The Effects of Emerging Technology Aviation Noise: an annual update

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Chapter 1
Introduction

1.1 The presence of emerging aviation technologies is an expanding area of aviation and includes vehicles such as Unmanned Aviation Systems (UAS) which are also known as drones[1], and Urban Air Mobility (UAM) aircraft, including air taxis, sometimes referred to as Unmanned Aerial vehicles (UAVs) and electric Vertical Take-Off and Landing vehicles (eVTOLs). This modern technology has several potential uses, for example aerial mapping and photography, military surveillance, search and rescue, delivery, and air taxis amongst many others. This presents new challenges for noise legislation and understanding of how these types of noise sources may impact people on the ground. In 2023 the CAA published CAP report 2505, which provided an overview of the current knowledge on the impacts of such emerging technology noise on humans over the past few years to the start of 2023. CAP 2692 was then published in 2024 as update to CAP 2505, and CAP 3086 was published in 2025.

1.2 This report aims to provide an update from the past year (March 2025 - March 2026) on the current knowledge around potential human impacts from noise generated by emerging flight technologies. The scope of this report does not cover the effects on humans from spaceflight vehicles, which is covered separately.

1.3 The report will provide an overview from the relevant findings presented at the Euronoise and Internoise conferences held in 2025, and any other published research findings from the past twelve months that relate to the human impacts of emerging technology noise. The CAA has not validated the research findings or conclusions included in this report, nor takes any view on their applicability to UK policy making.

[1] Although *UAS* is the regulatory term used by the CAA, there are various other terms in use within the sector for these types of aircraft. This is evident in the range of terminology used by the authors of the papers and studies which are summarised in this report.

Chapter 2

Euronoise 2025

2.1 The Euronoise conference was held in Malaga, Spain in June 2025. This chapter describes some of the most relevant findings to emerging technology aviation noise impacts that were presented at this meeting.

2.2 As with aviation noise, drones have the potential to cause annoyance to those on the ground. The first paper was authored by **Ramos-Romero et al** and presented an integrated noise-assessment framework developed within the **Im**pact and capacity **A**ssessment **F**ramework for **U**-space **S**ocietal **A**cceptance (ImAFUSA) project to evaluate how noise from drones and other Urban Air Mobility (UAM) vehicles affects communities. While much of the technical content focuses on noise metrics, one of the aims is to understand and predict how people perceive, detect, and are annoyed by UAM noise in real urban environments. U-space is Europe's digital air traffic management ecosystem for drones and urban air mobility. It is the European framework for managing unmanned aircraft (drones) operations safely, efficiently, and at scale in low-altitude airspace, typically over cities.

2.3 U-space supports Innovative/Urban Air Mobility (IAM/UAM) operations such as passenger drones, delivery drones, and autonomous aircraft. It includes systems to manage traffic, capacity, safety, environmental impacts, and societal acceptance. It aims to integrate drones as part of everyday airspace use, especially near populated areas.

2.4 ImAFUSA is a Horizon Europe research project developing an integrated assessment tool to evaluate the societal, environmental, and safety impacts of U-space operations. The tool will assess environmental noise, visual impacts, safety, and socio-economic effects of UAM operations. ImAFUSA aims to help cities, regulators, and industry plan drone operations that are acceptable to communities. The project is funded by EU Horizon Europe and UKRI.

2.5 A major focus of the paper is the noise assessment module, which uses both energy-based and perception-based metrics to understand how UAM noise affects people. The paper emphasises that traditional measures of loudness (like dBA) are not sufficient to understand how people actually experience noise. Instead, perception depends on factors such as:

- Loudness i.e. how strong the sound feels to a listener, and often the strongest predictor of annoyance.

- Tonality, UAM vehicles often produce tonal or whining components (e.g., rotor harmonics), which the human ear finds particularly disturbing.
- Sharpness is when high-frequency energy makes a sound seem “sharper” and more irritating.
- Fluctuation and Roughness. Many UAS produce amplitude modulation (“wobbling,” “pulsing,” “rough” textures), which increases annoyance even if the overall sound dBA is moderate.
- Repetition/Number of Events. Urban drone corridors will result in frequent overflights. Even if individual events are not loud, repetitive exposure is a key driver of community annoyance.

2.6 The paper discusses the concept of detectability, which accounts for how easy it is to hear a drone above background noise. Two scenarios are discussed, quiet or low-noise environments where drones become highly detectable, and annoyance is higher because the noise stands out strongly. The second is noisy urban environments, where background noise partially masks the drone. Perceived annoyance is reduced, even if the drone emits the same sound level. The framework includes a discounting index that reduces calculated noise impact when masking is strong, because people experience it as less intrusive.

2.7 The authors explain that annoyance due to UAM noise depends not just on how loud drones are, but on how they sound, how often they fly, how detectable they are above the local soundscape, and how these factors combine to shape daily experience in urban environments.

2.8 **Podwinska et al** explored the effects of time-variant characteristics of UAS noise on annoyance. This research examined how time-varying characteristics of noise produced by hovering UAS, especially modulation in amplitude and frequency, affect human annoyance.

2.9 Although hover is typically considered a “steady” operation, UAS noise is not steady: wind, control systems, and rotor interactions introduce fluctuations. The study investigates how these fluctuations influence perceived annoyance. The authors synthesised drone noise for two quadcopters: DJI Matrice 300 RTK (M3) (medium sized) and the XAG P40 (X1) (large sized). This method allowed precise control over time-variant acoustic features. The synthetic stimuli included:

- Tonal components (shaft, BPFs, harmonics)
- Broadband components
- Controlled manipulation of:
    i. Amplitude modulation (AM) depth (strength of loudness fluctuations)

ii. Frequency modulation (FM) frequency (speed of pitch fluctuations)

iii. Time-varying profiles (TVPs): constant, sigmoid, and aperiodic

iv. Slope: whether modulation increased over time

2.10 The listening test element of the study included 41 participants who were asked to rate short-term annoyance using a relative magnitude estimation scale. 50 synthesised, five second noise samples were played at 65 dBA, all level-normalised, and participants rated each sound relative to a reference baseline stimulus. Ratings were normalised per participant to account for variations in chosen numeric scales, and mixed-effects linear models assessed the influence of experimental variables.

2.11 Psychoacoustic metrics (loudness, roughness, sharpness, tonality, fluctuation strength, etc.) were computed and explored using PCA (Principal Component Analysis[2]). The findings indicated that modulation depth and modulation frequency strongly influence annoyance. Higher amplitude modulation depth (m) is found to be more annoying, and lower modulation frequency (FM) is observed to be more annoying, due to more noticeable “wobble” or slow beating in the sound. More pronounced and slower fluctuations in noise cause greater annoyance.

2.12 The authors also found that temporal evolution of modulation also affects annoyance. Time-varying profiles (TVPs) suggested that aperiodic modulation (irregular patterns) were found to be least annoying, and constant or sigmoid modulation was more annoying.

2.13 In terms of slope effects, a positive slope where modulation ramps up gradually was found to be less annoying than a constant strong modulation. More predictable and pronounced modulation patterns increase annoyance.

2.14 The drone type had only a small effect on annoyance. The larger X1 drone was rated slightly more annoying than M3, but there was no significant interaction between drone type and modulation characteristics. The acoustic behaviour (modulations) mattered far more than the drone model.

2.15 The PCA revealed that roughness, fluctuation strength, and impulsiveness were strongly positively associated with annoyance. These traits reflect fast or slow periodic fluctuations, temporal instability and abrupt or uneven acoustic events.

[2] Principal Component Analysis (PCA) is a statistical technique used to reduce the dimensionality of a dataset while preserving as much meaningful variation as possible. It transforms a large set of correlated variables into a smaller set of uncorrelated variables called principal components, which capture the most important patterns in the data.

These findings align with prior psychoacoustic annoyance predictions for rotorcraft.

2.16 Some loudness and tonality metrics were negatively correlated with annoyance within the PCA. It is explained that this is likely due to spectrum-shape changes inherent in modulation, not absolute tonality.

2.17 In conclusion, the results suggested that noise from hovering drones is more annoying when the modulation patterns are strong, slow, and regular, and least annoying when fluctuations are subtle, fast, and irregular.

2.18 **LeGriffon et al** evaluated how a large-scale drone parcel delivery system operating over Madrid affects urban noise exposure and quality of life. To do this, the authors developed and applied an integrated modelling toolchain combining flight mechanics, drone noise emission modelling, and urban noise propagation.

2.19 The case study uses DJI Matrice 600 drones flying across a 10km² urban area and explores how route patterns, flight altitudes, and traffic levels shape noise impacts at ground level. The toolchain includes:

- Flight Mechanics (DynaPyVTOL), modelling drone motion and propeller behaviour.
- Noise Source Modelling (CARMEN), computing tonal propeller noise along the flight path.
- Urban Noise Propagation (Noise Modelling), creating noise maps that reflect buildings, terrain, and drone trajectories.

2.20 These are all separate tools but linked together they become a toolchain that can generate full noise maps for an entire city. Noise indicators included L_{Aeq}, L_{Amax}, SEL, Time Above, Number Above, and metrics accounting for the number of flyovers.

2.21 The authors emphasise that noise pollution is one of the main societal concerns associated with drone operations in cities. As drones begin flying overpopulated areas, noise has clear implications for comfort, wellbeing, and quality of life. It is explained that this is why the study evaluates noise exposure at the neighbourhood level, including residential areas, recreational zones, hospitals, and sensitive sites.

2.22 The number of drone flights were found to strongly influence perceived noise burden. The scenario models up to 60 drone flights per hour, varying across the day, and noise maps show that afternoon periods, with higher flight frequency, lead to greater noise impact. Even when individual drones are not very loud, repeated events increase accumulated exposure, a critical factor for annoyance and fatigue for residents. This directly affects people living under busy corridors, who would experience a continuous sequence of audible events rather than isolated flyovers.

2.23 Two routing concepts were compared: A free route where drones follow the shortest path between the hub and destination, with lower average altitude (around 69 metres). The second was constrained airspace where drones follow pre-defined corridors in the city centre. These were higher altitude (around 125 metres).

2.24 Higher altitudes generally reduce noise at the ground, but in dense urban environments, higher-altitude flights can propagate sound more widely, because fewer buildings block the sound. Route choice can also shift noise towards or away from specific communities. This means routing policy can influence which neighbourhoods are affected and how many people receive noticeable noise exposure. In dense neighbourhoods, people might hear fewer intrusions from low-flying drones (due to building shielding) but experience broader noise coverage from corridor-based high-altitude operations.

2.25 The authors explain that the DJI Matrice 600 produces very low-frequency tonal noise, to which human hearing is less sensitive. A-weighting reduces these low frequencies substantially, meaning the drone used in this case study may be less annoying than other larger, faster, or more tonal UAM vehicles. The authors also note that other drone types could produce sharper, more perceptually intrusive noise, likely leading to higher annoyance. This is important for people because fleet composition can change community noise impact dramatically.

2.26 Low-frequency drone noise can be masked by city background noise, especially traffic. This reduces detectability and annoyance in some areas. However, in quieter neighbourhoods or parks, these drones would be more noticeable, increasing potential annoyance or disturbance for residents and visitors.

2.27 The study indicated that large-scale drone parcel delivery can measurably impact citizens’ noise exposure, especially through flight frequency, routing patterns, altitude, and urban geometry. The authors conclude that noise management and the need for careful planning of drone corridors, altitudes, and fleet types is essential for maintaining quality of life and achieving public acceptance.

2.28 **Picillo et al** presented their findings on a mid-fidelity framework for rotor noise prediction and perception in manoeuvring flight. The authors presented a mid/low-fidelity simulation framework for predicting rotor noise during short-time transient manoeuvres, such as rapid changes in propeller speed, for small drones and eVTOL systems. The goal was to understand how manoeuvre-induced noise differs from steady-state noise, and how these differences influence human perception, especially within the context of Urban Air Mobility (UAM).

2.29 The study uses numerical aero acoustic modelling, to evaluate both physical noise metrics (e.g., Sound Pressure Level, SPL) and psychoacoustic sound-quality metrics (e.g., loudness, sharpness). The results suggested that transient manoeuvres significantly alter noise patterns, with implications for public acceptance of drones.

2.30 The main findings were that rotor manoeuvres generate additional noise. Rapid changes in propeller angular velocity, speeding up or slowing down, were found to produce non-stationary noise components that are not present during steady rotation. These include overshoots in SPL at the start and end of the transient manoeuvre. The magnitude of these overshoots increases as the transient duration gets shorter (i.e., more abrupt manoeuvres).

2.31 Noise directivity changes strongly during manoeuvres. The direction in which noise radiates (directivity) becomes strongly time-dependent, especially within 0°-30° of the propeller axis. It is explained that observers aligned closer to the rotor axis experience low-frequency noise peaks linked to rapid thrust changes. Higher time-derivative (faster changing) profiles generated higher SPL and stronger perceptual effects such as sharpness peaks.

2.32 Psychoacoustic metrics were found to reflect transient noise. Loudness increases with angular velocity and with observer proximity to the rotor. Sharpness, associated with high-frequency prominence, exhibits distinct peaks during manoeuvres, magnified by faster or more abrupt changes. Sharpness is closely linked to perceived unpleasantness and annoyance, especially for tones and high-frequency noise, common in drone flight. Therefore, during manoeuvring (e.g., quick accelerations near vertiports, take-off/landing, sharp turns), people are likely to experience stronger negative perception than during steady flight.

2.33 The authors argue that psychoacoustic metrics should guide design and operation decisions, not just physical SPL reductions.

2.34 **Jiang** investigated how Advanced Air Mobility (AAM), such as air taxis and eVTOL services, could impact communities across West Yorkshire, England, with a particular focus on noise exposure and social equity. Rather than modelling a single flight path, the study evaluated noise exposure on a regional scale and examined how impacts differ across socio-economic groups.

2.35 Agglomerative hierarchical clustering (AHC) was used to identify eleven potential vertiport locations based on commuting demand and reflecting likely early stage AAM use cases. Two routing strategies were modelled:

- Distance-priority routes: Straight-line paths minimising travel distance.
- Noise-priority routes: Paths following major roads, to place flights over areas already exposed to high transport noise.

2.36 Three potential noise footprints (500m,1000m,1500m) were used to reflect uncertainty in AAM vehicle noise and future traffic volume. Noise exposure was assessed for all 7,345 Output Areas (OAs), categorised by deprivation scores using the 2019 English Indices of Multiple Deprivation (IMD).

2.37 The findings suggested that even under conservative assumptions, a significant number of communities would be exposed to >55 dB $L_{Aeq,16h}$ AAM noise. Up to 53% of OAs would be exposed under distance-priority routing with a 1500m noise footprint. Even with the smallest footprint (500m), 1 in 5 OAs (19-22%) would be exposed. Most OAs exposed to AAM noise are not already exposed to road or rail noise above 55 dB $L_{Aeq,16h}$. Up to 60% of exposed areas (with wide footprint) are currently quiet.

2.38 In terms of deprivation, the more deprived areas already had higher exposure to transport noise from roads and railways. AAM could further this inequality, with distance-priority routes, more than 30% of the most deprived OAs are exposed even under narrow (500m) footprints. Higher income areas would see noise exposure drop below 10%.

2.39 The results indicate that noise-priority routes help reduce but not eliminate inequality. Routing flights along major roads reduces disparities but comes with a trade-off. The inequality gap is smaller (e.g., 25% versus 10% exposure in highest versus lowest deprivation scale under 500m footprint). However, this shifts additional noise onto communities already burdened by road/rail noise, and noise-priority routing may unintentionally overburden deprived, high noise exposed neighbourhoods. The authors caution that more accurate noise modelling would improve the rigorousness of the study.

Chapter 3
Internoise 2025

3.1 This chapter contains findings that were presented at the Internoise 2025 conference, which was held in Sao Paulo, Brazil. The first paper is by **Chance and Zamboni** and is an experimental study on rotor aeroacoustics. This study investigates how unsteady rotor speeds, representative of real drone and UAM operations affect noise emissions and aerodynamic loads. It is explained that unlike steady revolutions per minute (RPM) certification tests, real drones frequently experience rapid RPM fluctuations caused by gusts, control system adjustments, and manoeuvres. These fluctuations are expected to significantly alter noise signatures and therefore may impact perception and annoyance.

3.2 The researchers conducted controlled experiments in an anechoic facility using a 0.3 m APC-type propeller. They imposed harmonic variations in rotational speed across a range of amplitudes and frequencies, while simultaneously measuring thrust, RPM, and far-field noise. The aim was to understand the aero acoustic mechanisms behind noise changes in unsteady conditions, providing insights relevant to the operations of drones, eVTOLs, and UAM vehicles.

3.3 These findings indicated that real operating conditions cannot be reliably predicted from steady-state performance curves alone. Thrust increases with RPM as expected, but in unsteady conditions, thrust behaviour deviates from steady predictions. At high modulation frequencies, thrust leads the change in RPM slightly, likely linked to aerodynamic lag effects. Large modulation (noise variability) amplitudes show thrust differs between acceleration and deceleration phases.

3.4 SPL generally increases with RPM, but the rate of increase varies unexpectedly across RPM ranges. Under unsteady RPM, low modulation frequencies (slow RPM oscillations) yield higher noise levels (up to +3 dB for large amplitudes), whereas high modulation frequencies generally reduce overall SPL.

3.5 Unsteady operating conditions were found to cause phase delays. Thrust and noise do not respond instantaneously to changes in RPM. These phase delays mean noise may peak at different times than expected, complicating prediction and modelling. The authors concluded that applying steady-state measurements to real UAM or drone operations will lead to erroneous noise predictions, because unsteady aerodynamics alters the tonal and broadband noise balance. Noise directivity patterns shift in transient conditions, and RPM-dependent noise relationships break down under modulation.

3.6 The study indicates that unsteady rotor speeds significantly alter both thrust and noise emissions, in ways that differ from steady-state assumptions commonly used in regulation and design. Because these unsteady conditions are inherent to real-world drone and UAM operations, relying on steady-RPM data may underestimate noise exposure and community annoyance.

3.7 The findings highlight the need for:

- Better modelling of transient aeroacoustics,
- Revised certification approaches that reflect real operational behaviour,
- Noise-aware control strategies,
- Careful integration of UAM into urban environments.

3.8 **Bauer** presented a study on community noise contribution from flight path sections with different transitional air-taxi flight conditions. The study was conducted under the PAULA project[3], and examines how different transitional phases of an eVTOL air-taxi flight, especially just after taking-off and before landing, contribute to community noise around vertiports. It aims to identify which segments of the flight path create the greatest noise burden for nearby residents and provides guidance on selecting observer (microphone) positions for noise impact and annoyance testing.

3.9 UAM vehicles undergo rapid changes in RPM, thrust, power, speed, and tilt-angle during the initial climb and final approach. These phases produce unique and often high-intensity noise signatures, which can significantly influence community acceptance. The study uses detailed simulations with thousands of noise sources to model SEL, maximum sound pressure level (L_{max}), and loudness at 47 observer locations near the modelled vertiport.

3.10 The findings indicated that the transition phase dominates noise near vertiports. The first 0-100 metres from the vertiport when the vehicle is taking off involves the greatest operational changes such as rapid rotor power-up, thrust build-up, and early lifting motion. It consumes around 44% of total take-off time and contributes the largest share of SEL and L_{max} to observers within approximately 200 metres.

3.11 Between 100 and 300 metres large changes in tilt-angle and rotor power occur, including shutting down parts of the propulsion system. Noise from this segment is still a strong contributor at hundreds of meters, and the sound signature

[3] The PAULA study is funded by the Bavarian State, and addresses the question of how UAM noise will be judged by the residents who are living near vertiports and how the overall acceptance of UAM can be described.

remains recognisable. Stationary “power-up” and “power-down” operations were found to produce significant noise. Even when the aircraft has not yet left the ground, or has just landed, the noise plateaus from rotor acceleration/deceleration were audible at all microphone positions.

3.12 Loudness LN(5%), which correlates with annoyance, was found to vary less across the trajectory than SEL or L_{max}. The 100-300 m section produces recognisable loudness patterns up to 700 m and beyond, especially the distinctive tones associated with tilt-wing transitions. Noise metrics at each observer point were dominated by whichever flight path section passes closest to their location, and not just by the loudest part of the flight.

3.13 The simulations indicate that people living to the side of the path may still experience noticeable noise events. It is explained that this challenges traditional assumptions that noise annoyance occurs mainly directly beneath flight corridors. The authors recommend carefully choosing monitoring/observer locations for realistic noise impact and annoyance testing and including distant and laterally displaced residents in impact studies. These findings emphasise that public acceptance of UAM will depend heavily on managing these early transitional noise impacts, not just cruise noise.

3.14 **Merino-Martinez and Quaroni** investigated how people perceive noise produced by an isolated propeller operating under different turbulent inflow conditions and blade pitch angles. It combines detailed aero acoustic wind-tunnel measurements with psychoacoustic listening experiments, making it one of the few studies that directly connects physical noise metrics with human annoyance responses.

3.15 The purpose of the study is explained that real-world communities react to tonal qualities as much as (or more than) to loudness, and certification metrics may miss that. By manipulating turbulence and blade loading and directly measuring human annoyance, the authors aim to give designers and policymakers evidence to prioritise tonality reduction and to develop noise assessment methods that better predict how people feel about propeller/UAM noise.

3.16 The main findings included that higher turbulence intensity (TI) created more broadband noise, raising overall loudness, but this also masked tonal peaks and reduced sharpness, making the noise less piercing and less tonal. Increasing turbulence intensity reduced perceived annoyance. Despite increasing overall noise energy annoyance ratings dropped from 7 or 8 out of 10 to around 5 out of 10 when TI exceeded around 2%. This indicates that tonal character influences annoyance more strongly than loudness does.

3.17 Higher blade pitch angles increased perceived annoyance. When the collective blade pitch angle was increased, broadband noise at high frequencies decreased, but thrust and blade loading increased, which raised annoyance.

3.18 Across all conventional and psychoacoustic metrics tested, tonality was the only metric showing a statistically significant correlation with annoyance ($\rho = 0.779$, $p = 0.001$). Loudness, sharpness, EPNL, PNLT and others showed no significant correlation. Combined metrics (tonality x loudness x sharpness) yielded higher correlations ($\rho = 0.875$).

3.19 This study concluded that human annoyance from propeller noise depends far more on tonality than on loudness. Increasing turbulence intensity, common in realistic drone and UAM operations raises broadband noise but reduces tonal content, resulting in lower annoyance. Meanwhile, higher blade loading (pitch angle) increases annoyance.

3.20 The authors explain that current regulatory noise metrics fail to predict these human responses, indicating the need for psychoacoustically informed noise standards for drones and eVTOLs.

3.21 To address several key challenges and knowledge gaps associated with the introduction of eVTOL aircraft into urban environments, **Aalmoes et al** investigated how people perceive the sound of an eVTOL aircraft (developed by Eve Air Mobility), compared with helicopters and a turboprop aircraft.

3.22 Communities are familiar with, and often annoyed by, the noise from helicopters and turboprop aircraft. To understand whether eVTOLs will be better or worse from a public perception and tolerance perspective, the study aimed to compare sound from eVTOLs to multiple helicopter models and one turboprop aircraft. This comparison helps determine if eVTOLs are perceived as quieter or less annoying, regardless of decibel levels.

3.23 The study aims to understand whether busy versus quiet urban environments change the perception of eVTOL noise, and whether seeing the aircraft affects annoyance. The authors explains that environmental sound levels and urban context “influence the perception of the event” and that the study includes events with and without the aircraft being visually present.

3.24 The study included 113 participants, and was conducted in New York, Orlando, and San Francisco. Participants were exposed to aircraft events in a virtual reality environment, for simulated eVTOL flyover and take-off sounds, and real recordings of three helicopters and one turboprop aircraft. Each sound was combined with local environmental audio (quiet and busy urban settings). For some events, the eVTOL’s visual presence was removed to test the impact of visibility on annoyance.

3.25 Annoyance was rated on a 0-10 scale for the question "How much did the sound of this flying event bother, disturb or annoy you in this environment?". Statistical analyses (repeated-measures ANOVAs) evaluated comparison of aircraft at equal sound levels, comparison with expected real-world differences (eVTOL assumed 5 dB quieter), the influence of background environment, and the effect of visual presence.

3.26 The results suggested that eVTOL flyovers are less annoying than helicopter flyovers at equal sound levels. eVTOL flyovers scored significantly lower annoyance than the two helicopter models, and no significant difference was found in annoyance between eVTOL and turboprop noise exposure at matched loudness. This is shown in Figure 1:

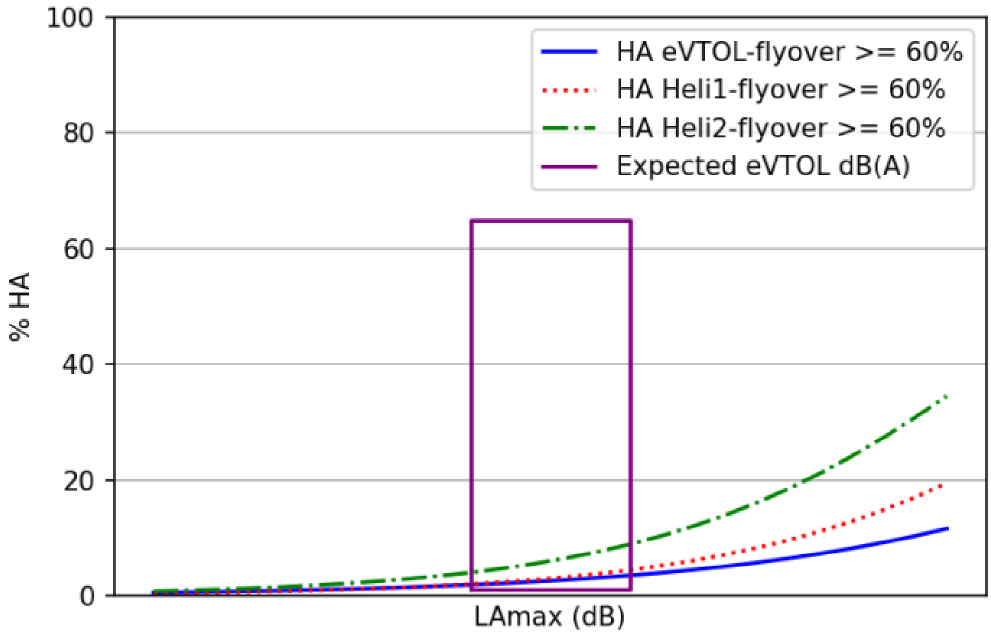

Figure 1: The difference between highly annoyed participants towards an eVTOL flyover and the two helicopter flyovers at the same sound pressure level dB(A). Due to the lower sound levels, the four highest annoyances scores (8-11) were used for determining the number of participants that were Highly Annoyed (HA). The purple box indicates for the x-axis expected L_{Amax} values for an eVTOL flyover. *Reproduced from Aalmoes et al.*

3.27 As it is expected that eVTOL aircraft will be quieter than either helicopters and turboprop aircraft at the same distance, another comparison was made where eVTOL sounds were played at a 5 dBA lower sound level than either the helicopter or turboprop aircraft. When played 5 dBA quieter than comparison aircraft, eVTOL noise was significantly less annoying than both helicopter and the turboprop noise across all measures.

3.28 The results suggested that environmental context matters for take-off noise. Take-off events were consistently less annoying in busier urban environments (Figure 2). Ambient sound influences annoyance but mainly for louder events (e.g., take-offs), not quieter flyovers. An overall effect was found of vehicle type on annoyance, one of the eVTOL take-offs ($M = 8.19$, $SD = 2.58$) was less annoying than the helicopter take-off ($M = 7.38$, $SD = 2.90$) $p = .047$.

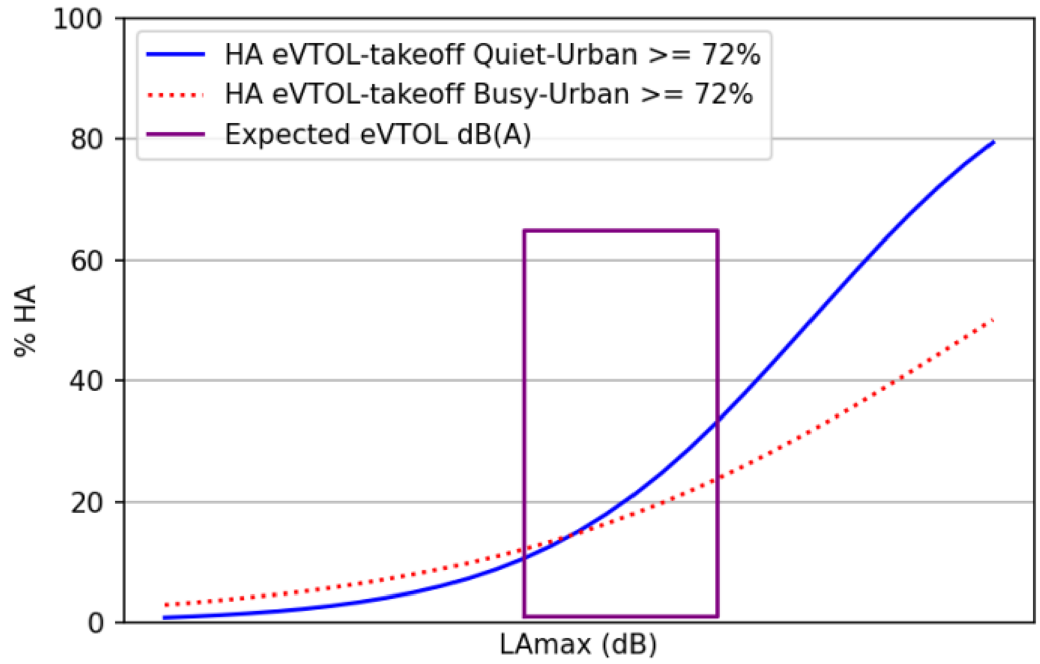

Figure 2: Annoyance curves for eVTOL take-off operation for the quiet urban and the busy urban environments. The purple box indicates for the x-axis expected L_{Amax} values for an eVTOL take-off. *Reproduced from Aalmoes et al.*

3.29 In terms of visual presence of the eVTOL aircraft, no significant impact was observed for flyovers, but for take-offs the annoyance level was higher when the eVTOL was visible. It is expected that the visual appearance of a nearby take-off of the eVTOL contributes to a higher annoyance.

3.30 The results were generally consistent across all three U.S. cities, supporting general trends in public perception. The authors suggest that these findings can help guide community engagement, UAM route planning, and eVTOL noise certification.

Chapter 4
Other Publications

4.1 There have been a number of other publications on the human impacts of emerging technology aircraft noise over the past twelve months. Many of these focus on the public acceptance of any proposed movements, and the arising considerations around this.

4.2 **Lee and Haan** examined the major factors around UAM noise using objective and subjective assessments. The study investigated how people perceive UAM noise, how it differs from helicopters and drones, and which acoustic characteristics most strongly influence annoyance. To do this, the authors conducted objective acoustic analyses (using sound quality metrics), and subjective listening tests with 108 participants. The aim was to identify major factors of UAM noise and propose suitable noise assessment standards.

4.3 The main objectives of the study were to:

- Determine the acoustic characteristics of UAM noise.
- Compare UAM noise with helicopter and drone noise.
- Understand how people perceive and rate UAM noise.
- Identify thresholds where human annoyance sharply increases.
- Propose new noise standards tailored to UAM.

4.4 Three aircraft types were chosen to compare acoustic signatures:

- UAM (OPPAV eVTOL)
- Helicopter (Robinson R44)
- Drone (Ceres 16h)

4.5 The authors explain the purpose of using these three types of aircraft was to benchmark UAM noise against familiar aircraft (helicopter/drone) and examine differences in sound quality metrics across propulsion types (electric versus combustion. For each flyover, the researchers extracted 20 seconds of sound, including ten seconds before passing the central microphone, and ten seconds after.

4.6 Due to UAM sound changing with distance, the researchers simulated different listening distances using distance attenuation formulas. They generated UAM noise at 50-78 dB, in 4 dB increments (representing altitudes from 300m down to

10m). 4 dB increments were chosen because 4 dB exceeds the Just Noticeable Difference (JND) for human perception and ensures participants can reliably distinguish differences.

4.7 The sound quality metrics loudness, sharpness, roughness, fluctuation strength and tonality were analysed. Participants evaluated UAM, helicopter, and drone noise at 59 dB, 63 dB and 79 dB, and listened to UAM noise at multiple distances at 50, 54, 58, 62, 66, 70, 74 and 78 dB SPL. To predict annoyance from physical metrics, the researchers ran the data through three PA models: Zwicker (general-purpose human annoyance model), More (for jet/aircraft noise, highly sensitive to sharpness) and NASA UAM-specific model (recently developed for eVTOL noise). This allowed them to compare how different models treat features like sharpness and validate which model aligns best with real human responses.

4.8 The findings revealed that UAM noise has a unique acoustic signature, with high sharpness (a shrill, high-frequency quality), and high tonality (prominent tones, perceived as pitch-like). These features largely come from electric motors and inverters, not rotors. While UAM loudness was lower than helicopters, it sounded sharper and more tonal, which shaped human reactions strongly. In subjective tests, UAM sharpness and tonality scores were consistently high, often higher than helicopter or drone scores. Participants described the noise as containing a steady low-frequency rotor hum, plus brief high-frequency peaks (which increased perceived tonality). This led to mixed interpretations where some listeners reported the noise as low-frequency, and others reported high-frequency peaks as dominant.

4.9 UAM noise annoyance was seen to increase at 72 dB, which resulted in 28% highly annoyed (mean annoyance score 7.0) , to 72% highly annoyed at 77 dB (mean annoyance score 8.8). Strong positive correlations were found with loudness, sharpness and roughness ($R^2 \geq 0.9$). No clear correlation was found with tonality, which was perceived inconsistently, making it harder to map directly to annoyance. It is explained that objectively, sharpness decreases at higher dB levels (due to frequency balance shifts), but subjectively, participants reported that sharpness increased as noise became louder. This mismatch suggests human perception of sharp or piercing sounds is non-linear and highly sensitive, making sharpness a key annoyance driver.

4.10 The helicopter was rated most annoying due to high loudness and was perceived as low-frequency and heavy. UAM was rated less annoying than helicopters, but more annoying than drones at equal dB. There were strong reactions to the high-frequency elements, and the UAM annoyance became high once sound levels exceeded 74 dB. Drone noise had the lowest perceived annoyance (mainly due to low dB).

4.11 The authors propose that the findings suggest that UAM noise standards must consider not only decibels, but also sound quality factors, especially sharpness and tonality.

4.12 **Lotinga et al** explored the development of psychoacoustic prediction models for short-term noise annoyance responses to UAS. The study aimed to develop prediction models for short-term human annoyance responses to sounds produced by UAS. As drones and UAS vehicles become more prevalent in urban and suburban environments, understanding how humans perceive these unfamiliar sounds is critical for UAS flight-path planning, noise-aware vehicle design, regulation and policy development and urban soundscape management.

4.13 The main aim of the study was to determine which acoustic and psychoacoustic metrics (e.g., loudness, sharpness, tonality) best predict human annoyance, and how these effects vary across different aircraft types, flight modes, and ambient environments.

4.14 The listening experiments within the study contained 42 adult participants (ages 19-58), who were exposed to 97 audio scenes combining:

- 3 UAS types (2 kg hexacopter, 6 kg quadcopter, 60 kg X8 multicopter),
- 3 operating modes (flyover, landing, take-off),
- 2 ambient environments (quiet park, busy city street),
- single-event or multiple-event flight sequences.

4.15 UAS sounds were taken from field recordings and embedded within real ambient environments. Participants rated annoyance using the 11-point ISO scale. They also indicated whether they noticed the UAS in each scene (a measure of detectability).

4.16 Over 100 metrics were evaluated, including sound level metrics (L_{Aeq}, L_{AE}), loudness (various models), sharpness, tonal loudness, roughness, fluctuation strength, impulsiveness and detectability.

4.17 The findings indicated as expected, A-weighted sound exposure level (L_{AE}) and psychoacoustic loudness metrics were the top predictors for both annoyance and high annoyance. Sharpness and tonal loudness were critical secondary predictors. These high-frequency features explain why some UAS designs (e.g., small hexacopters) are more annoying than others. The paper confirms that sound quality, not only loudness, drives human response.

4.18 The ambient environment was found to strongly affect annoyance. Models that included information about the environment type (park versus street) performed best. Quiet park environments led to higher annoyance for the same UAS noise level, because the drone is more perceptually prominent. Noisy street environments masked UAS noise and reduced annoyance.

4.19 Detectability correlated strongly with annoyance. UAS sounds that were more detectable within the ambient environment were also rated as more annoying. It is explained that detectability serves as a psychoacoustic measure of how much the UAS emerges from background noise.

4.20 UAS design type and flight mode was found to significantly influence responses. Even after accounting for acoustic metrics, small hexacopters (2 kg) were consistently rated more annoying (due to high sharpness and tonality). Larger multicopters (60 kg) were less annoying due to their lower sharpness and tonal content. Take-off and landing operations were found to be more annoying than steady flyovers. Annoyance increases as the number of flight events increases but the rate of annoyance increase slows at higher counts.

4.21 The high annoyance predictions were less stable than mean annoyance ratings. The dataset contained relatively few “high annoyance” responses (ratings 8-10), making models less stable for this outcome. However, the likelihood of high annoyance increased steeply with rising UAS sound level, especially in quiet environments. Figure 3 shows the annoyance exposure-response relationship comparison with other studies (Aalmoes, Gwak, Kwawi).

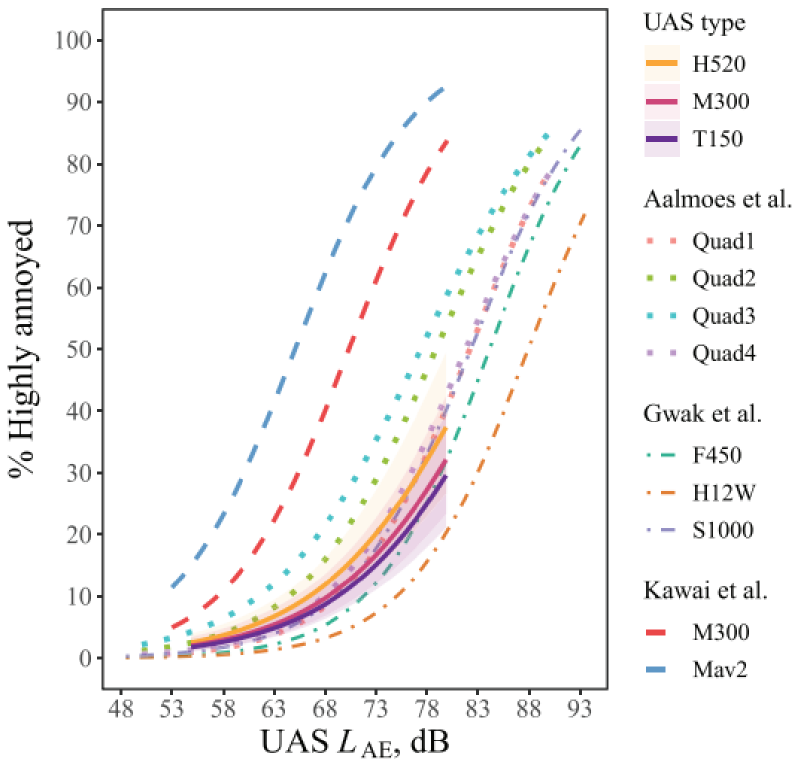

Figure 3: Exposure-response relationship comparison with estimated marginal mean regression and 95% CIs (flyover, take-off, and landing operations, (2-60 kg). Reproduced from Lotinga et al.

4.22 The authors explain that this comparison in Figure 3 indicates that the results of this experiment are more similar to those obtained by Aalmoes et al. (2021) than those obtained by Kawai et al. (2024), exhibiting a general tendency for relatively low rates of high annoyance. In comparison with Gwak et al. (2020) (hover operations), the results obtained in this study are similar, tending towards the upper values observed by Gwak et al. (2020).

4.23 The study demonstrated that both loudness and specific sound qualities (sharpness, tonal loudness) are essential for predicting short-term UAS noise annoyance. The context matters, ambient sound levels and type significantly affect how annoying a UAS is. Psychoacoustic metrics representing emergence, such as detectability, were found to improve annoyance model accuracy.

4.24 **Raza and Stansbury** published a review of current research, tools, challenges, and regulatory considerations related to noise from UAS and electric eVTOLs in the context UAM. The authors stress that sustainable UAM requires an integrated noise management framework that includes accurate prediction models, effective mitigation technologies, community perception considerations and appropriate regulations.

4.25 The paper reviews a wide range of methods from low-fidelity empirical tools to high-fidelity computational fluid dynamics (CFD) based simulations, including:

- NASA AEDT, AIRNOISEUAM, OVERFLOW
- CFD + Ffowcs Williams–Hawkings (FW-H) acoustic models
- Gaussian beam tracing for terrain/wind effects
- Machine learning models trained on large noise map datasets

4.26 Each approach was compared for model fidelity, operational applicability, and limitations (e.g., computational cost, missing data, simplified assumptions).

4.27 The authors also examined noise mitigation strategies, and explain that mitigation methods fall into three categories:

1. Passive (design-based). These include rotor spacing, blade spacing, blade count optimisation, low tip-speed designs, ducted rotors, propeller geometry optimisation and surface treatments (e.g., turbulators).
2. Active. Such as active noise control (ANC), rotor phasing and control authority methods.

3. Operational. For example, noise-optimised flight paths, low-noise landing/descent profiles, vertiport siting and airspace corridor planning, and traffic management strategies to minimise cumulative noise.

4.28 The study highlights trade-offs, for example, increasing rotor count reduces modulation but increases broadband noise.

4.29 A major part of the review examines international studies (Germany, South Korea, Spain, EASA, Turkey) on public attitudes toward UAM noise. The authors found that noise is consistently one of the top public concerns, often only second to safety. Annoyance is driven more by tonal ("mosquito-like"), modulated character than by decibel level alone, and perception changes with distance, duration, familiarity, context, and visual factors. Repetition, duration, and clustering of flights influence annoyance. VR and psychoacoustic experiments show that the environment and expectation of listeners shapes annoyance.

4.30 The study emphasises the need for standardised metrics and early community engagement. Cross-national findings included:

- Germany: noise was ranked as a top concern (52%); women showed more sensitivity than men.
- EASA EU-wide survey: noise was ranked as the second highest concern after safety; familiar sounds at the same decibel level are perceived as less annoying.
- Turkey: noise was rated as the fifth key barrier to UAM adoption; there was high variance in responses, suggesting strong sensitivity differences.
- South Korea: different noise metrics (WECPNL versus L_{den}) complicates global standardisation.

4.31 Noise annoyance was found to depend strongly on context. For example, urban background sound levels, time of day, activity (work, leisure, sleep), and expectations of noise (e.g., medical flights were tolerated more than delivery drones).

4.32 The authors concluded that UAS/eVTOL noise is a critical barrier to widespread UAM adoption. Significant progress has been made in prediction and mitigation, but no single method is sufficient. Accurate prediction requires combining aerodynamic simulations with psychoacoustic metrics. Real-world validation remains limited as most studies are laboratory based, and there is a need for interdisciplinary research combining acoustics, urban planning, and human factors. Future research should integrate high-fidelity modelling with machine learning and incorporate dynamic urban environments. It is recommended that mitigation must be multifaceted, and include vehicle design, airspace management, regulation and sufficient levels of community engagement.

4.33 **Upadrasta et al** examined how public acceptance of civil drones varies depending on the purpose of their use. While drone usage is expanding across Europe, societal acceptance remains inconsistent and highly purpose-dependent. This study aimed to address a gap in existing acceptance models by explicitly incorporating five major application categories into a new theoretical model. These were:

- Emergency and humanitarian aid
- Industrial purposes (construction, mining, agriculture, etc.)
- Transport and mobility (parcel delivery, food, medicines)
- Surveillance and monitoring (police, crowd monitoring, traffic, museums)
- Societal service facilitation (weather monitoring, inspection, research, forest health).

4.34 The authors developed a new drone acceptance model grounded in established behavioural theories:

- Theory of Planned Behaviour (TPB) capturing how attitudes, subjective norms, and perceived control shape behavioural intentions.
- Chamata and Winterton's inductive drone acceptance model, which distinguishes perceived benefit from perceived usefulness and emphasises perceived control.
- Risk theory, to incorporate perceived risks, a well-known predictor of public acceptance.

4.35 The final model includes four core determinants: perceived benefits, perceived risks, control opportunities (public ability to influence/regulate drone use), and social influence. An online survey was distributed in sixteen languages, across Europe, resulting in the inclusion of 601 participants aged 18-85. Analysis was conducted using structural equation modelling (SEM).

4.36 The results indicated that approximately 70% of respondents reported a positive attitude toward civil drones. Experience of drones is increasing, with 77% knew someone who owns or operates a drone, and 21% of respondents had owned one.

4.37 Acceptance was found to strongly depend on purpose. The highest acceptance was for emergency and humanitarian aid (mean = 4.62 on a 1-5 scale). Risks had no significant effect on acceptance, and public support was stable and consistent across demographics.

4.38 Societal service facilitation and industrial use were the next highest acceptance categories. For both categories, the perceived benefits drive acceptance more than risks, and there was an emphasis on efficiency, safety, and economic value. The next lowest acceptance was for transport and mobility (package delivery), which was most influenced by both benefits and risks. There was high uncertainty among the public, and safety, privacy, costs, noise, and misuse concerns weigh heavily.

4.39 The lowest acceptance was for surveillance and monitoring (Mean = 3.17). There were strong concerns around privacy and ethical issues. The benefits have weaker influence, and risks have strong negative influences. All differences between categories were statistically significant.

4.40 The authors explain that the study demonstrates that public acceptance of civil drones is not uniform, it varies depending on how drones are used. Emergencies resulted in consistently high acceptance; industrial and societal services resulted in strong acceptance driven by perceived benefits. Transport use had a high level of uncertainty, and balanced sensitivity to the risks and benefits, and surveillance use produced the lowest acceptance levels, where privacy concerns dominate. It is explained that the new model provides a flexible, purpose-sensitive framework that can help regulators, manufacturers, and service providers design strategies that are application-specific, targeted, and aligned with public expectations.

4.41 **Vogel et al** assessed the influence of indoor unmanned aerial vehicles on human cognitive performance and well-being. The study examines how indoor UAV operations affect human cognitive performance, well-being, and ergonomics, focusing on workplace contexts where drones may operate alongside employees. The study rationale was motivated by increasing interest in using UAVs for indoor logistics, inspection, and manufacturing tasks, and the authors investigated potential human-factor risks that could hinder successful adoption of drones in this context.

4.42 48 participants were included in the study (24 experimental, 24 control). Participants completed a cognitive Work Efficiency Test (WET), a complex multi-step reasoning task, for 12 minutes. The experimental group (EG) performed the task while UAVs flew autonomously indoors for 10 minutes behind a safety net, and the control group (CG) completed the same task without UAV presence. The UAV used was a Crazyflie 2.1 micro-drone, chosen for safety in indoor experiments.

4.43 The study assessed cognitive performance (number of correct WET solutions), flow experience (fluency, absorption, worry, skill-demand fit), mental effort, mental strain (functional and dysfunctional), user experience, and qualitative reports of distracting UAV characteristics. Additionally, control variables included trust in automation, cognitive failures, and intelligence.

4.44 In terms of cognitive performance, the EG solved slightly fewer tasks (M = 11.61) than the control group (M = 13.39). This difference was marginally significant (p = .055), meaning the study did not confirm a statistically significant performance drop, but results suggest a trend toward impairment. Indoor UAV presence may negatively affect cognitive performance, but the effect was small, possibly due to short exposure time (10 minutes) and the use of quiet micro-UAVs.

4.45 The only significant group difference was found in flow experience. EG reported significantly lower flow than CG (p = .027), meaning the UAV presence disrupted fluency and absorption, known to be key elements of deep concentration. Even if performance scores are not drastically reduced, motivation, engagement, and task immersion degrade when UAVs operate nearby.

4.46 No significant differences were observed between groups for mental effort, mental strain, and user experience. Both groups experienced similar levels of mental load and affective strain. The cognitive task itself was engaging enough that UAV presence did not substantially increase subjective workload, but it still reduced flow and possibly attention quality.

4.47 Participants listed 100 distraction factors, categorised into 10 themes. The main distractors were noise, movement/flight trajectories, proximity/distance, wind and air disturbance and visual distraction. Some UAV flight trajectories were noticed significantly more often than others, indicating different levels of visual distractibility. Participants described UAV noise as “annoying,” “irritating,” and “unexpected.”

4.48 The authors concluded that although statistical significance was weak for performance, even small, low-noise drones reduced the quality of concentration. Noise and motion are the biggest distractors, in line with other findings. It is suggested that companies must consider acoustic distraction, visual distraction, worker trust and perceived safety in order to integrate UAVs safely and effectively in indoor workplaces. The effects might be stronger in real industrial environments. The study used a quiet laboratory, small drones, and short flight durations; real-world workplaces likely have larger, louder drones, longer exposure and more complex multitasking demands. Therefore, cognitive and ergonomic impacts may be underestimated.

4.49 **Kumar et al** published a review of UAM research, focusing on air taxis, eVTOL aircraft, and drone delivery systems as emerging transportation modes. The review includes 54 studies selected from an initial pool of 612, covering technological, regulatory, environmental, and social dimensions of UAM adoption.

4.50 Across all reviewed studies, public perception emerges as the dominant non-technical determinant of UAM success. Safety perception alone accounts for around 40% of acceptance in modelling studies. The fear of mid-air collisions, autonomous malfunction, falling debris, and privacy breaches are factors affecting public willingness to use or live near UAM operations. Acceptance of UAM remains highly conditional on safety confidence, cost, noise impact, privacy, transparency of operations and familiarity with aviation technology.

4.51 The report highlights that eVTOL noise is perceived differently from helicopters. Although quieter overall in decibels, eVTOLs produce high-frequency tonal noise, perceived as more irritating to urban residents, and noise is highly sensitive to low-altitude operations, repeated overflights, and vertiport proximity.

4.52 Equity and social inclusion concerns are discussed in the review, with the authors cautioning that UAM could become an elite mode of transport, serving only high-income passengers, and this may create social inequity if lower-income groups are excluded from new air-mobility corridors. High initial ticket prices may exclude many users. Drone deliveries may benefit wealthier districts first, reinforcing spatial inequality. Social-sustainability models propose integrating UAM into public transport to ensure equitable access across areas.

4.53 Human factors are discussed by the authors. Trust in UAM varies by:

- Age: younger people (25-35) show higher acceptance and willingness to pay.
- Income: higher income users are more open to air taxis.
- Cultural experience with aviation: regions familiar with drones or helicopters show higher baseline acceptance.
- Technology openness: strongly correlates with UAM acceptance.

4.54 Trust is found to be affected by regulatory transparency, perceived operator competence, clarity of safety communication, and visibility of successful demonstrations. Live flight demonstrations have been found to increase acceptance by up to 25% in some populations.

4.55 For drone deliveries, the main concerns include the fear of falling objects, privacy intrusion from onboard cameras, noise from low-altitude flights, perceived cluttering of skies and distrust in autonomous navigation. These concerns directly influence public support for large-scale deployment.

4.56 The impact on the environment is discussed. Residents report concerns about increased urban energy demands, CO_2 emissions, impacts on local wildlife and green spaces, visual pollution and noise annoyance.

4.57 The authors highlight the human-centred design gaps thar currently exist, including accessibility for elderly or disabled passengers, emergency evacuation procedures, cabin comfort, clear interface systems for passengers and ethical crash-avoidance decision frameworks. Without these considerations, the authors suggest that UAM will suffer from low trust and low adoption rates.

4.58 **Maghsoodi's** Masters' thesis explored drone noise assessment methods and noise containment approaches. The aim of the study was to provide a comprehensive technical, acoustic, and human-factors analysis of drone noise, including how noise is generated, how it propagates, how people perceive it, and what engineering strategies can reduce its impact. The report combines laboratory measurements, psychoacoustic listening experiments, outdoor sound propagation modelling, and public acceptance surveys to assess the real-world challenges of drone noise for communities and regulators. The work also proposes a holistic drone-noise assessment framework to guide regulators, engineers, and service operators in minimising noise impact across urban and residential areas.

4.59 Drone noise was measured using ISO standards and controlled indoor sound-power tests. The results indicated that noise depends strongly on rotor count, propeller geometry, flight manoeuvres, altitude, wind, and drone mass. Heavier drones produce broadband noise, while small drones produce high-frequency tonal noise. Modelling results suggested that drone noise can easily penetrate buildings, especially through open or poor-quality windows, which is a potential concern for sleep disturbance. The recommended WHO nighttime indoor limit (42 dB $L_{Amax,\ indoors}$) was used to compute minimum safe distances drones must maintain from homes.

4.60 The report reviews several noise reduction techniques:

- Passive mitigation: improved propeller geometry, serrations, higher blade count, ducted fans, metamaterials, vibration isolation.
- Active mitigation: synchro-phasing, active noise control (ANC), multichannel ANC rings, magnetically excited blades, RotoSub active-cancellation propellers.
- AI-based optimisation: flight-path adaptation, machine learning-based noise prediction.

4.61 A controlled listening experiment compared drone noise with aircraft, helicopters, and road traffic by the use of controlled spatialised 3D playback to allow precise comparison across sources. The results suggested that at comparable levels of key sound metrics such as L_{AE}, L_{Aeq}, and overall loudness, the annoyance and perceived loudness of UAS, helicopters, and aircraft were found to be similar, with only minor variations of ±1-2 dB or Phon when sound levels were adjusted for equal annoyance or perceived loudness. However, to achieve equal annoyance, UAS noise required an increase of 3.3 dB compared to helicopters and 2.0 dB compared to aircraft. The authors explain the disparity in annoyance perception was more pronounced when comparing UAS to road traffic noise, with UAS sound requiring reductions between 11.2 and 17.3 dB/Phon, depending on the specific metric used. Smaller UAS models such as the DJI Mini 3 Pro and DJI FPV were perceived as more annoying than other UAS types, even when their L_{AE} levels were similar. While annoyance levels remained relatively consistent across different UAS, factors such as tonality, sharpness and the perception of proximity played a significant role in influencing how their noise was perceived.

4.62 The indoor noise assessment indicated that drone noise can exceed WHO limits for sleep disturbance even when drones fly at moderate altitude. Open windows drastically increase indoor noise penetration. The modelling results showed drones must maintain significant distances from residential buildings to prevent sleep interruption.

4.63 Survey results in the report suggest that only 49% of people express positive attitudes toward drones; with 43% negative, and 8% undecided. Acceptance is highest for emergency uses, and lowest for parcel delivery, photography and leisure drones. 71% of respondents would not use drone delivery due to privacy/noise concerns. Even among supporters of drones, many do not want them flying over their homes, especially at night.

4.64 The report highlights significant demographic trends. Women and older adults report higher concern and lower acceptance, while younger respondents (18-35 years) are more receptive to new drone services. It is stressed that noise regulation must consider vulnerable groups, including older residents and noise-sensitive populations.

4.65 The author concludes that future work requires that more attention should be given to measuring long-term effects of drone noise, especially in urban areas where sound from different sources overlaps. They also suggest that better tools are required that combine sound physics with how people feel about noise, to include psychological and social elements of responses to drone noise.

4.66 **Lingham et al** explored how a delivery drone impacts feelings of uncertainty, through the use of a VR experiment. As delivery drones become more common, for groceries, medical supplies, and emergency equipment, people will increasingly interact with them in public spaces. This study investigated how a drone’s approach trajectory affects feelings of uncertainty, and how its delivery method affects uncertainty, with the aim to understand what makes drone interactions feel safe, predictable, and trustworthy. The authors explain that feelings of uncertainty “is assumed to be an important mediator in situations with unknown outcomes” and has been linked to negative emotions and can be used as measure of anxiety in humans.

4.67 Forty five participants were included in the VR environment, and they were asked to watch a delivery drone bring an Automated External Defibrillator (AED) to a recipient in a public park.

4.68 Drone behaviour varied across the approach trajectory, which was either orthogonal (straight-line approach and vertical drop), or curve (smooth arcing approach). The delivery method was either landing (descends to ground), or cable drop (hovers at 7 metres and then lowers package). Participants reported uncertainty in real time with a slider, answered questionnaires, sketched trajectories, and took part in interviews.

4.69 The findings suggested that curved trajectories reduced uncertainty, and participants felt safer, more trusting and more able to understand drone intentions with this approach. In addition, a curved approach stayed within their field of view, felt more "natural," and avoided the discomfort of a drone appearing suddenly overhead. Orthogonal approaches created strong feelings of uncertainty, fear that the drone might descend onto them, and a perception that it was flying "directly overhead," which felt threatening.

4.70 The findings indicated that cable delivery is strongly preferred over drone landings. Cable drops increased feelings of certainty and trust, made the drone's intentions clear, and kept the drone further away from people, reducing the noise and perceived risk. Landing the drone triggered safety concerns (rotor blades, collision risk), was less predictable ("When is it going to land? How fast?") and created confusion during post-delivery hovering. Participants found hovering, especially after delivery, confusing and sometimes alarming.

4.71 The authors found that clear communication reduces the level of uncertainty. Participants wanted drones to communicate:

- Intentions ("landing," "delivering," "leaving")
- Purpose ("medical delivery")
- Safety cues (lights or sounds)
- Sender/recipient information

4.72 Suggested solutions include the use of lights or sound cues, mobile phone alerts, and recognisable medical/drone branding that clearly indicates the use case. The participants' sketches revealed that many drew the orthogonal path as closer to them than it actually was, and curved paths were generally drawn accurately suggesting that curved paths are easier for humans to interpret spatially.

Chapter 5
Summary

5.1 The report has reviewed new research findings (March 2025-March 2026) on how noise from emerging aviation technologies (UAS/drones, eVTOLs, and Urban/Advanced Air Mobility platforms) affects people. It has summarised work presented at Euronoise and Internoise 2025, as well as other recent academic publications. The emphasis of the report has been on human perception, annoyance, detectability, and public acceptance.

5.2 The findings suggest that across many studies, annoyance was found to depend not just on loudness (dBA), but on:

- Modulation characteristics (slow or strong amplitude modulation increases annoyance)
- Tonality (prominent tones are the strongest annoyance predictor in several studies)
- Sharpness (high-frequency content is perceived as shrill and irritating)
- Roughness and fluctuation strength (irregularities in sound texture drive annoyance)
- Detectability (how much the drone noise stands out from the background).

5.3 These features often matter more than overall dB levels, indicating that traditional noise metrics may be insufficient for UAS/UAM.

5.4 Noise in real operations differs significantly from steady-state predictions. Multiple studies (Picillo; Chance & Zamboni; Bauer) showed that unsteady rotor speeds create transient noise peaks that aren't reflected in certification-style steady-RPM metrics. Manoeuvres (take-off, landing, tilt transitions) generate disproportionately high noise. These dynamic conditions alter noise directivity, psychoacoustic sharpness, and perceived unpleasantness. This means that existing noise modelling and certification methods may underestimate real-world annoyance.

5.5 From large-scale modelling work (LeGriffon; Jiang), the number of flights is a major driver of community burden, i.e., repetition matters. Higher altitudes reduce loudness but can cause wider propagation in dense urban areas. Routing affects which communities are exposed; quiet areas suffer more because of low background masking. Noise-priority routing (following roads) can reduce inequality but may compound noise burdens in already deprived areas, highlighting that noise impacts therefore have strong social-equity dimensions.

5.6 Noise is consistently one of the top concerns around emerging technology aviation, often second only to safety, and the findings suggest that noise mitigation requires integrated approaches. The research shows that emerging technology aviation noise is governed less by loudness and more by sound quality, especially modulation, sharpness, tonality, and detectability. Unsteady flight dynamics, repetition of events, and urban context heavily influence annoyance. Public acceptance varies strongly with use-case and perceived fairness. To manage noise effectively, new metrics, better modelling, more real-world studies, and integrated mitigation approaches are required. Understanding the role of non-acoustic factors, and impacts on sleep and health effects, alongside the work on sound quality metrics and annoyance, will continue to be important for developing noise policy in this area.

5.7 It is intended that update CAP reports will be produced on an annual basis, and will include findings presented at relevant conferences, and from published work in this rapidly growing area of research.

Chapter 6

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