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U-Space Social and Environmental Performance Indicators

Tatjana Krstić Simić [1,*], Emir Ganić [1], Bojana Mirković [1], Miguel Baena [2], Ingrid LeGriffon [3] and Cristina Barrado [4]

[1] Faculty of Transport and Traffic Engineering, University of Belgrade, 305 Vojvode Stepe, 11000 Belgrade, Serbia; e.ganic@sf.bg.ac.rs (E.G.); b.mirkovic@sf.bg.ac.rs (B.M.)
[2] Nommon Solutions and Technologies, 4 Pl. Carlos Trías Bertrán, 28020 Madrid, Spain; miguel.baena@nommon.es
[3] DAAA, ONERA, Institut Polytechnique de Paris, 92322 Châtillon, France; ingrid.legriffon@onera.fr
[4] Computer Architecture Department, Technical University of Catalonia, 7 Carrer d'Esteve Terradas, Castelldefels, 08860 Barcelona, Catalunya, Spain
* Correspondence: t.krstic@sf.bg.ac.rs; Tel.: +381-11-3091-231

Abstract: The social potential of Urban Air Mobility (UAM) as a greener and faster transportation system in and around urban environments is indisputable. Nevertheless, the success of UAM introduction and its wide use will strongly depend on acceptance by the citizens and future UAM users. The impact on overall quality of life, as a multidimensional concept that encompasses physical health, mental and emotional well-being, economic status, education, and the environment, is becoming a significant issue. This paper aims to describe the performance framework for the assessment of the social and environmental impact of UAM. The specific objectives are to identify the full range of UAM's impacts on citizens' quality of life and to propose a set of indicators that enables the quantification and assessment of the identified impacts. Firstly, the main issues (focus areas) were identified, namely, noise, visual pollution, and privacy concerns, followed by access and equity, economic aspect, emissions, public safety, and impact on wildlife. In the next step, for each identified focus area, performance indicators were defined along with the several cross-cutting areas for a geographical, temporal, demographic, socioeconomic, and behavioral resolution. The proposed performance framework could enable more efficient mitigation measures and possibly contribute to wider adoption of the UAM operations.

Keywords: Urban Air Mobility; social acceptance; environment; drone; Unmanned Aircraft; performance indicators

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1. Introduction

A new air transport concept, known as Innovative Air Mobility (IAM) or Advanced Air Mobility (AAM), aims at bringing the transportation of people and goods to the sky. Enablers of this rapidly emerging transport services are new electric aircraft taking off and landing vertically, piloted remotely or with a pilot on board, and developing towards fully autonomous aircraft in the future. Urban Air Mobility (UAM) is the subset of IAM operations conducted within urban environments. According to EASA, UAM is "a new safe, secure and more sustainable air transportation system for passengers and cargo in urban environments, enabled by new technologies and integrated into multimodal transportation systems" (https://www.easa.europa.eu/en/what-is-uam accessed on: 19 September 2024). It encompasses delivering goods by drones (Unmanned Aircraft—UA, also Unmanned Aerial Vehicles—UAVs and Unmanned Aerial Systems—UASs, when air vehicles are considered together with communication, command, and control systems) and the transport of passengers with larger electric-powered Vertical Take-Off and Landing aircraft (eVTOL, also VTOL Capable Aircraft—VCA), including for medical or emergency purposes. Apart from these three key use cases, the aerial services may extend to surveillance, inspections, mapping, rescue, and firefighting, as well as other services that can be performed by UAs or eVTOLs.

It is foreseeable that UAM operations could start in next few years, and numerous studies are being directed towards creating the necessary conditions for the successful implementation of UAM operations, involving safety and security, environmental impact, and public acceptance. UAM, as a new air transportation system, offers the potential for greener and faster mobility of passengers and cargo in and around urban environments. UAM is designed to improve the current system by utilizing the airspace above congested urban areas, thus reducing pressure and reliance on ground-based infrastructure, rather than replacing the existing means of transportation. Although the potential societal benefits of UAM are indisputable, the success of UAM introduction and its widespread use will strongly depend on the confidence of and acceptance by the citizens and future UAM users.

The European Union Aviation Safety Agency (EASA) conducted a comprehensive study in 2021 on the societal acceptance of UAM operations. The survey results were highly uniform across the EU, but also showed that user diversity strongly influences both acceptance and perceived hindrances. EU citizens generally have a positive attitude towards UAM, where the notion of public interest contributes significantly to the acceptance (e.g., medical or emergency transport or connecting remote areas), expecting faster, more environmentally friendly and better connectivity. However, citizens strive to limit their own exposure to safety, noise, security, and environmental impacts, and so they engage in and play an active role in UAM implementation. The results clearly indicate that the integration of UAM must respect citizens' quality of life [1].

Quality of life refers to the overall well-being and satisfaction that individuals experience in various aspects of their lives. It is a multidimensional concept that encompasses physical health, mental and emotional well-being, social relationships, economic status, education, and the environment. Different people and cultures may prioritize these dimensions differently, but together they contribute to an individual's or a community's overall sense of happiness, fulfilment, and contentment [2,3]. Quality of life is often assessed through surveys and indices that consider a range of indicators to measure and compare the well-being of individuals or communities [4].

Current UAM performance frameworks include different indicators related to a number of issues (such as noise and gas emissions, visual pollution, safety, security, access and equity, and economic issues) in order to evaluate UAM's environmental impact (discussed in the following sections). However, they are still too generic and aggregated to properly capture the broad variety of impacts of UAM operations.

To capture the full range of UAM's impacts on citizens' quality of life, a set of U-space social and environmental performance indicators (PIs) is proposed in this research (some of which can be found in the literature, while some are newly proposed). The aim was to capture the highest possible level of geographical, temporal, demographic, socioeconomic, and behavioral resolution, in order to enable the analysis of the interaction between UAM impacts and factors, such as, for example, age, gender, place of residence, level of income, and occupational status. For that purpose, a list of so-called cross-cutting areas (with related sub-areas) is introduced. The presented performance framework is developed under the MUSE (Measuring U-space Social and Environmental Impact) Project.

Section 2 provides a systematic literature review of academic and non-academic studies, reports, and project deliverables to identify the most relevant UAM impacts on citizens' quality of life and classify them according to their nature. The proposed set of novel and updated U-space social and environmental indicators for the proposed focus areas, as well as the usability and influence of the cross-cutting factors (geographical, temporal, demographic, socioeconomic, and behavioral) on the proposed indicators, are introduced in Section 3, complemented with the measurement mechanisms provided in Appendix A. The final section summarizes the work carried out and the main conclusions.

2. UAM Impacts on Citizens' Quality of Life and Their Assessment

A comprehensive literature review was conducted, and over 70 publications covering the definition and conceptualization of quality of life or social acceptance and references addressing one or more specific areas of impact of UAM operations are included in this analysis.

Quality of life in general is discussed in [1,5–9], while Europeans' quality of life is assessed through the surveys conducted by the European Foundation for the Improvement of Living and Working Conditions [10] and by EUROSTAT indicators related to the overall quality of life [11].

Thirty-eight reviewed references—[1,6–9,12–44] (Table 1)—cover the conceptualization of the social acceptance of UAM. Almost half of them (18) mention particular areas of impact, like noise or privacy concerns, while others define general aspects of the social impact.

Based on the reviewed publications, UAM impacts were classified based on their nature into the following categories: social acceptance, noise [1,5,6,12,14,17,21,23,24,34,37–39,42,45–62], visual pollution [1,5,14,17,19,23,24,34,37,42,61,63], privacy concerns [1,5,12,14,17,19,23,24,34,37,64,65], access and equity [5,14,19,24,25,37,38,59], economic aspects [5,16,24,34,35,59,66], emissions [5,19,37,59,66,67], and other (environment, safety, security, costs, wildlife, etc.) [1,5,12,14–17,19,21,23–25,34,35,37–39,56,59,61,64,66,68–71] (Table 1). Most references are not limited to one field of impact.

Table 1. Areas of interest and approach for assessment of UAM impacts.

Nature of Impact	No. of Publications	Qualitative Assessment	Quantitative Assessment	Review Paper	Discussion Paper
Social acceptance	39	[1,12–14,16,22,24,26,30–32,34,38–40,42,44]		[8,33,35,36,41,43]	[6,7,9,15,17–21,23,25,27–29,37,43]
Noise	32	[1,5,6,12,14,24,34,38,39,42,45,55,61]	[**5**,6,**24**,**37**,45–47,50,**55**,**56**,**57**,58,**61**]	[49,52,54,60,62]	[17,21,23,48,51,53,59]
Visual pollution	12	[1,5,14,24,34,42,61,63]	[**5**,**24**,**37**,**61**,**63**]		[17,19,23]
Privacy concerns	12	[1,5,12,14,24,34,65]	[**5**,**37**]	[64]	[17,19,23]
Access and equity	8	[5,14,38]	[**5**,**24**,**37**]		[19,24,25,59]
Economic aspects	7	[5,16,24,34]	[**5**,**66**]	[35]	[59]
Emissions	6	[5]	[**5**,**37**,**66**,**67**]		[19,59]
Other (environment, safety, security, costs, trust, wildlife, efficiency, etc.)	26	[1,5,12,14,16,24,34,38,39]	[**5**,**24**,**37**,**56**,**61**,**66**,69]	[35,64,68,70,71]	[15,17,19,21,23,25,59]

Table 1 summarizes references by the area of UAM impact and the approach to assess that impact. The approaches are classified into qualitative (e.g., conducted survey) and quantitative assessment (proposed performance indicators), review, or different impact discussion paper. Review papers provide a literature review on the research related to UAM social acceptance and different areas of UAM impacts (primarily noise), while papers classified as discussion papers consider the significance of those issues, both without a survey conducted or a quantification of those impacts. Bold, underlined reference numbers indicate research with performance indicator definitions and/or calculations. Ten papers with newly proposed or previously defined performance indicator calculations were identified.

Issues of social acceptance of UAM are assessed in the literature qualitatively, e.g., through public surveys and questionnaires (e.g., [14,42,61]) or by proposing and analyzing different objective or subjective measures to capture the benefits and/or negative impacts of UAs and eVTOLs [24,37,55] (Table 1). The results of the conducted surveys show a high level of subjectivity and different perception among the individuals, but some consistencies are also observed. For example, the results suggest that people with greater knowledge, understanding, or personal experience with the use of drones generally become more open to drone usage [61]. Research conducted in the study [42] shows that experiencing drone flights in virtual simulation changes the attitude and concerns of the participants, e.g., participants' worries about noise and privacy related to drones significantly decreased.

Noise, followed by visual pollution and privacy concerns, are the most frequently mentioned negative impacts related to the implementation of UAs and eVTOLs. Visual pollution is mostly mentioned together with noise issues in the context of public perception and UAM acceptance [1,5,14,24,34,42,61].

Different noise metrics and measurement methods could be found in the related research, but there is no consensus upon which measures are the most appropriate for UA noise, since UAs generate noise differently than other vehicles (e.g., airplanes) [61]. Even more, some research papers question the significance of noise generated by UAs, especially with an expected altitude of high-speed operations above 200 ft (≈60 m) [46]. Likewise, the majority of subjective parameters, visual pollution, and privacy concerns are difficult to quantify, and the literature review showed only a few research papers related to the quantification of these issues.

Noise and visual impacts, as two very important areas of interest related to the environmental key performance area (KPA), are evaluated in the research projects DACUS [24] and PJ.19–W2 [37]. Several performance indicators (PIs) related to trajectory and area-based exposure or annoyance are proposed for noise impact calculation, as well as several PIs related to the number of people who reported visible drones or being annoyed by visible drone operations during the day or within an area during a period of time for visual pollution calculation. In the DACUS project, visual pollution and privacy concerns are considered jointly as a single issue.

The AIRMOUR project [61] investigates the public's view on noise and visual pollution by conducting a set of interviews and surveys. The results indicate that the majority of the public is not overly concerned, but there is a portion of people who appraise the impact to be high, even from a single UA or eVTOL. An image-based questionnaire is used in order to learn more about visual pollution. The results show a lot of subjectivity in visual pollution perception by individuals, but some regularities are also observed, such as visual pollution increasing with the number of visible UAs (and that increase is not linear), visual pollution decreasing with increasing distance (of the observer from the visible UAs), and informing people about the purpose of the UA flight resulting in better acceptance of higher levels of visual pollution. Two functions for visual pollution calculation, based on the number and the minimum distance from the visible UAs, as well as on their purposes, are proposed [61].

One of the proposed indicators for the assessment of UAM in a case study of Upper Bavaria is related to noise emissions and is expressed through an index based on emitted dB in a zone divided by the population density in this zone [5]. The indicator related to visual pollution is expressed as an index based on kilometers travelled above a zone, also divided by the population density in this zone. Privacy concerns are considered as the sum of affected dwellings due to take-offs and landings in a buffer area around each vertiport [5].

In the EASA guidelines on the noise measurement of UAs [60], objective noise evaluation metrics are defined based on the A-weighted sound exposure level (L_{AE}) and the A-weighted equivalent continuous sound pressure level (L_{Aeq}) for a hover flight measurement and for the ambient noise, as well as based on the maximum A-frequency-weighted sound pressure level (L_{Amax}). The overall sound pressure level was calculated by using numerical simulation, and the noise footprint was obtained from [47]. Noise measurements of two UAs of different performance (quadrotor and hexarotor) in flying up and down, hovering, and overflight procedures are conducted in [6]. An acoustic flight test was performed on the prototype of an all-electric vertical take-off and landing aircraft, and the results are provided in [58]. The results of a study evaluating the human perception of the noise produced by four different small quadcopter UAs are presented in [55]. The research presented in [57] develops a modelling framework for setting recommendations for drone operations to minimize community noise impact. Maximum noise level (L_{Amax}) and sound exposure level (SEL), as received in typical indoor environments, were used to define drone minimum distance to meet World Health Organization (WHO) recommendations. The effect of UA noise on public health is still not fully understood [52], and a range of other open questions remains to be tackled by future studies.

As seen from Table 1, more often a qualitative approach (survey) has been applied to assess the impact of drones on society and the environment, compared to quantitative measures.

Quantifying the impact of the UAM operations is the only way to move towards their introduction and create a sustainable environment. The aim of our research is to take one step forward towards the definition of a systematic performance framework for quantifying the impact of UA and eVTOL operations. We first define core areas of impact and propose indicators under each area, relying on the existing literature and the experience with social/environmental impact of aircraft operations. Based on the results of the qualitative research, we define cross-cutting/transversal areas that would enable the measured impacts to be disaggregated. There are lower and higher impacted groups, periods, etc. Differentiating between them will allow more efficient mitigation measures to be proposed and possibly contribute to wider adoption of UAM operations.

3. U-Space Social and Environmental Performance Framework

Our approach to developing the U-space social and environmental performance framework consisted of two phases, as presented in Figure 1. In the first phase, we proposed a draft performance framework (see Appendix B) based on the comprehensive literature review described in the previous section. In the second phase, the initially proposed focus areas (FAs) and the related performance indicators for the performance framework were validated.

The stakeholder consultation processes consisted of several activities aimed at validating the developed U-space environmental and social performance framework. The proposed indicators, measurement mechanism, required input data, and calculation methodology/algorithms were validated through the MUSE 1st Stakeholder Workshop, during which several brainstorming sessions were conducted combined with the survey questionnaire for the participants (see Appendix C). In addition, the stakeholder consultation process included a working session with several External Expert Advisory Board (EEAB) members in Madrid and a presentation of the MUSE project and current results at several scientific conferences.

The MUSE 1st Stakeholder Workshop was held on 23 November 2023 at EUROCONTROL's Aviation Learning Centre, Luxembourg. The workshop was organized as part of the AiRMOUR Masterclass 2, which brought together more than 80 experts from various fields, including partners from several projects and initiatives related to MUSE, as well as experts from city authorities, the UAM industry, the medical sector, etc. Among the registered attendees, 33 of them participated in the MUSE 1st Stakeholder Workshop.

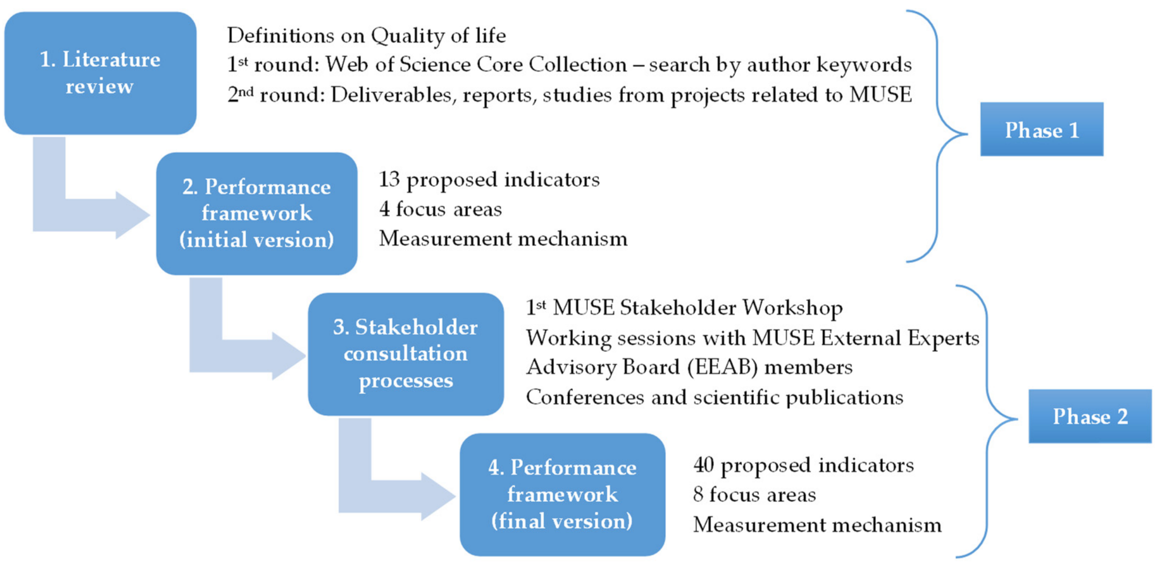

Figure 1. U-space social and environmental performance framework methodology.

Based on the feedback obtained from the workshop participants (through several brainstorming sessions and individual questionnaires), as well as from the EEAB members and other relevant stakeholders, new performance indicators were proposed and the initial performance framework was further upgraded during consortium members' brainstorming sessions.

The performance framework described in this chapter represents the final version, including the feedback from all the relevant stakeholders.

3.1. Focus Areas and Cross-Cutting Areas

The list of proposed focus areas is as follows:

- Noise (NO),
- Visual pollution (VP),
- Privacy concerns (PC),
- Access and equity (AE),
- Economic aspects (EC),
- Emissions (EM),
- Wildlife (WL),
- Public safety (PS).

The chosen FAs are also in line with the SESAR performance framework provided in the PJ19-W2 [37]: SESAR Performance Framework U-space Companion Document and the related projects (DACUS [24], AiRMOUR [61], etc.). For each of the given FAs, the related PIs have been proposed and defined (Section 3.2).

While creating indicators, it is important to keep in mind that people's subjective perceptions of quality of life differ amongst individuals and across cultural boundaries. Previous research has discovered that some demographic parameters, such as gender, age, socioeconomic status, occupation, annual income, industry, nature of work, and educational qualification, are related to public acceptance of drones [1,22,34]. For example, compared to older people, younger people are often more inclined to utilize emerging technologies. Furthermore, females were found to be more frightened about autonomous robots and artificial intelligence [22]. The level of urbanization can affect visual pollution, since people reported being more visually annoyed by drone operations in rural areas compared to urban areas. The purpose of flying should also be considered when analyzing the impact of UA operations on the population, since public acceptance is higher for medical purposes, infrastructure surveying, and emergency transport compared to delivery of goods and passenger transport.

In order to encompass all the aforementioned influences and subjectivity, a rigorous assessment of UAM's social and environmental impact requires a comprehensive indicator system that provides the highest possible level of spatial, temporal, demographic, socioeconomic, and behavioral resolution. Besides the PIs, a list of possible cross-cutting areas is proposed. All the indicators proposed can be combined with different cross-cutting areas in order to enable the analysis of the interaction between UAM impacts and factors such as age, gender, place of residence, level of income, occupational status, etc. Such an approach can generate hundreds of different indicators that could be tailored to the specific challenges and needs of various communities.

Keeping in mind all the aforementioned dependencies, as well as feedback obtained from relevant stakeholders, the proposed indicators should take into account in the cross-cutting areas presented in Table 2. Different cross-cutting areas could also be combined for some indicators. The usability and influence of the proposed cross-cutting areas on the proposed indicators could vary among communities, stakeholders, or scenarios.

Table 2. Cross-cutting areas.

Cross-Cutting Area	Sub-Area	Factor
Geographical	Level of urbanization Land use Purpose of use of the facility	Urban, suburban, rural Recreational, residential, industrial, commercial Hospital, school, sports venue, military, industry, governance
Temporal	Time Day Season	Morning, evening, night, school time, work time Weekday, weekend Winter, spring, summer, autumn
Purpose of flying	Purpose of flying	Delivery of goods, medical, infrastructure surveying, emergency transport, passenger transport
Demographic	Age Gender	Age groups (<25, 25–44, 45–64, >65) Female, male, other
Socio-economic	Occupational status Income level	Employed, unemployed, student, pupil, retired Low, average, high
Phase of flight	Phase of flight	Take-off, landing, cruise, hover
Activity type	Activity type	Home, work, education, other

3.2. Performance Indicators

The proposed indicators are, as already mentioned, designed so as to enable the maximum possible level of geographical, temporal, demographic, and socioeconomic resolution. This enables the analysis of the interaction between UAM impacts and factors such as age, gender, place of residence, level of income, occupational status, etc., as well as the aggregation and evaluation of UAM's impact at different spatial scales (e.g., neighborhood, municipality, metropolitan area) for different time periods (e.g., daytime vs. night-time, working days vs. weekends) and along different dimensions (e.g., impact on different population groups).

While most of the proposed indicators have one dimension, some are composite indicators, representing a mathematical combination of individual indicators that represent different dimensions of a concept being measured. The purpose of composite indicators is to provide a comprehensive overview or summary measure that reflects the multidimensional aspects of the concept under consideration. It should be noted that presenting only aggregated information might result in the loss of relevant details about the number of people affected. For instance, a certain composite indicator could yield a result of 1000, but it could represent either one event affecting 1000 people or 1000 events with a single person affected. From the perspective of UAM acceptability, knowing the precise number of people affected seems crucial. Therefore, it is pivotal to combine indicators measuring affected people with those measuring the composite effects, which will allow multidimensional aspects of UAM's impacts on the population to be captured. If needed, all proposed composite indicators can be transformed into one-dimensional indicators by setting various thresholds established by additional parameters, such as the number of events, duration, etc.

The following subsections detail the indicators per focus area. The origin of each PI is provided, indicating whether the PI is newly introduced by the MUSE project, modified from a previous study, or adopted from an existing study. For the five main focus areas, more detailed descriptions and measurement mechanisms of the proposed PIs are provided in Appendix A.

3.2.1. Noise

Noise is the most addressed negative effect related to the UAM implementation. UA noise is an environmental noise characterized by high frequencies and high tonality.

Noise pollution has both physiological (physically measurable causes and effects) and psychological (subjective) elements [61].

Taking into account all perceptions, the mechanisms by which aircraft noise affects citizens are likely to be very diverse. Previous research has shown that it is important to distinguish between acoustic and non-acoustic factors. The most important acoustic influence factors are identified [24]: event number and spacing, event duration, sound pressure level, temporal and spectral characteristics of the sound, etc. Non-acoustic factors, recognized as those with the highest influence, are [24] ground environment (population density, land use), (personal) noise sensitivity, local activity, and time of the day.

Many different metrics and measurement methods for noise could be found in the related research. Still, there is no consensus on which measures are the best for UA noise, since, compared to other transportation modes (e.g., airplanes), UA noise signatures are very characteristic due to dissimilar noise generation mechanisms [61] and very different operational conditions (hovering, low altitude flying, etc.).

Taking into consideration all the aforementioned points regarding the noise impact of UAs on the population, seven performance indicators are proposed within the noise FA, as presented in Table 3.

Valuable comments and suggestions were provided during the stakeholder consultation process, and the majority of them have been incorporated in the proposed indicators. However, some of the "remaining" comments could indicate directions for future research, such as:

- The interaction between noise levels, time of exposure, and exposed people's "acceptance" of the given noise could be considered in order to obtain acceptance thresholds (e.g., low noise levels may be accepted by more people during longer periods and high noise levels only during short periods).
- Furthermore, the noise indicators should include the notion of human annoyance and not only be based on acoustic, objectively measurable, metrics. In order to do so, noise annoyance curves are needed to indicate the relationship between objective noise levels (integrated and/or event-based) and an annoyance measure (such as the number of highly annoyed people, for example). The creation of these curves is, however, very localization-dependent and requires multiple studies with field surveys and laboratory listening tests to hopefully yield realistic numbers.
- Sharp changes in noise level (when the drone noise exceeds a predefined acceptable level) can have a greater impact on noise perception than exposure to a constant level of noise).
- Most noise indicators refer to outdoor noise levels. Sound insulation could result in the fact that people indoors are exposed to only a fraction of the outdoor sound, and the thresholds could differ from the outdoor ones.
- The correlation of noise, visual pollution, and privacy should also be addressed.

Temporal, geographical (especially land use and purpose of use), and purpose of flying were identified (by the relevant stakeholders) as the most important cross-cutting areas for the proposed noise indicators.

Table 3. Noise PIs.

Performance Indicator	Unit	Description	Source
NO-1: Area-based people's exposure to noise (L_{Aeq})	person	The number of people exposed to an equivalent noise level higher than a certain threshold in dBA for a fixed period of time within an area.	Modified U.NOI2, Area-based exposure, [37]; Modified SOC2, Area-based noise exposure [24].
NO-2: Area-based people's exposure to day–evening–night noise level (L_{den})	person	The number of people exposed to a noise level higher than a certain threshold in dBA over a whole day (24 h) within an area.	Modified U.NOI2, Area-based exposure, [37]; Modified SOC2, Area-based noise exposure [24].

Table 3. *Cont.*

Performance Indicator	Unit	Description	Source
NO-3: Trajectory-based people's exposure to noise (L_{AE})	person	The number of people exposed to a sound exposure level higher than a certain threshold in dBA for a single drone operation for a time period fixed by the drone trajectory within an area.The same can be carried out for a single drone operation for NO-1.	Modified U.NOI1, Trajectory-based exposure [37]; Modified SOC1, Trajectory-based noise exposure [24].
NO-4: Area-based person–event index	N. person	The number of events N exceeding a certain noise level in dBA multiplied by the number of people exposed over a fixed period of time within an area.	MUSE; Person–Event Index detailed in [72].
NO-5: Duration of area-based people's exposure to noise	D. person	A certain duration D of noise levels exceeding a certain threshold in dBA multiplied by the number of people exposed over a fixed period of time within an area.	MUSE
NO-6: Area-based people's exposure to event emergence	dB. person	Difference between the noise generated by the overflying drones and local background noise level multiplied by the number of people exposed over a fixed period of time within an area.	MUSE; Sound Emergence detailed in [73].
NO-7: Area-based intermittent exposure to noise	%. person	The number of people multiplied by the ratio of intermittent and continuous sound (Intermittence Ratio) over a fixed period of time within an area.	MUSE; Intermittence Ratio detailed in [74].

3.2.2. Visual Pollution

According to the general definition of visual pollution as a negative impact that an individual may experience by viewing a visual pollutant and its movement, where a visual pollutant is defined as "any object or artificial structure that degrades visual quality or distracts the individual, i.e., a subjective experience for each observer" [61], a UA or an eVTOL may be considered a visual pollutant. Visual pollution is a psychological issue [61]. As mentioned in Section 2, visual pollution is difficult to quantify (being a subjective parameter), and a small amount of research deals with the given issue.

The DACUS project categorizes visual pollution influence factors as those related to the operational management of the missions: the number of flights overhead, hovering time overhead, height and ground environment (population density, land use), and those related to the technical characteristics of the drone system, such as the size of the drone and its configuration [24].

This research proposes nine performance indicators within the visual pollution FA, as listed in Table 4.

Future research should address several remarks and suggestions raised by relevant stakeholders, namely:

- An initial acceptable visual pollution threshold should be established; even the acceptable level will change over time (people's reaction will probably change after the "novelty" aspect fades away). Virtual reality simulation is also (besides surveys and interviews) one of the possibilities to determine the threshold, i.e., acceptable level of visual pollution.
- The "visible area" should be clearly defined, whether it considers only the visible area of the sky or buildings as well. Since visual pollution is a relatively new field of study, there is a need to measure and collect more data to be able to make reliable predictions of the impact of UAM visual pollution for different geographical areas with different demographic and socio-economic population profiles.
- The relation between visual pollution and privacy concerns should be investigated.

The following areas are recognized as the most relevant cross-cutting areas for the proposed visual pollution indicators: temporal, geographical (level of urbanization), demographic (age groups), and socio-economic (occupational status).

Table 4. Visual pollution PIs.

Performance Indicator	Unit	Description	Source
VP-1: Trajectory-based people exposed	person	The number of people exposed to a single drone operation, i.e., the sum of individual persons that are able to see the drone.	Modified U.NOI5, Visual trajectory-based exposure [37]; Modified SOC5, Trajectory-based visual pollution exposure [24].
VP-2: Trajectory-based people exposed by concentration threshold	person	The number of people exposed to a visual pollution concentration * higher than a threshold for a single drone operation.	MUSE
VP-3: Trajectory-based people exposed by temporal and concentration threshold	person	The number of people exposed to a visual pollution concentration * higher than a threshold for a period longer than T for a single drone operation.	MUSE
VP-4: Trajectory-based visual exposure	person. vp. h	Total visual pollution exposure perceived by the people exposed to a single drone operation.	MUSE
VP-5: Area-based people exposed	person	The number of people exposed to UAM traffic within an area.	Modified U.NOI6, Visual area-based exposure [37]; Modified SOC6, Area-based visual pollution exposure [24].
VP-6: Area-based people exposed by concentration threshold	person	The number of people exposed to a visual pollution concentration * higher than a threshold at least once a day within an area.	MUSE
VP-7: Area-based people exposed by temporal and concentration threshold	person	The number of people exposed to a visual pollution concentration * higher than a threshold for a period longer than T along the day within an area.	MUSE
VP-8: Area-based visual exposure	person. vp. h	Total visual pollution concentration * perceived by the people exposed to UAM traffic within an area.	MUSE
VP-9: Visual exposure per kilometer	person/km	Kilometers traveled above a zone multiplied by the population density in that zone.	Modified “Visual pollution” [5].

* One of the proposed visual pollution concentration calculation methods is adapted from the AiRMOUR project [61]; see Appendix A.

3.2.3. Privacy Concerns

Privacy concerns are related to visual pollution and noise issues; namely, seeing drones (visual pollution) and being seen by drones (privacy concern) are reciprocal. Hearing drones could influence privacy issues twofold: Hearing some noise could trigger some concerns, as could not hearing the drone. If one can hear the drone, it is better to see it, too.

The purpose of the drone and its equipment (primarily with/without an onboard camera) will probably have an impact on people’s perception, but this requires further analysis. Again, people typically have no information about a drone’s equipment, and it is much more likely that they will always expect a drone to have a camera.

As for visual pollution, privacy concerns related to UAM exposure are a relatively new field of study, and there are not many studies that deal with this issue in depth. Mostly, its importance is mentioned. There is a need to conduct surveys and interviews to collect more data to be able to establish an interdependency between privacy concerns and different UA exposure characteristics.

Five performance indicators are defined within the privacy concern FA and are presented in Table 5.

The general stance of the stakeholder consultation process was that the extent to which the citizens are informed about the UAM operation is pivotal. Transparency and trust towards authorities (i.e., when they ensure that privacy is respected) are essential in mitigating this issue. An application that shows the purpose of drones flying may mitigate the anxiety related to drone operations. This is certainly an issue that should be addressed.

The following cross-cutting areas have been recognized as those with higher importance for the given focus area: phase of flight (the impacts on privacy are more likely to occur during take-off and landing, as well during hovering), geographical/land use in combination with temporal cross-cutting areas, and demographic/gender base (e.g., women might be more concerned than men about privacy).

Table 5. Privacy concern PIs.

Performance Indicator	Unit	Description	Source
PC-1: Trajectory-based people visually annoyed	person	Total number of people annoyed by (the presence of) a single drone operation.	Modified U.NOI7, Visual trajectory-based annoyance [37]; Modified SOC7, Trajectory-based visual pollution annoyance [24].
PC-2: Trajectory-based people exposed to hovering drones	person	Total number of people visually exposed to a hovering drone at a distance less than a certain threshold for a single drone operation.	MUSE
PC-3: Area-based people visually annoyed	person	Total number of people annoyed by the presence of UAs within an area during an observed time period.	Modified U.NOI8, Visual area-based annoyance [37]; Modified SOC8, Area-based visual pollution annoyance [24].
PC-4: Area-based people exposed to hovering drones	person	Total number of people visually exposed to hovering drone(s) at a distance less than a certain threshold within an area during an observed time period.	MUSE
PC-5: Area-based duration of visual exposure to different hovering drones	person. vp (hovering drones).h	The accumulated visual exposure to hovering drones in a given area for a given time.	MUSE

3.2.4. Access and Equity

Access and equity are fundamental principles in various fields, including healthcare, education, social services, and more. Ensuring access and equity for the population involves addressing disparities and barriers that may prevent certain individuals or groups from enjoying the same opportunities and benefits as others. Shared access to UAM services by different population groups shall be achieved equitably, i.e., different population groups should be treated with equity when using UAM services.

Achieving access and equity requires a holistic and collaborative approach in performing UAM services. It involves understanding and addressing the unique needs of different populations to create a more just and inclusive society.

Four performance indicators are newly proposed (by the MUSE project) within the access and equity FA, and they are presented in Table 6.

Table 6. Access and equity PIs.

Performance Indicator	Unit	Description
AE-1: Deliveries of goods to areas with limited or no transport connections	number	The number of deliveries of goods and equipment to areas with limited or no transport connections during the observed time period.
AE-2: Reduced travel time for healthcare-related deliveries	seconds	The amount of time reduced for healthcare-related deliveries by UAs compared to the delivery by road transport during the observed time period.
AE-3: Deviation of noise exposure from mean value	number	The amount by which the noise exposure within an area deviates from the mean value for all the areas.
AE-4: Deviation of visual pollution exposure from mean value	number	The amount by which visual pollution exposure within an area deviates from the mean value for all the areas.

3.2.5. Emissions

The environmental impact and greenhouse emissions profile of UAs depend largely on whether they are powered by conventional fuels, batteries (electric), or hybrid systems. UAs powered by gasoline or diesel engines emit CO_2 and other greenhouse gases during operation. The amount varies with the UA's size, engine efficiency, and operational duration. Electric- and hydrogen-powered UAs produce zero direct emissions during flight, thus becoming a cleaner (at the source) alternative for operations traditionally performed by fuel-powered aircraft. The environmental impact of electric UAs includes the emissions associated with manufacturing the drones and batteries, as well as generating the electricity used to charge them. If the electricity comes from renewable sources, the overall carbon footprint can be lower than that of conventional fuel-powered UAs.

UAs can perform certain tasks more efficiently than manned vehicles or ground-based alternatives, thus potentially reducing overall emissions. Nevertheless, the environmental impact of battery production (currently with a very short life cycle) and disposal is a concern for electric and hybrid UAs. The final impact of the introduction of those new technologies should be carefully analyzed. Sustainable battery technologies and recycling programs are critical to minimizing these impacts.

This research defines five performance indicators for the emissions aspects FA, as presented in Table 7.

Table 7. Emissions aspect PIs.

Performance Indicator	Unit	Description	Source
EM-1: Actual average CO_2 emission per flight	kg CO_2 per flight	Total amount of CO_2 emitted by a given number of flights (based on the emissions index of the fuel used, e.g., conventional or sustainable fuel) divided by the number of flights	Same as U.ENV1, Actual average CO_2 emission per flight [37].
EM-2: Trajectory-based energy consumption	kwh	The amount of energy consumed by a single drone operation (based on the type of UAM and trajectory).	MUSE
EM-3: Trajectory-based CO_2-eq emission	kg CO_2-eq	The amount of CO_2-eq emitted by a single drone operation.	MUSE
EM-4: Area-based CO_2-eq emission	kg CO_2-eq/h	The amount of CO_2-eq emitted by UAs within an area during the observed time period.	MUSE
EM-5: Area-based CO_2-eq emission decrease	kg CO_2-eq/h	The amount of CO_2-eq emitted less for the observed deliveries with UA introduction (compared to road traffic delivery) within an area during the observed time period.	MUSE

3.2.6. Other Areas of UAM Impact

The following focus areas are also mentioned in the literature as important issues: economic impact [5,16,24,34,35,59,66] and impact on wildlife [24,70,71]. Additionally, we introduce the public safety focus area as one of the positive social aspects of UAM introduction (discussed below). These three focus areas are included as a placeholder for a broader performance framework. Although some indicators and measurement mechanisms are proposed, there are too many uncertainties that prevent a clearer deliberation of whether they will remain an issue in the future and to what extent, or whether some will be resolved on a higher level (e.g., safety issues with regulations, etc.).

Economic Aspects

The economic impact of UAM on the population can be profound, encompassing aspects such as job creation, infrastructure development, and shifts in the real estate market. UAM initiatives can create jobs in manufacturing, operations, maintenance, air traffic management, and regulation. This includes both direct jobs in the design and production of UAM vehicles and indirect jobs in the broader ecosystem. The development of UAM requires substantial investment in new infrastructure, including vertiports and electric charging facilities. This can stimulate construction and engineering sectors, but it also requires careful urban planning to integrate with the existing transportation systems.

The need for vertiports and other UAM-related infrastructure could change how urban spaces are used, affecting land values and possibly leading to conflicts over land use priorities. Although improved connectivity caused by enhanced accessibility of certain areas using UAM could potentially increase the value of commercial properties, it is more likely that exposure to regular/frequent drone operations would lead to a decrease in residential property values. UAM could also cause the loss of some jobs (e.g., delivery vehicle drivers) or create new jobs (requiring some specific skills, e.g., pilots).

There are two performance indicators defined within the economic aspects FA, and they are listed in Table 8.

Table 8. Economic aspect PIs.

Performance Indicator	Unit	Description	Source
EC-1: Area of positive economic influence	km^2	Area * expressed in km^2 that would fall into the zone with new jobs as a consequence of drone operations.	MUSE
EC-2: Area of negative economic influence	km^2	Area * expressed in km^2 that would fall into the zone where property values decrease as a consequence of exposure to regular/frequent drone operations.	Modified "Housing cost", Change in housing cost as an impact of land-use change from UAM [5].

* The number of dwellings, people, or new jobs within an area could also be calculated instead of the area.

Public Safety

UAs have become increasingly prevalent in a variety of public and private safety applications due to their versatility, advanced capabilities, and cost-effectiveness. They offer several benefits across different sectors, including military, law enforcement, border security, and private security operations.

UAs can provide live video feeds, allowing for real-time monitoring of events, activities, or areas of interest. This capability is crucial for situational awareness in public safety operations, disaster response, and law enforcement activities. Drones can cover large and difficult-to-reach areas more efficiently than ground-based patrols or manned aircraft, which makes them ideal for border surveillance, wildlife monitoring, and critical infrastructure inspection. UAs can be quickly deployed to assess situations from the air, providing immediate information to decision-makers and response teams on the ground.

UAs can operate both day and night, as they are equipped with technologies such as thermal imaging and night vision cameras, thus extending the operational capabilities of public safety forces beyond traditional means. The aerial perspective offered by drones provides a strategic advantage, allowing for better coordination and management of ground forces during operations.

However, with these capabilities, their use also raises considerations related to privacy, legal and ethical use, airspace regulation, and vulnerability to malicious use or cyberattacks. Addressing these challenges through comprehensive policies, regulations, and best practices is essential to maximizing the benefits of UA services while minimizing potential risks. Maintaining public safety has a higher priority than the consequences they "bring", like noise, visual pollution, and privacy concerns. For example, it is now the case that military aircraft operations are exempt from noise assessment in aviation.

In related performance frameworks (e.g., in [24,37]), the proposed PIs for security and safety refer to U-space system and UA operations, as commonly used in aviation. In line with societal (and environmental) impact assessment, we propose the public safety focus area as one of the positive social aspects of UAM introduction. Two performance indicators are proposed within this focus area, as shown in Table 9. The indicators assume that people in an area "exposed" to drones hovering above could feel safer.

Table 9. Public safety aspect PIs.

Performance Indicator	Unit	Description	Source
PS-1: Area-based exposure to hovering drones	drones	Total number of drones hovering at a height below a certain threshold within an area during the observed time period.	MUSE
PS-2: Area-based duration of exposure to hovering drones	minutes	Total duration of drones hovering at a height below a certain threshold within an area during the observed time period.	Modified U.NOI11, Privacy based on area exposure [37].

Wildlife

Drone traffic affects wildlife in a variety of ways. Various studies show that different types of animals show different responses and sensitivity to drone traffic [24,70,71]. As a result, it should be possible to determine different levels of annoyance. For example, it seems that approach speed, angle, and color are perceived differently by various types of animals, and therefore further surveys should be conducted [24].

One of the usual ways to partially protect nature from a negative impact is to establish no-drone zones in areas with a high density of sensitive species. Since wildlife is not limited to these areas, some indicators could be introduced to measure the impact on wildlife.

The DACUS project proposes four performance indicators (WL-1, WL-2, WL-3, WL-4) within the wildlife FA, which allows the impact of drone traffic on wildlife to be monitored based on exposure and annoyance [24].

Following sustainable practices of airports, UAM operations should be assessed based on their disruptions to natural habitat as well. Assessing the exposure or annoyance of one particular species to specific drones or trajectories is not likely. For that reason, in order to assure wildlife preservation, the total amount of wildlife within an area of impact should be measured on a regular basis, e.g., once a year, after achieving a certain traffic level, after introducing new vehicles, etc. Therefore, two performance indicators (WL-5, WL-6) are proposed in addition to the four PIs defined by the DACUS project, and all six are listed in Table 10.

Table 10. Wildlife aspect PIs.

Performance Indicator	Unit	Description	Source
WL-1: Exposure of wildlife for a given trajectory	wildlife	Total amount of wildlife exposed within noise and appearance contours.	Same as WLD1, Trajectory-based noise and visual exposure [24].
WL-2: Exposure of wildlife for a traffic scenario	wildlife	Total amount of wildlife exposed within an area during the observed time period.	Same as WLD2, Area-based noise and visual exposure [24].
WL-3: Annoyance level for single trajectory	wildlife	Total amount of affected wildlife within noise and appearance contours.	Same as WLD3, Trajectory-based noise and visual annoyance [24].
WL-4: Annoyance level for a traffic scenario	wildlife	Total amount of affected wildlife within an area during the observed time period.	Same as WLD4, Area-based noise and visual annoyance [24].
WL-5: Disruption of wildlife for a traffic scenario—noise contour	wildlife	The difference between the total amount of wildlife within noise contours for the two consecutive measurements.	MUSE
WL-6: Disruption of wildlife for a traffic scenario—wildlife appearance contour	wildlife	The difference between the total amount of wildlife within their appearance contours for the two consecutive measurements.	MUSE

4. Conclusions

The main goal of this paper was to define a set of social and environmental performance indicators (PIs) of the future urban air mobility system. These indicators are capable of capturing the full range of impacts on citizens' quality of life produced by nearby air traffic. Indicators and measuring mechanisms are detailed herein for the defined main focus areas: noise, visual pollution, privacy concerns, access and equity, emissions, economic aspects, public safety, and wildlife.

The perspective on the quality of life, which encourages a comprehensive and human-centered approach to well-being, covering physical, psychological, social, and environmental dimensions, was integrated into the proposed performance framework and considered when defining the focus areas and the related performance indicators.

The presented PIs can be discretized with the highest possible level of detail, such as geographical, temporal, demographic, socioeconomic, and behavioral resolution. These PIs, presented as the cross-cutting areas, shall enable the analysis of the interaction between the UAM's societal impacts and the population factors, such as age, gender, place of residence, level of income, occupational status, etc.

The application of the proposed performance framework to a list of futuristic but credible drone traffic scenarios in a large city will follow as immediate research. The obtained values will be assessed by a powerful visualization tool, an interactive dashboard where the results can be disaggregated per cross-cutting area and end users can study the relationships between indicators.

Potential users of the proposed performance framework will be the governance board of the U-space. At present, the governance of U-space is still unknown, but relevant stakeholders that we envision in it are municipalities, citizens' associations, urban planners, health officers, environmental health specialists, and regional authorities, in addition to national civil aviation authorities and airspace/U-space service providers.

The availability of objective data, capturing the actual values of noise, visual pollution, emissions, and other socio-economic factors of urban air traffic, are a key element in the hands of the U-space authorities. Only the continuous monitoring of social performance indicators will ensure that the economic growth provided by the urban drones is sustainable for the environment and preserves the quality of life of the inhabitants of the city.

Future work includes the collection of subjective data, through interviews and surveys, and the study of human sensitivity that helps to establish the performance framework thresholds (e.g., acceptable noise or visual pollution levels). This work shall take into account the different geographical areas and the different demographic and population profiles that help the U-space board make informed decisions about the potential restrictions that need to be set for urban drone flights to permit their peaceful coexistence with the population they serve.

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Appendix A. Definition and Measurement Mechanisms for Performance Indicators

A.1. Noise-Related Indicators

A.1.1. NO-1: Area-Based People's Exposure to Noise (L_{Aeq})

The equivalent noise level at a receiver is calculated by summing all noise contributions in dBA (A-weighted noise levels) at a single time step and then taking the mean value over the considered time period.

For example, if the time period is 1 h, at receiver X at 8 A.M. there could be 150 persons exposed to an $L_{Aeq,1\,h}$ of 65 dBA. At the same receiver one hour later, at 9 A.M., 50 persons could be exposed to an $L_{Aeq,1\,h}$ of 75 dBA.

A.1.2. NO-2: Area-Based People's Exposure to Day–Evening–Night Noise Level (L_{den})

The day–evening–night noise levels (L_{den}) are calculated at all receiver points. These are calculated as follows:

$$L_{den} = 10 \log \left[\frac{12}{24} \times 10^{\left(\frac{L_D}{10}\right)} + \frac{4}{24} \times 10^{\left(\frac{L_E+5}{10}\right)} + \frac{8}{24} \times 10^{\left(\frac{L_N+10}{10}\right)} \right] \tag{A1}$$

where the subscripts D, E, and N stand for Day, Evening, and Night. They are respectively calculated over a fixed period of time of 12 h (e.g., between 7 A.M. and 7 P.M.) for the day level, 4 h (e.g., between 7 P.M. an 11 P.M.) for the evening level, and 8 h (e.g., between 11 P.M. and 7 A.M.) for the night level. This indicator is officially named by the 2002/49/EC Directive of the European Parliament and of the Council of 25 June 2002.

This integrated metric covers all the traffic during the day. The number of people exposed to an L_{den} value higher than a fixed threshold can also be counted within an area.

A.1.3. NO-3: Trajectory-Based People's Exposure to Noise (L_{AE})

For this indicator, we do not look at the whole fleet at the same time but single out operations. The point of this indicator is the comparison between the impact of two drone types performing the same mission, or the same drone type flying at different altitudes or speed.

Once an operation is singled out, the noise level at a receiver point, coming from the targeted drone, is summed over its whole trajectory, leading to the A-weighted sound exposure level. The start and stop of the measurement are determined by a threshold of maximum noise level minus 15 dBA, for example. This threshold is yet to be determined and will probably depend on local background noise levels.

For a drone operation, we will therefore obtain L_{AE} levels at all exposed receivers, and we can count the number of people affected by certain L_{AE} levels.

This trajectory-based approach can also be applied to NO-1, where the L_{AE} metric is replaced by an L_{Aeq} metric. However, the time integration period has to be determined.

A.1.4. NO-4: Area-Based Person–Event Index

The notion of "event" here is not to be mistaken with a single drone flyover, since several drones could be flying close enough to be considered one single event. The definition of "event" will depend on the limit (maximum level minus a certain value of dB, e.g., 5 dB) that we choose to suppose an event to be finished.

The person–event index (PEI) is calculated as follows:

$$\mathrm{PEI}(x) = \sum_{T} P_N \times N \tag{A2}$$

where x is a threshold in dBA, e.g., $L_{Aeq,5\,s}$, P_N is the number of persons affected, and N is the number of events, all summed over a fixed period of time T (e.g., 1 h).

The person–event index is calculated by multiplying the number of people exposed to N noise events exceeding x dB(A), with the number of events N. This indicator therefore includes the notion of the number of events above a certain threshold. The threshold value x could be adapted to local background noise levels.

A.1.5. NO-5: Duration of Area-Based People's Exposure to Noise

This indicator is calculated by multiplying the total duration of noise events above a specified noise level over a set time interval with the number of people exposed.

It is calculated in a same way as NO-4, except that we do not count the number of events but rather the duration of time of the fixed noise threshold being exceeded.

A.1.6. NO-6: Area-Based People's Exposure to Event Emergence

The event emergence indicator depends not only on the noise generated by the overflying drones but also on local background noise levels.

The emergence can, for instance, be calculated by subtracting the equivalent noise level that is exceeded 5% of the time period from the noise level that is exceeded 90% of the time period. The time period needs to be determined, but can be set at 1 h.

$$EE = L_5 - L_{90} \tag{A3}$$

Typically, L_5 will include the highest noise levels generated by the punctual drone flyovers, while L_{90} correctly represents the ambient background noise level.

Certain event emergence levels can then be chosen as thresholds to be multiplied by the number of people exposed in a certain area.

A.1.7. NO-7: Area-Based Intermittent Exposure to Noise

The intermittence ratio (IR) is different than the event emergence indicator, since it includes the intermittent character of the punctual noise sources. It includes the ratio between the events' energy and the total energy (including background noise and drones). It is calculated as follows:

$$IR = \frac{10^{0,1 \times L_{eq,T1,Events}}}{10^{0,1 \times L_{eq,T2,tot}}} \times 100 \tag{A4}$$

The total noise level (denominator) is calculated over a time period T_2 that is, of course, different than the event calculation time period T_1. The event existence is defined by a threshold, for instance, $L_{eq,T2,tot}$ + 3 dB (always relative to the total noise). All events verifying this condition are summed and lead to the numerator of the IR equation above.

The resulting percentage indicates the ratio of intermittent and continuous sound.

For example, a few flyovers that exceed the mean background noise level by a certain threshold for a certain amount of time will lead to a non-zero IR, while a hovering drone over the whole considered time period will result in IR = 0%, since it is a constant.

We can then multiply the number of people exposed to certain IR percentages.

Note: It should be mentioned that PIs that involve multiplying the number of exposed people with a duration, the number of occurrences, or even sound levels should be considered with care. They should not serve as a means of comparison between scenarios. Sound pressure and the number of exposed people should be multiplied in a logarithmic way. All PIs involving multiplication with the number of people are to be considered in combination with the more classical PIs, such as NO-1 to NO-3.

A.2. Visual Pollution-Related Indicators

A.2.1. VP-1: Trajectory-Based People Exposed

VP-1 adds the population affected by a single drone operation at each discretized time interval, excluding the people already counted in previous time intervals. A cut-off distance for drone visibility is set based on the size of the drone, or a fixed distance.

This indicator may be used to compare different possible drone trajectories for the same OD pair, together with the NO-1 indicator, especially for frequently used OD pairs, which affect different "zones of interest". The measurement mechanism consists of the following steps:

1. Calculate the area from where the drone is visible at discretized time intervals.
2. Filter the population present in the affected area in the same interval.
3. Count the number of people seeing the drone for the first time.

A.2.2. VP-2: Trajectory-Based People Exposed by Concentration Threshold

This indicator represents the amount of people exposed to a visual pollution concentration higher than a threshold for a single drone operation.

To make different studies and visualizations, the threshold for visual pollution concentration needs to be configurable.

Two different methods for calculating visual pollution concentration (VPC) are proposed:

$$\mathrm{VPC} = \text{Drone Visible Area}/\text{Free Sky Visible Area} \tag{A5}$$

$$\mathrm{VPC} = 47.76 \times (\mathrm{Num}^{0.65}/\mathrm{Dist}^{\,0.67}) + 1.37 \tag{A6}$$

where Num is the number of UAs that can be seen and Dist is the distance from the observer to the closest UA (equation proposed by the AiRMOUR project, [61]).

This indicator also requires the cut-off distance, as defined in VP-1, while the area from where the drone is visible is reduced to capture only the places affected by a VPC higher than a certain threshold.

The measurement mechanism consists of the following steps:

1. Calculate the VPC in the area from where the drone is visible at discretized time intervals (the contours of the VPC threshold define the new affected area delimitation for each time discretization).
2. Filter the people present in the affected area at the same interval.
3. Count the number of people who have been exposed to a VPC exceeding the defined threshold.

A.2.3. VP-3: Trajectory-Based People Exposed by Temporal and Concentration Threshold

The visual pollution concentration can be calculated as proposed in VP-2: as a ratio of a drone and free visible sky area or as proposed in the AiRMOUR project, depending on the number of visible UAs and the distance from the observer to the closest UA. The threshold for visual pollution concentration needs to be configurable in order to conduct different studies and visualizations.

The indicator is defined in the same manner as in VP-2; however, the area from where the drone is visible is reduced to capture only the places affected by a VPC higher than a certain threshold during a time period longer than T.

The measurement mechanism consists of the following steps:

1. Calculate the VPC in the area from where the drone is visible at discretized time intervals (contours of the VPC threshold define the new affected area delimitation for each time discretization).
2. Filter the population present in the affected area in the same interval.
3. Count the number of people who have been exposed to a VPC exceeding the defined threshold during a period of time exceeding the defined time period.

A.2.4. VP-4: Trajectory-Based Visual Exposure

The visual pollution concentration can be calculated in the same manner as proposed in VP-2 and VP-3.

The trajectory-based visual exposure can be calculated as:

$$\mathrm{VP4} = \sum_{\mathrm{i}} \int_{\mathrm{t}=0}^{\mathrm{t_f}} \mathrm{people_{it}} \cdot \mathrm{VPC_i(t)dt} \tag{A7}$$

where $i \in \mathrm{I}$, I is the set of all squares resulting from the spatial discretization of visual pollution and population mapping (*people*), t represents the time, and t_f is the final time of study.

A.2.5. VP-5: Area-Based People Exposed

This represents the total number of people seeing a drone for a given time period (e.g., 1 h) within a given zone.

This indicator uses the same principles and metric as VP-1. However, it aims to determine the visual impact of a traffic scenario over a particular area.

A.2.6. VP-6: Area-Based People Exposed by Concentration Threshold

In addition to the two proposed methods for calculating the visual pollution concentration for VP-2 and VP-3 (Equations (A5) and (A6)), VPC for this indicator can be calculated as the number of visible drones.

The threshold for visual pollution concentration needs to be configurable in order to conduct different studies and visualizations. This indicator uses the same principles and metric as VP-2. However, it considers the aggregated visual pollution produced by all drones flying at the same time.

A.2.7. VP-7: Area-Based People Exposed by Temporal and Concentration Threshold

For this indicator, the visual pollution concentration can be calculated in the same manner as proposed in VP-6. The thresholds for visual pollution concentration and duration of exposure need to be configurable in order to conduct different studies and visualizations. This indicator uses the same principles and metric as VP-3. However, it considers the aggregated visual pollution produced by all drones flying at the same time.

A.2.8. VP-8: Area-Based Visual Exposure

The visual pollution concentration can be calculated in the same manner as proposed in VP-6 and VP-7.

The area-based visual exposure can be calculated as:

$$\mathrm{VP8} = \sum_{\mathrm{i}} \int_{\mathrm{t}=0}^{\mathrm{t_f}} \mathrm{people_{it}} \cdot \mathrm{VPC_i(t)dt} \tag{A8}$$

where $i \in \mathrm{I}$, I is the set of all zones resulting from the spatial discretization of visual pollution and population mapping (*people*), t represents the time, and t_f is the final time of study.

This indicator uses the same principles and metric as VP-4. Nevertheless, it considers the aggregated visual pollution produced by all drones flying at the same time.

A.2.9. VP-9: Visual Exposure Per Kilometer

Project to a 2D population grid and integrate the population density along the obtained line. This population density may vary with time, and then the line integral should be parametrized with time.

$$\mathrm{VP9} = \sum_{\mathrm{n}} \int_{\mathrm{t}=0}^{\mathrm{t_f}} \mathrm{pop(x_n(t), t)dt} \tag{A9}$$

where n is the drones, x_n is the parametric trajectory of drone n, and *pop* is the population density.

A.3. Privacy Concern-Related Indicators

A.3.1. PC-1: Trajectory-Based Visually Annoyed People

This indicator represents the cumulative number of people estimated to be annoyed due to visual exposure to a single flight, obtained from the number of exposed persons (VP-1), by taking into account annoyance sensitivity values related to the land use (residential, industrial, commercial area) in the affected zones. Similar to the existing annoyance relationship used for noise impact, annoyance sensitivity values related to visual exposure can be established.

The indicator is calculated by multiplying the total number of exposed persons (indicator VP-1) with the specific sensitivity in the area, which is represented as the percentage of persons annoyed [%A], or the percentage of persons highly annoyed [%HA], related to the land use.

Annoyance sensitivity values are taken from the DACUS project, with the assumption that all drones have a camera (usually people have no information about drone equipment, and it is much more likely that people will always expect a drone to have a camera), as presented in Table A1. Different equipment of drones, e.g., with or without a camera, and the purpose of the drone flight will probably play a significant role in people's perception. However, this requires further analysis.

Table A1. Annoyance sensitivity values [24].

Type of Area	%A	%HA
Commercial	30	20
Industrial	60	40
Residential	80	60

As with VP-1, this can be calculated for the whole trajectory (origin → destination), representing the total number of people annoyed in all affected zones, or for the "zones of interest", representing the total number of people annoyed in the selected zones.

A.3.2. PC-2: Trajectory-Based People Exposed to Hovering Drones

This indicator represents the total number of people visually exposed at least once to a single drone operation during its hovering phases at a distance of less than a certain threshold.

The population affected by a single drone operation will be calculated the same way as for the VP-1 indicator and filtered for visual exposure to hovering drone(s) at a distance not larger than a predefined threshold.

A.3.3. PC-3: Area-Based Visually Annoyed People

This indicator represents the total number of people annoyed due to visual exposure for a given time period (e.g., 1 h) within a given zone, obtained from the number of exposed persons (VP-5), by taking into account annoyance sensitivity values in the affected zones (same as for PC-1).

The indicator is calculated by multiplying the total number of persons exposed to UAs within an area in a period t (indicator VP-5) with the annoyance sensitivity values for the given area, related to the land use.

A.3.4. PC-4: Area-Based People Exposed to Hovering Drones

This indicator represents the total number of people visually exposed at least once to UAs hovering at a distance of less than a predefined threshold within an area during the observed time period.

The population present in the affected area in the given discretized time interval will be calculated likewise for the VP-5 indicator, filtered for visual exposure to a hovering drone at a distance not larger than a predefined threshold.

A.3.5. PC-5: Area-Based Duration of Different Visual Exposure to Hovering Drones

This indicator represents the accumulated visual exposure to hovering drones in a given area for a given amount of time. It considers the duration of time that a different number of instantaneously hovering drones (within the zone) is visible by a certain number of persons, multiplied by the given number of drones and multiplied by the number of people exposed to that number of visible hovering drones with the given exposure duration for all (combination of) numbers of persons exposed for a certain time period to n instantaneously visible hovering drones and for all numbers of instantaneously hovering drones within the given area during the observed time period (e.g., 1 h).

$$\mathrm{PC5} = \sum_{i} \int_{t=0}^{t_f} \mathrm{people}_{it} \cdot n_i(t)\,dt \tag{A10}$$

where $i \in$ I, I is the set of all zones resulting from the spatial discretization of visual pollution and population mapping (*people*), t represents the time, t_f is the final time of study, and n is the number of instantaneously visible hovering drones.

A.4. Access and Equity-Related Indicators

A.4.1. AE-1: Deliveries of Goods to Areas with Limited or No Transport Connections

This indicator represents the number of deliveries of goods and equipment to areas with limited or no transport connections. The areas with limited or no transport connections are defined using GIS tools and transport networks.

A.4.2. AE-2: Reduced Travel Time for Healthcare-Related Deliveries

This indicator can be used to measure the amount of time reduced for healthcare-related deliveries by UAs compared to delivery by road transport. Drones can be used for the transportation of various medications, blood samples, or even organs between two hospitals. Furthermore, they can be used to efficiently transport medical supplies to persons living in rural places as well as those afflicted by natural disasters or catastrophes.

This indicator is calculated by subtracting the time required for healthcare-related delivery by a drone from the amount of time required for the same delivery using a road transport vehicle (i.e., an ambulance).

A.4.3. AE-3: Deviation of Noise Exposure from Mean Value

This indicator represents how much noise exposure within an area deviates from the mean value for all areas. Noise exposure can be measured by any of the proposed indicators within the noise focus area. The deviation of noise exposure from the mean value can be represented as:

Absolute difference from the mean value (the unit is the same as for the selected noise indicator);

Relative difference from the mean value (the unit is the percentage);

The number of standard deviations σ (the unit is the same as for the corresponding indicator):

$$\sigma = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \overline{x})^2} \tag{A11}$$

A low standard deviation indicates that the pollution tends to be clustered closely around the mean value of all zones (indicating equity among the exposed population), while a high standard deviation indicates that the pollution is spread far from the mean. The standard deviation is expressed in the same unit as the indicator it represents.

A.4.4. AE-4: Deviation of Visual Pollution Exposure from Mean Value

This indicator has the same measurement mechanism as previously described for AE-3, except that instead of noise exposure, the deviation of visual pollution exposure from the mean value can be measured by any of the proposed indicators within the visual pollution focus area.

A.5. Emissions-Related Indicators

A.5.1. EM-1: Actual Average CO_2 Emission Per Flight

This indicator is calculated as the total amount of fuel burned by the given number of flights, multiplied by the CO_2 emission index (CO_2 emitted per kg of fuel used, e.g., conventional or sustainable fuel) and divided by the number of flights [37].

As with fossil or sustainable fuels, the emissions to be considered for electric drones are well-to-wheel and can vary considerably depending on the sustainability of the electricity used.

For electric drones, the value of this indicator is calculated based on the types of drones (battery energy used for flights) and on the existing energy mix of the country where UAs operate, i.e., as follows:

$$\text{EM1} = \text{Battery energy} \cdot \text{CI}/\text{Number of flights} \tag{A12}$$

where CI is the carbon intensity, i.e., kg of CO_2 emissions released to produce a kWh of electricity, according to the energy mix of the country where UAs operate.

For example, for a flight using 25 Kwh of electricity produced in France [37]:

$$CO_2 \text{ emissions} = 25 \text{ Kwh} \cdot 0.0573 \text{ kg}CO_2/\text{Kwh} = 1.4 \text{ kg } CO_2$$

A.5.2. EM-2: Trajectory-Based Energy Consumption

This indicator is calculated as the amount of energy consumed by a single drone operation (based on the type of UA and trajectory).

A.5.3. EM-3: Trajectory-Based CO_2-eq Emissions

This indicator represents the amount of CO_2-eq emitted by a single drone operation.

It is calculated based on the type of drone (battery energy), trajectory or duration of flight, and is based on the existing energy mix of the country where UAs operate:

$$\text{EM3} = (\text{Battery energy}/\text{UA range}) \cdot \text{CI} \cdot \text{Flight distance} \tag{A13}$$

or

$$\text{EM3} = \text{Battery energy} \cdot \text{CI} \cdot \text{Duration of flight} \tag{A14}$$

where CI is the carbon intensity, i.e., kg of CO_2-eq emissions released to produce a kWh of electricity, according to the energy mix of the country where UAs operate.

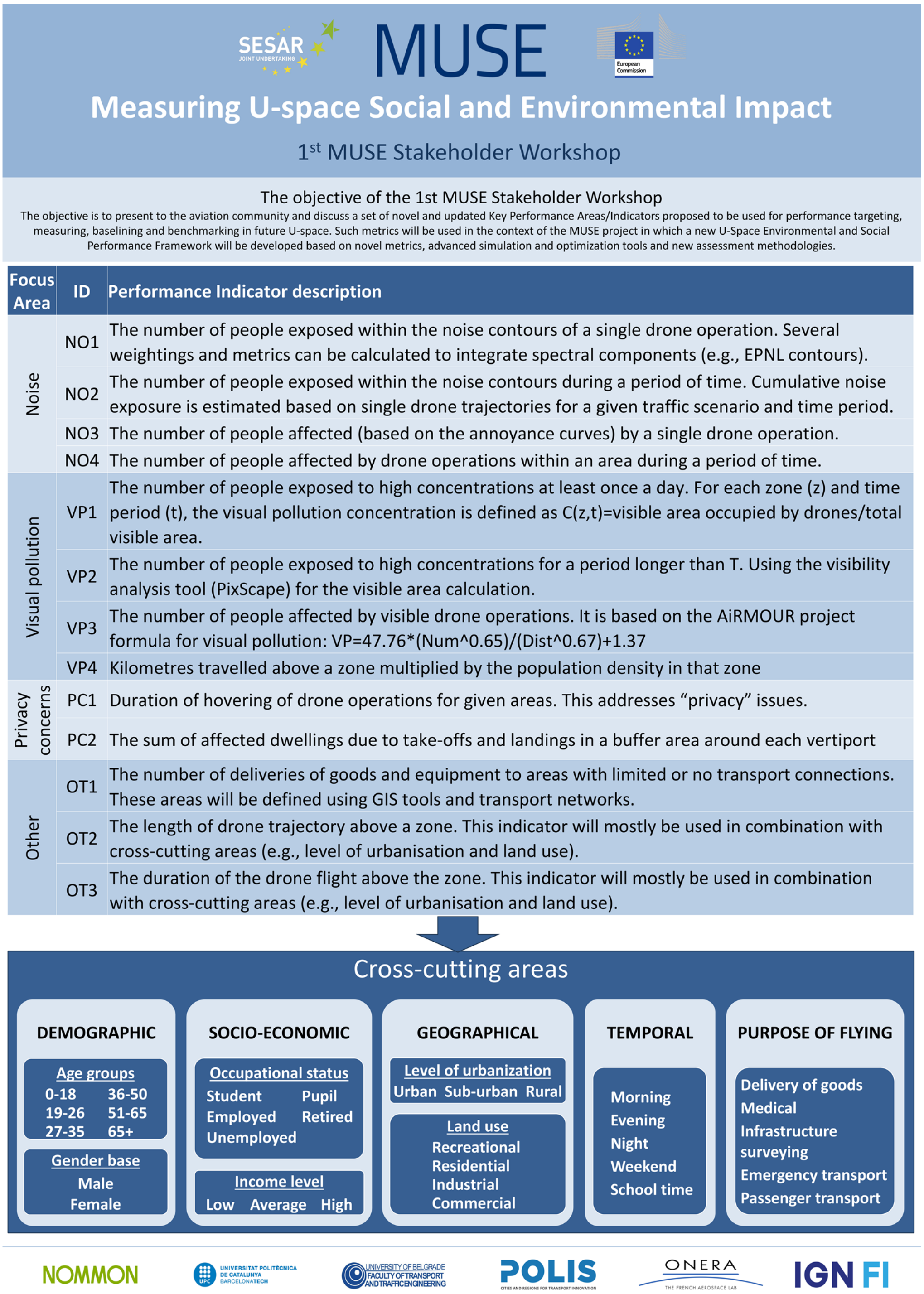
A.5.4. EM-4: Area-Based CO_2-eq Emissions

This indicator represents the amount of CO_2-eq emitted by UAs within an area during the observed time period, based on the type of UA (battery energy), the trajectory or duration of flight, and based on the existing energy mix of the country where UAs operate.

A.5.5. EM-5: Area-Based CO_2-eq Emissions Decrease

The decrease in CO_2-eq emitted for the observed deliveries with the introduction of UAs (compared to road traffic delivery) within an area during the observed time period. This represents the difference between the total amount of CO_2-eq emitted by cars (for the road trajectory depending on OD) that could be replaced by drones and the total amount of CO_2-eq drone emissions for the given deliveries. The number of cars replaced by UAs for the traffic scenario (day) can be calculated as the number of drone operations during the observed time period (day) divided by the number of deliveries per car (assumed value).

Appendix B. The 1st MUSE Stakeholder Workshop Poster



SESAR JOINT UNDERTAKING

MUSE

European Commission

Measuring U-space Social and Environmental Impact

1st MUSE Stakeholder Workshop

The objective of the 1st MUSE Stakeholder Workshop

The objective is to present to the aviation community and discuss a set of novel and updated Key Performance Areas/Indicators proposed to be used for performance targeting, measuring, baselining and benchmarking in future U-space. Such metrics will be used in the context of the MUSE project in which a new U-Space Environmental and Social Performance Framework will be developed based on novel metrics, advanced simulation and optimization tools and new assessment methodologies.

Focus Area	ID	Performance Indicator description
Noise	NO1	The number of people exposed within the noise contours of a single drone operation. Several weightings and metrics can be calculated to integrate spectral components (e.g., EPNL contours).
	NO2	The number of people exposed within the noise contours during a period of time. Cumulative noise exposure is estimated based on single drone trajectories for a given traffic scenario and time period.
	NO3	The number of people affected (based on the annoyance curves) by a single drone operation.
	NO4	The number of people affected by drone operations within an area during a period of time.
Visual pollution	VP1	The number of people exposed to high concentrations at least once a day. For each zone (z) and time period (t), the visual pollution concentration is defined as C(z,t)=visible area occupied by drones/total visible area.
	VP2	The number of people exposed to high concentrations for a period longer than T. Using the visibility analysis tool (PixScape) for the visible area calculation.
	VP3	The number of people affected by visible drone operations. It is based on the AiRMOUR project formula for visual pollution: VP=47.76*(Num^0.65)/(Dist^0.67)+1.37
	VP4	Kilometres travelled above a zone multiplied by the population density in that zone
Privacy concerns	PC1	Duration of hovering of drone operations for given areas. This addresses "privacy" issues.
	PC2	The sum of affected dwellings due to take-offs and landings in a buffer area around each vertiport
Other	OT1	The number of deliveries of goods and equipment to areas with limited or no transport connections. These areas will be defined using GIS tools and transport networks.
	OT2	The length of drone trajectory above a zone. This indicator will mostly be used in combination with cross-cutting areas (e.g., level of urbanisation and land use).
	OT3	The duration of the drone flight above the zone. This indicator will mostly be used in combination with cross-cutting areas (e.g., level of urbanisation and land use).

Figure A1. The 1st MUSE Stakeholder Workshop Poster.

Appendix C. Questionnaire for the Workshop Participants

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Measuring U-space Social and Environmental Impact

SESAR 3 JU Exploratory Research Project
Grant Agreement: *101114858 –* ***Call:*** *HORIZON-SESAR-2022-DES-ER-01*
SESAR Topic*: WA1-3 'Fundamental Science and Outreach for U-space and Urban Air Mobility'*

Workshop Questionnaire

Objective of the workshop

The objective of this workshop is to present to the aviation community and discuss a set of novel and updated Key Performance Areas/Indicators proposed to be used for performance targeting, measuring, baselining and benchmarking in future U-space. Such metrics will be used in the context of the MUSE project in which a new U-Space Environmental and Social Performance Framework will be developed based on novel metrics, advanced simulation and optimization tools and new assessment methodologies.

Please fill out the questionnaire by marking agree/indifferent/disagree for the statements and possibly provide additional comments.

1.	Are you a member of the MUSE External Expert Advisory Board?	Yes	No
2.	Your affiliation?		
3.	Your field of expertise?		
4.	Your name and email address (optional)		

SESAR Funded by the European Union

Questionnaire for participants

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Figure A2. Questionnaire for the Workshop Participants.

5.	The proposed list of Focus Areas is comprehensive	Agree	Partially agree/disagree	Disagree
6.	Please comment on other areas that should be included in your opinion			
7.	The proposed indicators are relevant for each focus area	Agree	Partially agree/disagree	Disagree
8.	Please specify indicators that you consider not relevant and explain why			
9.	Could you possibly propose some new indicators per certain focus areas? (optional)			
10.	The proposed indicators are measurable	Agree	Partially agree/disagree	Disagree
11.	Please comment on which indicator measurability will be an issue and explain why			
12.	The proposed cross-cutting areas are appropriate	Agree	Partially agree/disagree	Disagree
13.	Please comment on which cross-cutting areas are the most relevant for the proposed indicator(s) and explain why			
14.	The proposed focus areas/indicators adequately explain future U-Space societal and environmental impacts – overall	Agree	Partially agree/disagree	Disagree
15.	Please add here any suggestions for improvement/enhancement of the proposed MUSE U-Space Social and Environmental Performance Framework			

Thank you!

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Questionnaire for participants

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Figure A3. Questionnaire for the Workshop Participants.

References

1. EASA. *Study on the Societal Acceptance of Urban Air Mobility in Europe*; EASA: Cologne, Germany, 2021.
2. The WHOQOL Group. The World Health Organization quality of life assessment (WHOQOL): Position paper from the World Health Organization. *Soc. Sci. Med.* **1995**, *41*, 1403–1409. [CrossRef] [PubMed]
3. OECD. Executive summary. In *How's Life? 2020: Measuring Well-Being*; OECD Publishing: Paris, France, 2020.
4. World Health Organization. *Programme on Mental Health: WHOQOL User Manual*; WHO/HIS/HSI Rev. 2012.03; World Health Organization: Geneva, Switzerland, 1998.
5. Al Haddad, C.; Fu, M.; Straubinger, A.; Plötner, K.; Antoniou, C. Choosing Suitable Indicators for the Assessment of Urban Air Mobility: A Case Study of Upper Bavaria, Germany. *Eur. J. Transp. Infrastruct. Res.* **2020**, *20*, 214–232. [CrossRef]
6. Ivošević, J.; Ganić, E.; Petošić, A.; Radišić, T. Comparative UAV Noise-Impact Assessments through Survey and Noise Measurements. *Int. J. Environ. Res. Public Health* **2021**, *18*, 6202. [CrossRef] [PubMed]
7. UIC2—UAM Initiative Cities Community/EU's Smart Cities Marketplace. Urban Air Mobility and Sustainable Urban Mobility Planning—Practitioner Briefing. 2021. Available online: https://civitas.eu/sites/default/files/practitioner_briefing_urban_air_mobility_and_sump.pdf (accessed on 20 September 2024).
8. Wang, N.; Mutzner, N.; Blanc het, K. Societal acceptance of urban drones: A scoping literature review. *Technol. Soc.* **2023**, *75*, 102377. [CrossRef]

9. Price, G.; Helton, D.; Jenkins, K.; Kvicala, M.; Parker, S.; Wolfe, R. Urban Air Mobility Operational Concept (OpsCon) Passenger-Carrying Operations. NASA/CR—2020–5001587. 2020. Available online: https://ntrs.nasa.gov/api/citations/20205001587/downloads/UAM%20Passenger-carrying%20OpsCon%20-%20v14%20GP%20accept.pdf (accessed on 20 September 2024).
10. Eurofound. *European Quality of Life Survey 2016: Quality of Life, Quality of Public Services, and Quality of Society*; Publications Office of the European Union: Luxembourg, 2017.
11. EUROSTAT. Quality of Life. Information on Data. Available online: https://ec.europa.eu/eurostat/web/quality-of-life/information-data (accessed on 1 December 2023).
12. Lidynia, C.; Philipsen, R.; Ziefle, M. Droning on about drones—Acceptance of and perceived barriers to drones in civil usage contexts. In *Advances in Human Factors in Robots and Unmanned Systems, Proceedings of the AHFE 2016 International Conference on Human Factors in Robots and Unmanned Systems, Walt Disney World, FL, USA, 27–31 July 2016*; Springer: Berlin/Heidelberg, Germany, 2017; pp. 317–329. [CrossRef]
13. Goyal, R.; Reiche, C.; Fernando, C.; Serrao, J.; Kimmel, S.; Cohen, A.; Shaheen, S. Urban Air Mobility (UAM) Market Study. HQ-E-DAA-TN65181. 2018. Available online: https://ntrs.nasa.gov/api/citations/20190000519/downloads/20190000519.pdf (accessed on 20 September 2024).
14. Yedavalli, P.; Mooberry, J. An Assessment of Public Perception of Urban Air Mobility (UAM). Airbus. 2019. Available online: https://www.airbus.com/sites/g/files/jlcbta136/files/2022-07/Airbus-UTM-public-perception-study%20-urban-air-mobility.pdf (accessed on 20 September 2024).
15. CORUS Consortium. *U-Space Concept of Operations*, Deliverable D6.3, H2020-SESAR-2016-1, Grant 763551. 25 October 2019. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5c8b46d99&appId=PPGMS (accessed on 20 September 2024).
16. Macias, M.; Barrado, C.; Pastor, E.; Royo, P. The future of drones and their public acceptance. In Proceedings of the 2019 IEEE/AIAA 38th Digital Avionics Systems Conference (DASC), San Diego, CA, USA, 8–12 September 2019; pp. 1–8.
17. Kraus, J.; Kleczatský, A.; Hulínská, Š. Social, technological, and systemic issues of spreading the use of drones. *Transp. Res. Procedia* **2020**, *51*, 3–10. [CrossRef]
18. Jing, P.; Xu, G.; Chen, Y.; Shi, Y.; Zhan, F. The determinants behind the acceptance of autonomous vehicles: A systematic review. *Sustainability* **2020**, *12*, 1719. [CrossRef]
19. Prichard, M.; Rinsler, D.J.; Moore, M.; Turner, N.; Villa, I.; Nathan, A.; Hamadi, Y. Uber Air: Designing for the Community; Uber Elevate. 2020. Available online: https://canadianaam.com/wp-content/uploads/2021/05/Uber-Air-Designing-for-the-Community.pdf (accessed on 20 September 2024).
20. Community Air Mobility Initiative (CAMI). *Components of Public Acceptance for AAM and UAM*; Community Air Mobility Initiative (CAMI): Bainbridge, WA, USA, 2020.
21. Deloitte Consulting LLP. *UAM Vision Concept of Operations (ConOps) UAM Maturity Level (UML) 4*; Deloitte Consulting LLP: Philadelphia, PA, USA, 2020.
22. Tan, L.K.L.; Lim, B.C.; Park, G.; Low, K.H.; Yeo, V.C.S. Public acceptance of drone applications in a highly urbanized environment. *Technol. Soc.* **2021**, *64*, 101462. [CrossRef]
23. UK CAA. *Advanced Air Mobility: Taking a Use Case Approach. CAP2122*; UK CAA: Crawley, UK, 2021.
24. DACUS Consortium. Performance Framework, Deliverable D5.3, H2020-SESAR-2019-2, Grant 893864. 10 November 2021. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5e4b320aa&appId=PPGMS (accessed on 20 September 2024).
25. Wisk Aero LLC. *Building Social Acceptance for Advanced Air Mobility—Key Learnings and Insights from Years of Local Engagement*; Wisk Aero LLC: Mountain View, CA, USA, 2021.
26. Keller, M.; Hulinská, Š.; Kraus, J. Integration of UAM into cities–the public view. *Transp. Res. Procedia* **2021**, *59*, 137–143. [CrossRef]
27. ASSURED-UAM Consortium. Urban Mobility Integration Strategies. Deliverable D1.3, H2020-MG-2020-SingleStage-INEA, Grant 101006696. 6 May 2021. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5dccbb000&appId=PPGMS (accessed on 20 September 2024).
28. ASSURED-UAM Consortium. Financing and Public Acceptance. Deliverable D2.4, H2020-MG-2020-SingleStage-INEA, Grant 101006696. 30 November 2021. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5e565e9d0&appId=PPGMS (accessed on 20 September 2024).
29. Vertical Aerospace. *The Future of Advanced Aerial Mobility*; Vertical Aerospace: Bristol, UK, 2021.
30. Park, S.W. *Social Acceptability of Urban Air Mobility by Aircraft Category and Autonomous Phases*; KDI School of Public Policy and Management: Sejong-si, Republic of Korea, 2021.
31. USpace4UAM Consortium. Report on Public Acceptance Studies. Deliverable D4.3, H2020-SESAR-2020-1, Grant 101017643. 15 December 2022. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5f538becf&appId=PPGMS (accessed on 20 September 2024).
32. TindAIR Consortium. Social Acceptance Assessment Report. Deliverable D5.4, H2020-SESAR-2020-1, Grant 101017677. 18 November 2022. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5f596885d&appId=PPGMS (accessed on 20 September 2024).
33. Smith, A.; Dickinson, J.E.; Marsden, G.; Cherrett, T.; Oakey, A.; Grote, M. Public acceptance of the use of drones for logistics: The state of play and moving towards more informed debate. *Technol. Soc.* **2022**, *68*, 101883. [CrossRef]

34. AiRMOUR Consortium. Public and Stakeholder Acceptance—Interim Report. Deliverable D4.1, H2020-MG-2018-2019-2020, Grant 101006601. 29 June 2022. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5ee219c32&appId=PPGMS (accessed on 20 September 2024).
35. Çetin, E.; Cano, A.; Deransy, R.; Tres, S.; Barrado, C. Implementing mitigations for improving societal acceptance of urban air mobility. *Drones* **2022**, *6*, 28. [CrossRef]
36. Biehle, T. Social sustainable urban air mobility in Europe. *Sustainability* **2022**, *14*, 9312. [CrossRef]
37. PJ19-W2 CI Consortium. DES Performance Framework—U-space Companion Document. Deliverable D4.7, H2020-SESAR-2019-1, Grant 874473. 3 April 2023. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5faa899d0&appId=PPGMS (accessed on 20 September 2024).
38. Silva, A.T.; Duarte, S.P.; Melo, S.; Witkowska-Konieczny, A.; Giannuzzi, M.; Lobo, A. Attitudes towards Urban Air Mobility for E-Commerce Deliveries: An Exploratory Survey Comparing European Regions. *Aerospace* **2023**, *10*, 536. [CrossRef]
39. Kellermann, R.; Biehle, T.; Mostofi, H. Modelling public attitude towards drone delivery in Germany. *Eur. Transp. Res. Rev.* **2023**, *15*, 38. [CrossRef]
40. Melo, S.; Silva, F.; Abbasi, M.; Ahani, P.; Macedo, J. Public Acceptance of the Use of Drones in City Logistics: A Citizen-Centric Perspective. *Sustainability* **2023**, *15*, 2621. [CrossRef]
41. Lotz, V.; Kirste, A.; Lidynia, C.; Stumpf, E.; Ziefle, M. User Acceptance of Urban Air Mobility (UAM) for Passenger Transport: A Choice-Based Conjoint Study. In Proceedings of the International Conference on Human-Computer Interaction, Copenhagen, Denmark, 23–28 July 2023; pp. 296–315.
42. Stolz, M.; Laudien, T. Assessing Social Acceptance of Urban Air Mobility using Virtual Reality. In Proceedings of the 2022 IEEE/AIAA 41st Digital Avionics Systems Conference (DASC), Portsmouth, VA, USA, 18–22 September 2022; pp. 1–9.
43. Chiacchiera, A.; Raper, D.; Elliff, T.; Agouridas, V. *Urban Air Mobility and Sustainable Development—White Paper*; Aerospace, Security and Defence Industries Association of Europe (ASD) and Envisa: 2023. Available online: https://umbraco.asd-europe.org/media/wdjpbxrf/asd-urban-air-mobility-white-paper-january-2023.pdf (accessed on 20 September 2024).
44. Park, G.; Park, H.; Park, H.; Chun, N.; Kim, S.-H.; Lee, K. Public Perception of UAM: Are we ready for the new mobility that we have dreamed of? In Proceedings of the Human Factors and Ergonomics Society Annual Meeting, Atlanta, GA, USA, 10–14 October 2022; Volume 66, pp. 40–44.
45. The National Academies Press. *National Academies of Sciences Engineering and Medicine, Assessing Community Annoyance of Helicopter Noise*; The National Academies Press: Washington, DC, USA, 2017.
46. Bulusu, V.; Polishchuk, V.; Sedov, L. Noise Estimation for Future Large-Scale Small UAS Operations. In Proceedings of the INTER-NOISE and NOISE-CON Congress and Conference Proceedings, NoiseCon17, Grand Rapids, MI, USA, 12–14 June 2017; Volume 255, pp. 864–871. Available online: https://www.ingentaconnect.com/contentone/ince/incecp/2017/00000254/00000002/art00106 (accessed on 20 September 2024).
47. Casalino, D.; van der Velden, W.C.; Romani, G. Community noise of urban air transportation vehicles. In Proceedings of the AIAA Scitech 2019 Forum, San Diego, CA, USA, 7–11 January 2019; p. 1834.
48. Eißfeldt, H. Supporting urban air mobility with citizen participatory noise sensing: A concept. In *Companion, Proceedings of the 2019 World Wide Web Conference, San Francisco, CA, USA, 13–17 May 2019*; ACM: New York, NY, USA, 2019; pp. 93–95.
49. Martinez, A.J.T. Drone Noise: A New Public Health Challenge in Urban Areas. In Proceedings of the Environmental Protection UK Conference (EPUK), Birmingham, UK, 13 November 2019.
50. Glaab, P.; Wieland, F.; Santos, M.; Sharma, R.; Tamburro, R.; Lee, P.U. Simulating Fleet Noise for Notional UAM Vehicles and Operations in New York. In Proceedings of the 2019 IEEE/AIAA 38th Digital Avionics Systems Conference (DASC), San Diego, CA, USA, 8–12 September 2019; pp. 1–10. [CrossRef]
51. Rizzi, S.A.; Huff, D.L.; Boyd, D.D.; Bent, P.; Henderson, B.S.; Pascioni, K.A.; Sargent, D.C.; Josephson, D.L.; Marsan, M.; He, H.; et al. *Urban Air Mobility Noise: Current Practice, Gaps, and Recommendations*; NASA/TP-20205007433; NASA Langley Research Center: Hampton, VA, USA, 2020. Available online: https://ntrs.nasa.gov/citations/20205007433 (accessed on 20 September 2024).
52. Torija, A.J.; Clark, C. Psychoacoustic Approach to Building Knowledge about Human Response to Noise of Unmanned Aerial Vehicles. *Int. J. Environ. Res. Public Health* **2021**, *18*, 682. [CrossRef] [PubMed]
53. DACUS Consortium. Drone DCB Concept and Process. Deliverable D1.1, H2020-SESAR-2019-2, Grant 893864. 8 February 2021. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5d95ef5ef&appId=PPGMS (accessed on 20 September 2024).
54. Schäffer, B.; Pieren, R.; Heutschi, K.; Wunderli, J.M.; Becker, S. Drone Noise Emission Characteristics and Noise Effects on Humans—A Systematic Review. *Int. J. Environ. Res. Public Health* **2021**, *18*, 5940. [CrossRef]
55. Hui, C.T.J.; Kingan, M.J.; Hioka, Y.; Schmid, G.; Dodd, G.; Dirks, K.N.; Edlin, S.; Mascarenhas, S.; Shim, Y.-M. Quantification of the Psychoacoustic Effect of Noise from Small Unmanned Aerial Vehicles. *Int. J. Environ. Res. Public Health* **2021**, *18*, 8893. [CrossRef]
56. Kettisen, A. Information Visualization of Performance Indicators for Drones in Urban Areas—A Complementary Module for the Visual Research Tool UTM50. Master's Thesis, Linkoping University, Linköping, Sweden, 2022.
57. Ramos-Romero, C.; Green, N.; Roberts, S.; Clark, C.; Torija, A.J. Requirements for Drone Operations to Minimise Community Noise Impact. *Int. J. Environ. Res. Public Health* **2022**, *19*, 9299. [CrossRef]

58. Pascioni, K.A.; Watts, M.E.; Houston, M.; Lind, A.; Stephenson, J.H.; Bain, J. Acoustic Flight Test of the Joby Aviation Advanced Air Mobility Prototype Vehicle. In Proceedings of the 28th AIAA/CEAS Aeroacoustics 2022 Conference, Southampton, UK, 14–17 June 2022; pp. 1–19. [CrossRef]
59. Council of Mayors (SEQ). *Bringing Advanced Air Mobility (AAM) to Brisbane, South East Queensland (SEQ), Australia*; Identifying and Implementing the Opportunities AAM Presents for SEQ; Council of Mayors (SEQ): Brisbane City, QLD, Australia, 2023.
60. EASA. *Guidelines on Noise Measurement of Unmanned Aircraft Systems Lighter than 600 kg Operating in the Specific Category (Low and Medium Risk)*; EASA: Cologne, Germany, 2023.
61. AiRMOUR Consortium. Noise and Visual Pollution Tools and Concepts. Deliverable D4.3, H2020-MG-2018-2019-2020, Grant 101006601. 23 August 2023. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e50200cdab&appId=PPGMS (accessed on 20 September 2024).
62. UK Civil Aviation Authority. *Emerging Technologies: The Effects of eVTOL Aircraft Noise on Humans, CAP 2505*; UK Civil Aviation Authority: Crawley, UK, 2023.
63. Thomas, K.; Granberg, T.A. Quantifying Visual Pollution from Urban Air Mobility. *Drones* **2023**, *7*, 396. [CrossRef]
64. Siddiqi, M.A.; Iwendi, C.; Jaroslava, K.; Anumbe, N. Analysis on security-related concerns of unmanned aerial vehicle: Attacks, limitations, and recommendations. *Math. Biosci. Eng.* **2022**, *19*, 2641–2670. [CrossRef]
65. AiRMOUR Consortium. UAM Citizen Privacy Handbook. Deliverable D4.4, H2020-MG-2018-2019-2020, Grant 101006601. 17 May 2023. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5fc781e1a&appId=PPGMS (accessed on 20 September 2024).
66. Min, H. Leveraging Drone Technology for Last-Mile Deliveries in the e-Tailing Ecosystem. *Sustainability* **2023**, *15*, 11588. [CrossRef]
67. Zhao, P.; Post, J.; Wu, Z.; Du, W.; Zhang, Y. Environmental impact analysis of on-demand urban air mobility: A case study of the Tampa Bay Area. *Transp. Res. Part D Transp. Environ.* **2022**, *110*, 103438. [CrossRef]
68. Ramos, S.; Cruz, T.; Simões, P. Security and Safety of Unmanned Air Vehicles: An Overview. In Proceedings of the European Conference on Information Warfare and Security, Online, 24–25 June 2021; pp. 357–368. [CrossRef]
69. ASSURED-UAM Consortium. UAM ELCC+E Estimation. Deliverable D2.3, H2020-MG-2020-SingleStage-INEA, Grant 101006696. 31 October 2021. Available online: https://ec.europa.eu/research/participants/documents/downloadPublic?documentIds=080166e5e52453c5&appId=PPGMS (accessed on 20 September 2024).
70. Mulero-Pázmány, M.; Jenni-Eiermann, S.; Strebel, N.; Sattler, T.; Negro, J.J.; Tablado, Z. Unmanned aircraft systems as a new source of disturbance for wildlife: A systematic review. *PLoS ONE* **2017**, *12*, e0178448. [CrossRef] [PubMed]
71. Rebolo-Ifrán, N.; Graña Grilli, M.; Lambertucci, S.A. Drones as a Threat to Wildlife: YouTube Complements Science in Providing Evidence about Their Effect. *Environ. Conserv.* **2019**, *46*, 205–210. [CrossRef]
72. UK Civil Aviation Authority ERCD. *ERCD Report 1104: Environmental Metrics for FAS*; UK Civil Aviation Authority ERCD: Crawley, UK, 2011.
73. *Standard ISO 1996-1: 2016*; Acoustics—Description, Measurement and Assessment of Environmental Noise—Part 1: Basic Quantities and Assessment Procedures. International Organization for Standardization: Geneva, Switzerland, 2016.
74. Wunderli, J.; Pieren, R.; Vienneau, D.; Cajochen, C.; Probst-Hensch, N.; Röösli, M.; Brink, M. Intermittency ratio: A metric reflecting short-term temporal variations of transportation noise exposure. *J. Expo. Sci. Environ. Epidemiol.* **2016**, *26*, 575–585. [CrossRef]

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