicators. Further analyses, which linked indoor and outdoor sound events by estimating brute sound insulation, confirmed that indoor sound events rarely have a direct external origin. These findings suggest that a commonly used linear regression approach between outdoor noise levels and sleep quality may not be suitable. However, it is important to note that these measurements were conducted in a Nordic country, where high thermal insulation—and consequently

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high acoustic insulation—could significantly influence the results. Thus, these conclusions regarding the indoor sound climate may not be generalizable across other EU regions.

The analysis of measurements highlighted the significance of diurnal patterns, prompting the exploration of more specific indicators tailored to children's daily activities. The Equal-Life machine-learning-based surrogate model for advanced road traffic noise indicators provides hourly values for metrics such as the number of events exceeding a threshold and L_{A50} (refer to Section 4.1 for a comprehensive list). These hourly indicators can be aggregated in various ways over a 24-hour period, depending on the child's age and activity schedule. Based on a priori considerations, several potentially relevant configurations were proposed to complement the Equal-Life indicators, SDI and ARP. All these indicators are calculated using the surrogate software, which has been made available to the research community. The models can be applied in various contexts depending on the data at hand: using local traffic data when available, the Equal-Life traffic model from D3.2, or the default configuration based on OpenStreetMap (OSM). For the development of the latter, a hybrid approach was employed. Measurements taken at the most exposed façade were used to infer the relationship between OSM road type, connectivity, and traffic intensities. The resulting "pseudo-traffic intensities" represent plausible traffic estimates derived from the observed measurements.

From an exposome perspective, the variety of noise indicators must be contextualized within their broader environment. Traffic noise indicators, for example, are linked to metrics characterizing neighbourhood activities, such as proximity to major roads, road network connectivity, and the degree of urbanization. They are also associated with indicators of co-exposures driven by similar underlying factors, such as NO_2 levels or perceived traffic safety. However, accidental correlations may arise within specific areas or populations, complicating interpretations. To address this complexity, a knowledge graph was introduced as a tool for systematically mapping and exploring relationships. By integrating all known associations into the graph, researchers can examine multiple interactions and dependencies from various perspectives. In this deliverable, knowledge from D7.2 regarding one outcome—ADHD—was combined with relationships identified from a specific group of exposures: home sound environments. The introduction of the knowledge graph partly compensates for the possible critique that only simple Spearman correlation is used to show the potential validity of some of the new indicators. From an exposome perspective, it is not crucial to identify the specific exposure paths that influence outcomes. This approach can be extended in the coming months to incorporate additional exposome components and outcomes, broadening the scope of the analysis.

By integrating our insights into the effects of noise exposure and proposing novel metrics, alongside providing software for their efficient calculation, we anticipate that researchers beyond the current Equal-Life consortium will engage in broader investigations of noise effects. This collaborative effort has the potential to overcome the limitations outlined in the initial discussions and advance the understanding of noise-related impacts on health and development.

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