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An investigation into human response to unmanned aerial vehicle noise

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ABSTRACT

It is predicted that urban air mobility, including the use of small to medium sized unmanned aerial vehicle (UAV) delivery systems, will be introduced into cities across the globe within the next 15 years. It is known, however, that noise is one of the main limiting factors for the wider adoption of these vehicles. Neither the metrics nor the methods used for conventional aircraft seem to be optimal for this novel source of noise. This research will aid in developing suitable psychoacoustic methodologies and metrics, specifically designed to quantify the community noise impact of these vehicles. This paper describes a psychoacoustic experiment used to gather participant responses to UAV sound recordings, performing a variety of different operations at differing distances. Results from this psychoacoustic experiment will be used to correlate perceptions of UAV noise with objective sound quality metrics, and build new regression relationships that could describe the impact of a given UAV on a community, as well as give insight into the key sound quality metrics that contribute to the perceived annoyance. Future extension to the research may include assessing the impact of introducing drone noise to a variety of soundscapes, evaluating the differences in psychoacoustic responses when introducing more accurate reproduction methods, such as virtual reality systems, and how these could be incorporated into a standardised human response measurement procedure.

1. INTRODUCTION

Unmanned Aerial Vehicles (UAVs), also known as drones, present an exciting new logistical and acoustical challenge that should be addressed to unlock substantial economic and societal benefits [1]. The implementation of a completely new source of transport and logistics also brings into question the severity of noise exposure to the health of the public from these vehicles. The potential benefits of urban air mobility (UAM) and UAVs are profound, including travel time reduction for both the user of the UAV and ground-based vehicles due to reduced congestion, as well as a decrease in air pollution from fossil-fuel emissions [2]. It is known, however, that noise pollution is one of the most significant causes of adverse health problems, second to air quality. Factors that could affect a person’s health introduced by noise include annoyance, sleep disturbance, and hypertension [3]. Without proper exploration into the noise emissions of these aerial vehicles, the adoption of them as a new source of transportation and a logistical tool could be limited.

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Previous research has tried to fill in the main gaps in the understanding of how drones will be perceived and exercised upon successful integration into our transportation and delivery infrastructures. When compared to conventional aircraft, such as fixed wing vehicles like cargo or passenger jets, drone noise can be seen to include significantly more high frequency and tonal noise radiation [4]. Furthermore, where conventional fixed wing aircraft observe a large amount of atmospheric absorption due to the typically long distance between the source and receiver, drone operations, such as delivery and transportation, are expected to be much closer to the public. This, combined with the already high-frequency characteristic of UAVs, will lead to an extremely high-pitched noise perceived during operations [5].

As well as frequency content, multiple researchers have found that certain sound quality metrics (SQMs) are well correlated with the perceived annoyance of UAV noise. These SQMs were developed to quantify auditory sensations specifically experienced by the human ear [6], and include loudness, sharpness, tonality, roughness, fluctuation strength and impulsiveness. Loudness quantifies the sensation of sound intensity perceived by the ear. Sharpness quantifies the ratio of high frequency content perceived by the ear. Tonality quantifies the presence of tonal components perceived by the ear. Roughness and fluctuation strength quantify the presence of slow and fast temporal fluctuations perceived. Impulsiveness quantifies the presence of sudden changes in the sound level perceived by the ear. It has been shown that metrics such as sharpness, tonality and fluctuation strength are strongly correlated with the perceived annoyance of rotorcraft, and hence may be significant indicators of the perceived annoyance to drone noise [7]. Research has also proven that the loudness, sharpness, and fluctuation strength were derived to be statistically significant variables in predicting the perceived annoyance of hovering drone noise [4]. Although there appears to be clear dispute over the prevalence of impulsiveness being a controlling factor in perceived annoyance to rotorcraft and helicopter noise [8], it may be deemed appropriate to assess the impact of impulsiveness on perceived annoyance for small to medium UAV.

This paper presents the initial results of an ongoing research aiming to understand how communities will respond to the noise generated by drone operations. The research described in this paper will investigate the perceived annoyance, loudness and pitch of typical small and medium sized UAV noise emissions when operating at a variety of distances, and performing various operations. An analysis will be described that aims to understand the main factors that contribute to the perceived annoyance of UAV noise, and build regression models that can give insight into the key SQMs that should be mitigated to improve the human perception of these new vehicles.

2. METHODOLOGY

The research methodology consists of 2 individual subjective tests, although only a detailed description and analysis will be discussed regarding the first subjective test, and details of the second subjective test will be released in a future publication. The first test aims to evaluate noise characteristics of UAV sound files that correlate to human psychoacoustic responses of annoyance, loudness and pitch. The second test will assess the perceived annoyance, loudness, drone dominance and soundscape pleasantness of the UAV sound files put into context of a variety of soundscapes representing typical urban and rural environments. These environments include busy city centres, roadsides, parks and suburban areas. The efficiency of these environments to mask and reduce the perceived annoyance and dominance of the UAV sound files will be assessed.

2.1. UAV sound stimuli

44 recorded UAV sound files were gathered which represented 8 individual UAV models of varying weight, performing several operations at different distances such as flyovers, take-offs, landings and hovering. These UAV sound files were presented to the participants in the first subjective test, and were edited to be 4 seconds long [9]. Table 1 gives details of each of the UAV sound files.

Table 1: UAV stimuli included in subjective test 1.

Sound	UAV	UAV Weight (kg)	Operation	Distance (m)	Calibrated LAeq
1	DJI Inspire	2.85	Flyover	15	52
2	DJI Inspire	2.85	Flyover	7.5	58
3	DJI Inspire	2.85	Landing	7.5	64
4	DJI Inspire	2.85	Takeoff	2	70
5	Intel Falcon	1.2	Flyover	30	54
6	Intel Falcon	1.2	Flyover	60	47
7	DJI Matrice 600	9.1	Takeoff	3	71
8	DJI Matrice 600	9.1	Hover	40	65
9	DJI Matrice 600	9.1	Flyover	40	57
10	DJI Mavic	0.743	Flyover	15	51
11	DJI Mavic	0.743	Flyover	30	46
12	DJI Mavic	0.743	Flyover	60	37
13	DJI Mavic	0.743	Maneuvering	7.5	51
14	DJI Mavic	0.743	Maneuvering	7.5	53
15	DJI Mavic	0.743	Takeoff	7.5	59
16	DJI Phantom 3	1.216	Maneuvering	2	68
17	DJI Phantom 3	1.216	Takeoff	2	64
18	DJI Phantom 3	1.216	Landing	2	62
19	DJI Phantom 3	1.216	Hover	2	69
20	DJI Phantom 3	1.216	Ascending	2	64
21	DJI Phantom 3	1.216	Flyover	2	61
22	DJI Phantom 3	1.216	Flyover	2	63
23	DJI Phantom 3	1.216	Flyover	2	66
24	DJI Phantom 3	1.216	Flyover	5.4	56
25	DJI Phantom 3	1.216	Flyover	5.4	59
26	DJI Phantom 3	1.216	Flyover	5.4	57
27	DJI Phantom 3	1.216	Hover	2.2	62
28	DJI Phantom 3	1.216	Hover	5.1	56
29	DJI Phantom 3	1.216	Hover	2.2	67
30	DJI Phantom 3	1.216	Hover	3.6	67
31	DJI Matrice 200	4	Flyover	46	56
32	DJI Matrice 200	4	Flyover	46	45
33	DJI Matrice 200	4	Takeoff	30	50
34	DJI Matrice 200	4	Landing	30	52
35	DJI Matrice 200	4	Hover	1.2	56
36	Yuneec Typhoon	2	Flyover	46	48
37	Yuneec Typhoon	2	Flyover	46	44
38	Yuneec Typhoon	2	Takeoff	30	46
39	Yuneec Typhoon	2	Landing	30	52
40	Yuneec Typhoon	2	Hover	1.2	57
41	Gryphon GD28X	11.8	Takeoff	30	53
42	Gryphon GD28X	11.8	Landing	30	54
43	Gryphon GD28X	11.8	Maneuvering	30	57
44	Gryphon GD28X	11.8	Hover	1.2	60

It has been found that when UAV are in flight, they constantly adjust for adverse weather conditions, such as strong winds, by implementing micro-adjustments in the rotational speeds of the UAVs rotors in order to maintain the vehicles stability. These micro-adjustments cause rapid fluctuations in the acoustic signature, and may negatively impact the perceived annoyance of the stimuli [10]. Therefore, it was decided to include UAV performing a variety of operations, to understand the main operating conditions that could be deemed the most annoying. Furthermore, a variety of operating distances were included, to assess the impact of audible distance and loudness on perceived annoyance, loudness and pitch. Measurement data, including measurement distance and sound level, was provided with the UAV stimuli to calibrate the sound files to specific L_{Aeq} values.

This was to maintain the variance in loudness that is typically observed when varying operational distance. To calibrate the sounds, a calibration system was designed. This system is described in figure 1.

First, the BSWA 308 meter was calibrated to a 94dB, 1kHz sine wave, and attached to the output of the Norsonic 336 microphone pre-amp. UAV stimuli 1 was played out of the laptop, through the AKG k501 and Dragonfly headphone pre-amp, and into the microphones located inside the ears of the HATS. The signal from the HATS microphones is then amplified by a set level and the BSWA 308 meter measured the level.

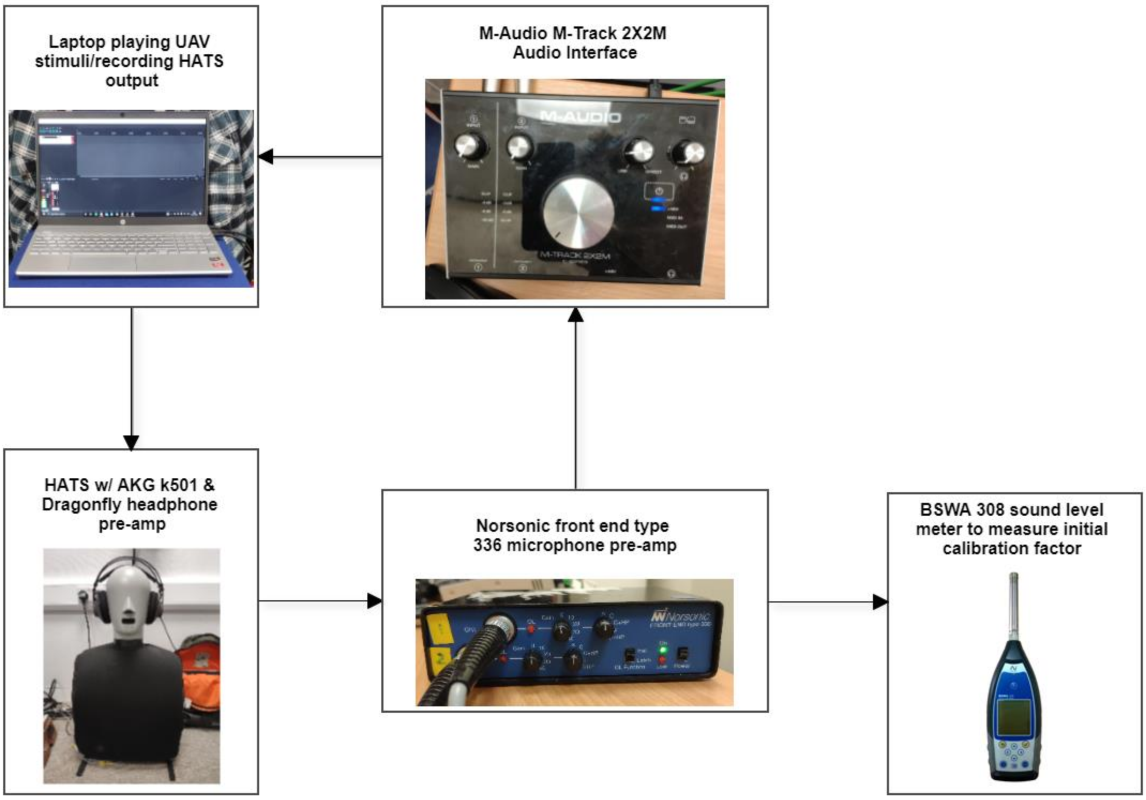

Figure 1: Calibration set up used for subjective test 1 UAV stimuli.

An initial calibration factor is measured, which is the difference between the measured value by the BSWA 308, and the desired L_{Aeq} as provided with the UAV stimuli. This calibration factor was then saved, and used to adjust the levels of the other UAV stimuli via MATLAB. This system was initially designed to record all UAV stimuli through the AKG k501, as this would have been the setup used for the stimuli playback had the experiment been carried out within a laboratory environment, and would be necessary to include the frequency response of the headset when calculating SQMs. Due to the restrictions of the COVID-19 lockdown, the experiment was taken online, so SQM analysis was carried out using the calibrated raw files rather than the AKG k501 recorded files, as these were used in the online subjective testing methodology.

2.2. Online subjective testing

The Web Audio Evaluation Toolkit (WAET) [11] was used to build the testing interface for both subjective tests. The interface incorporates sliders that the participant uses to give their responses of annoyance, loudness, and pitch for the first test. It was decided to include loudness and pitch as response values, as well as annoyance, to investigate the correlations between perceived annoyance audible distance, perceived loudness and calculated SQMs, as well as how the perceived distance of a UAV stimuli impacts the perceived annoyance. The online test took around 20 minutes to complete, and included all UAV stimuli once. The participant listened to one UAV stimuli, as many times as they needed, by pressing on a slider. They then gave their response values of annoyance, loudness, and pitch. Once the participant was sufficiently satisfied with their responses, they then proceeded to the next sound. The order of the UAV stimuli was randomised for each participant.

Prior to the test commencing, a safety precaution stage took place. Due to the online nature of the test, it was difficult to prepare for the vast number of different playback systems that may be employed for the test by the participant. Therefore, it was deemed appropriate to introduce safety stages to mitigate any potential risk to participant health. This was done by presenting the participant a practice page, similar in design to the main experiment pages, but with 5 UAV stimuli that vary across the whole L_{Aeq} range. The participants were then asked to adjust their system playback level so that the quietest sound was audible, but the loudest sound was not at an uncomfortable level. The participant was then asked that once they had appropriately adjusted their system playback level, that they do not adjust it for the remainder of the experiment. As well as this safety stage, participants were asked to input their participant ID, which was sent to them via email prior to the test, their age, and also asked to match the levels of a series of tones, in order to understand their frequency sensitivity. This information can be used to explain any anomalies that may occur in the response data (although that analysis is not included in this paper). Furthermore, a channel checking stage is included to ensure that stereo playback is being used. Participants were also given the option to add written comments on any of the UAV stimuli pages, if they so wished. A total of 49 participants completed the test, with consent being given at the start of the test via tick boxes.

2.3. Analysis

The analysis is split into 3 key stages. Stage 1 will be an initial analysis of the response data gathered from the online subject testing and calculated SQMs. Simple regression correlations are assessed between the objective metrics and the subjective response values. Firstly, to calculate the values of loudness, sharpness, tonality, roughness, fluctuation strength and impulsiveness, the HEAD Acoustics ArtemiS SUITE 12.5 software was implemented to calculate the SQMs quickly and effectively against time for each UAV stimuli. Loudness was calculated following the DIN 45631/A1 method [12]. Sharpness was calculated following the Aures model, as the UAV stimuli have an observably large variance in loudness [13]. Tonality was calculated following the Aures model [14]. Roughness, fluctuation strength and impulsiveness were calculated following the derived models by Sottek [15] [16]. Then, 5th percentile values were calculated for each metric, omitting the first 0.5 seconds of each metric calculation. The 5th percentile, or the value that is exceeded for 5% of the stimuli time interval, is commonly used in psychoacoustic analysis to mitigate the effect of noisy data, and omitting the first 0.5 seconds of each metric calculation removes any potential transient effects that could influence the SQM values [17]. Once these 5th percentile values were calculated, they were used in a linear regression analysis to observe any correlations between the SQMs and the response values of annoyance, loudness and pitch. This has been carried out in the IBM SPSS statistics software, allowing for efficient and precise models and methods to be utilised, and for creating regression result descriptors and plots. A simple linear regression analysis has been used to evaluate the statistical significance of the SQMs. The linear regression creates an equation which linearly correlates perceived annoyance to several predictor variables, and has a general equation which is described by equation 1:

$$Y_i = \gamma_0 + \gamma_1 X_{1i} + \cdots + \gamma_n X_{ni} + e_i \tag{1}$$

Where Y_i is average perceived annoyance of sound i, γ_0 is the y-axis intercept of the model, γ_n is the correlation coefficient that pairs with X_{ni}, the n-th SQM 5th percentile value of sound i, and e_i, the residual error. A backwards stepwise regression method was implemented in the model to choose the most statistically significant variables to include in the linear regression model. Backwards stepwise regression determines which variables to include in a model by first including all variables in the model, and then removing the metric that has the smallest reduction in R^2 value, or the most statistically insignificant variable. This process is repeated until no variables can be removed without a significant reduction in R^2.

The stage 2 of the analysis will be a simple, initial investigation into the effects of distance on the perceived annoyance, loudness and pitch for the UAV stimuli performing flyover operations. In total, 18 of the UAV stimuli were of flyover operations at distances varying from 2 metres to 60 metres. The intrusiveness of UAVs will no doubt be a key factor in the acceptance of UAV as a viable form of delivery, as well as other services. If the relationships between operation distance and perceived annoyance, loudness and pitch can be understood, then these relationships can be used to determine acceptable situations where UAV can operate effectively while also mitigating any potentially negative effects of their presence as a sound source.

Stage 3 consists of a multilevel linear regression analysis, to identify the significance of subject-dependent responses of perceived annoyance. Multilevel linear regression has been used previously to investigate the factors contributing to annoyance for rotorcraft and small UAV, and has found to be a useful tool in discovering key variables [4] [7]. Multilevel linear regression is a method that integrates no pooling and complete pooling of data between subjects. No pooling would mean that a regression analysis for each subject's response data would be built, meaning that a regression relationship would be described for each subject. Complete pooling suggests an aggregation of all response data, so a regression analysis would build a correlation between the independent data and the response data for the whole subject group. This multilevel regression groups by subject, therefore assuming a partial pooling of the subject data and a normal distribution across subjects of regression. It is first useful to determine whether a multilevel regression model is appropriate for understanding any grouping effects that may be causing variance in the response data. This is done by using a very simple, fixed intercept model with no predictor variables to understand the effect of clustered data on the dependent variable by assessing the interclass correlation coefficient (ICC), which is a ratio of the variance of the subject-dependent intercept estimates from the simple model, and the sum of this variance with the variance of the fixed intercept value estimated by the model. The model is described by equations 2 and 3:

$$Y_{ij} = \beta_{0j} + e_{ij} \tag{2}$$

$$\beta_{0j} = \gamma_{00} + u_{0j} \tag{3}$$

Where Y_{ij} is the perceived annoyance of sound i from participant j, β_{0j} is the sum of γ_{00}, the overall mean intercept for all subjects, and u_{0j}, the subject-dependent intercept offset. e_{ij} is the residual error per subject. From this, estimates of the variance of subject-dependent intercept values and the estimate of variance of the fixed intercept value can be used to calculate the ICC. If the ICC calculation yields a statistically significant result, then it can be assumed that clustering effects in the model contribute to the value of the dependent variable, and a more detailed multilevel model should be introduced. The next stage is to introduce predictor variables into the mixed model. A multilevel regression model, with a variable intercept per participant but fixed slopes of SQMs, has a general equation which is described by equation 3 and 4:

$$Y_{ij} = \beta_{0j} + \gamma_{10}X_{1i} + \cdots + \gamma_{n0}X_{ni} + e_{ij} \tag{4}$$

γ_{n0}, which does not vary per subject, is the regression coefficient of the n-th SQM 5$^{\text{th}}$ percentile value of sound i. Furthermore, introducing subject-dependent regression slope coefficients for each SQM can reveal more information about the variance between how participants perceive these metrics, but previous literature has found that introducing subject-dependent slopes for this style of SQM analysis yielded little improvement to model accuracy when compared to the increase in accuracy introduced by including subject-dependent intercepts [7]. Therefore, a subject-dependent slope and intercept model was omitted from this analysis. Metrics will be removed from this model to investigate the reduction in R^2 between the model's predicted values of annoyance and the measured response values, to determine the significance of each metric as predictor variables.

3. RESULTS

3.1. Simple correlation analysis

A simple correlation analysis looked at regression relationships between the calculated SQMs and the response data gathered during online subjective test 1. Firstly, the SQMs and dependent variables (responses of annoyance, loudness and pitch) were regressed against each other to illustrate any obvious correlations between variables, and the correlation coefficients are presented in table 2. Some of the SQMs yield a strong correlation with the response values given by the test participants. For perceived annoyance, the most significant correlations are those with loudness (DIN45631), sharpness (Aures) and fluctuation strength, indicating that these SQMs may be good candidates for predicting perceived annoyance in a regression model. Furthermore, perceived annoyance also correlates strongly with perceived loudness and pitch. This result would suggest that participants thought that not only the loudness but also frequency content relating to pitch to be significant factors influencing annoyance. Pitch correlated strongly with sharpness and tonality, as well as roughness and impulsiveness, meaning these metrics may be useful in quantifying how frequency content can be manipulated to reduce perceived annoyance. Perceived loudness correlated strongly with the SQM loudness (DIN45631), indicating that it is an applicable metric to represent the perceived loudness of UAV stimuli.

Table 2: Correlation coefficients between SQMs and response values.

		Loudness (DIN45631)	Sharpness (Aures)	Fluctuation strength	Tonality (Aures)	Roughness (Hearing model)	Impulsiveness	Annoyance	Loudness (perceived response)	Pitch
Annoyance	Pearson Correlation	.899**	.899**	.401**	0.254	0.193	-0.160		.960**	.614**
	Sig. (2-tailed)	0.000	0.000	0.007	0.097	0.210	0.298		0.000	0.000
Loudness (perceived response)	Pearson Correlation	.921**	.871**	.467**	0.150	0.290	-0.083	.960**		.438**
	Sig. (2-tailed)	0.000	0.000	0.001	0.331	0.056	0.594	0.000		0.003
Pitch	Pearson Correlation	.501**	.549**	-0.003	.477**	-.337*	-.368*	.614**	.438**	
	Sig. (2-tailed)	0.001	0.000	0.983	0.001	0.025	0.014	0.000	0.003	

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Using the SQMs, a simple linear regression model was built using a backward stepwise method of determining the most statistically significant metrics to be included, with the iterations of this method being displayed in table 3. The first model included all SQMs as predictor variables; loudness, sharpness, tonality, roughness, fluctuation strength and impulsiveness. The second model had roughness removed as a predictor variable, due to it having a p-value of 0.624, meaning it offered a statistically insignificant contribution to predicting annoyance. The third model excluded tonality as a predictor variable, due to it having a p-value of 0.603, but the increase in adjusted R^2 is only 0.002 when this metric is removed. Thus, the final model contained loudness, sharpness, fluctuation strength and impulsiveness as predictor variables for perceived annoyance, all with p-values of less than 0.05. Loudness yielding the strongest significance, having the largest standardised regression coefficient of 0.472, and a p-value of almost 0. Sharpness, fluctuation strength and impulsiveness had standardised coefficients of 0.433, 0.143 and -0.114, and p-values of 0.001, 0.014 and 0.039, respectively.

Table 3: Accuracy of simple linear regression iterations using backwards stepwise selection.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.944[a]	0.891	0.873	0.06016655
2	.943[b]	0.890	0.876	0.05956483
3	.943[c]	0.889	0.878	0.05900900
a. Predictors: (Constant), Impulsiveness, Sharpness (Aures), Fluctuation strength, Roughness (Hearing model), Tonality (Aures), Loudness (DIN45631)				
b. Predictors: (Constant), Impulsiveness, Sharpness (Aures), Fluctuation strength, Tonality (Aures), Loudness (DIN45631)				
c. Predictors: (Constant), Impulsiveness, Sharpness (Aures), Fluctuation strength, Loudness (DIN45631)				

These values suggest that as you increase the loudness, sharpness, and fluctuation strength of a sound, the perceived annoyance of that sound decreases. Furthermore, as the impulsiveness of a sound increases, the perceived annoyance decreases. As previously stated, literature is inconclusive on whether impulsiveness should be deemed a controlling factor on perceived annoyance for larger rotorcraft vehicles, such as helicopters. In literature cases where it is deemed a significant indicator, the impulsiveness of a sound stimuli is accredited to the main rotor blade-vortex interaction (BVI), or “blade slap”, which is more prevalent with larger rotorcraft [8]. The scale and dimensions of the blades of UAV used to create the subjective test stimuli differ drastically to those of larger rotorcraft, and the impulsiveness of these stimuli may be deemed to be more acceptable because of this. This is a topic that needs further investigation.

3.2. Perceived responses as functions of distance

Values of average perceived annoyance, loudness and pitch for each UAV stimuli performing flyover operations were plotted against UAV measurement distance to illustrate the importance of correctly positioning UAV operations to mitigate adverse effects on the public. Figure 3 presents the plots of each response variable against distance. Perceived annoyance and perceived loudness have very strong logarithmic correlations with distance, having R^2 values of 0.7408 and 0.8158, respectively. There is still a logarithmic correlation between perceived pitch and distance, but the residual differences from the trendline are greater. This may be due to the high frequency content being less prominent in stimuli which are measured from further away, as air absorption comes into play. Since perceived pitch correlates significantly with sharpness, as the high frequency content, and consequently the sharpness of a UAV stimuli, then a decreased in perceived pitch is to be expected. These plots show that a person’s perceived annoyance towards a UAV will increase drastically as it comes into proximity to them. Furthermore, this is only considering the acoustical characteristics of the UAV, and does not consider non-acoustic factors, such as feelings of danger when UAVs are operating very close to an individual. In future studies, it would be of benefit to introduce visual stimuli paired with UAV audio stimuli, to assess how the visual perceptibility of UAVs could affect perceived annoyance and loudness.

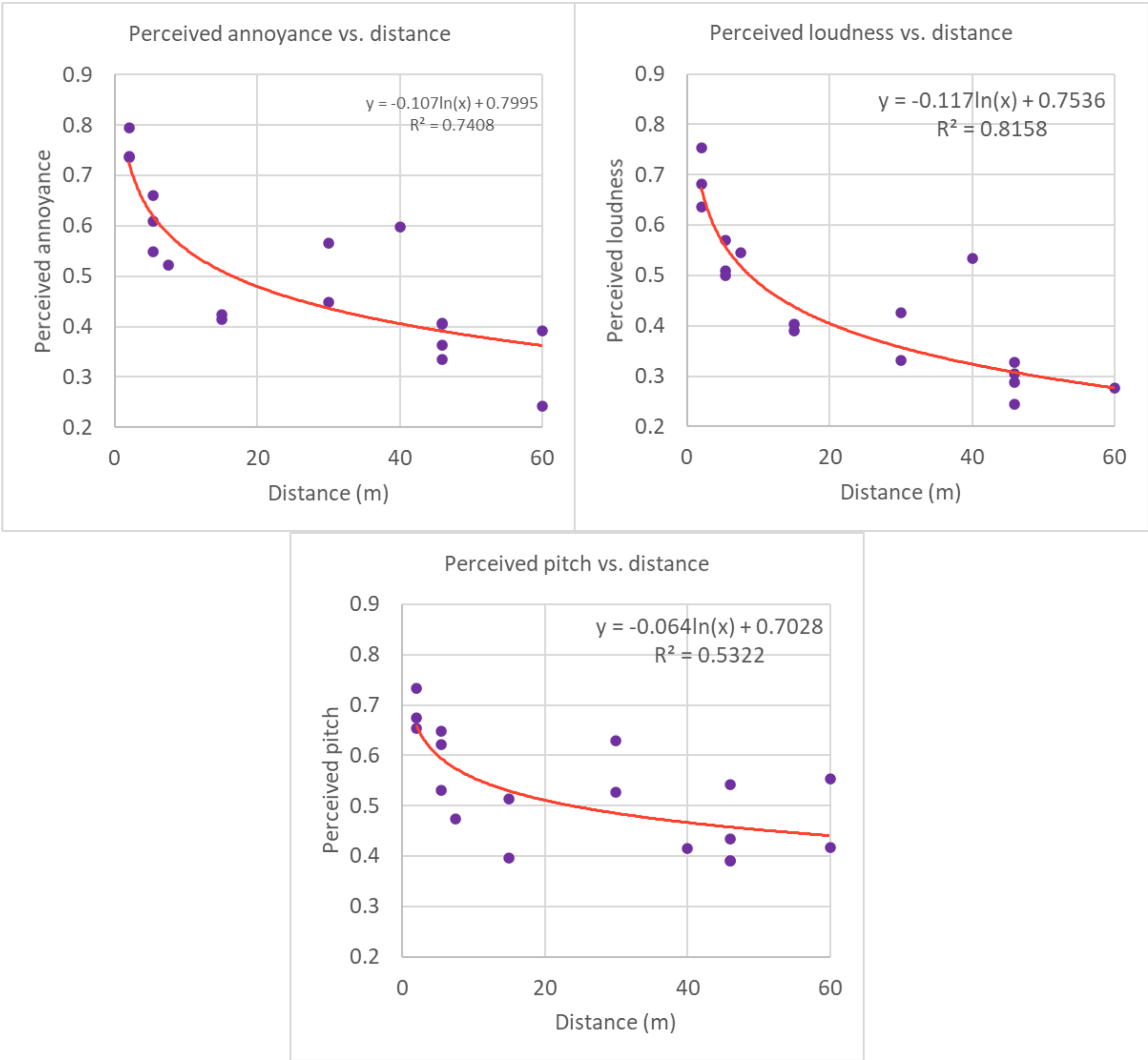

Figure 2: Plots of average perceived annoyance, loudness and pitch against distance for UAV stimuli performing flyover operations.

3.3. Multilevel linear model analysis

A simple fixed intercept model with no predictor variables is used to determine whether any variance in the dependent variable, perceived annoyance, is controlled by grouping or clustering effects within the data. This follows the simple model described by equations 2 and 3. Table 4 shows the estimated fixed intercept for the simple model, which is the mean average of all responses of perceived annoyance for each UAV stimuli. The residual variance, σ_{eij}^2, and the variance of the subject-dependent intercepts, σ_{u0j}^2, are then used to calculate the ICC, illustrated in equation 7:

$$ICC = \frac{\sigma_{u0j}^2}{\sigma_{u0j}^2 + \sigma_{eij}^2} \tag{7}$$

Using the values given in table 4, this gives an ICC of 0.185, meaning that only 18.5% of the variance in annoyance is explained by the participant, and other effects, like the sound quality of the UAV stimuli, are explaining the rest of the variance. This is to be expected, considering the multitude of UAV stimuli that was included in the experiment, each with varying acoustic and non-acoustic characteristics. This gives a strong case for using a more complex multilevel linear regression model. The next model built included a variable subject-dependent intercept, and all SQMs as predictor variables with fixed slopes.

Table 4: Estimates of fixed and covariance parameters for fixed intercept model with no predictor variables.

		Estimate	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Fixed	Intercept (γ_{00})	0.608795	0.016204	0.000	0.576214	0.641376
Covariance parameters	Residual (σ_{eij}^2)	0.051423	0.001584	0.000	0.048410	0.054624
	Intercept (σ_{u0j}^2)	0.011698	0.002627	0.000	0.007533	0.018165

Table 5 explains the significance of each SQM within the variable intercept and fixed regression slope model. As seen in the previous linear regression model, loudness, sharpness and fluctuation strength are strong predictors for the perceived annoyance. Now the model uses subject-dependent intercept values, but fixed regression slope coefficients, tonality and roughness are deemed to be significant predictor variables for annoyance, but impulsiveness is not. Previously, when using fixed intercept and regression coefficient values, impulsiveness was deemed a statistically significant predictor variable. This means that the relationship between impulsiveness and annoyance varies between participant, and cannot be deemed an effective predictor from this data. Again, the effect of impulsiveness on perceived annoyance should be further investigated, using an experimental methodology where impulsiveness is specifically controlled for.

Table 5: Estimates of fixed effects for multilevel model with subject-dependent intercepts and fixed regression slopes.

Parameter	**Estimate**	**Std. Error**	**df**	**t**	**Sig.**	**95% Confidence Interval Lower**	**95% Confidence Interval Upper**
Intercept	0.074151	0.043616	1332.371	1.700	0.089	-0.011413	0.159715
Loudness	0.008036	0.000775	2101.000	10.373	0.000	0.006517	0.009556
Sharpness	0.109507	0.013534	2101.000	8.091	0.000	0.082967	0.136048
Fluctuationstrength	2.465645	0.283398	2101	8.700	0.000	1.909875	3.021414
Tonality	-0.218453	0.088759	2101	-2.461	0.014	-0.392518	-0.044387
Roughness	-0.447973	0.200772	2101	-2.231	0.026	-0.841706	-0.054240
Impulsiveness	-0.169949	0.091062	2101.000	-1.866	0.062	-0.348529	0.008632

To illustrate the effectiveness of these metrics in predicting perceived annoyance, each metric shall be removed from the model individually to assess the reduction in R^2 between the predicted and observed values of annoyance. Figure 3 shows that, as expected from the results above, the biggest reduction in R^2 between the predicted and observed annoyance values is due to the removal of loudness, followed by fluctuation strength, and then sharpness. Tonality, roughness, and impulsiveness caused a significantly smaller reduction in R^2 value when removed from the model. This result strengthens the case for using loudness, sharpness, and fluctuation strength as predictors of annoyance for the UAV stimuli tested.

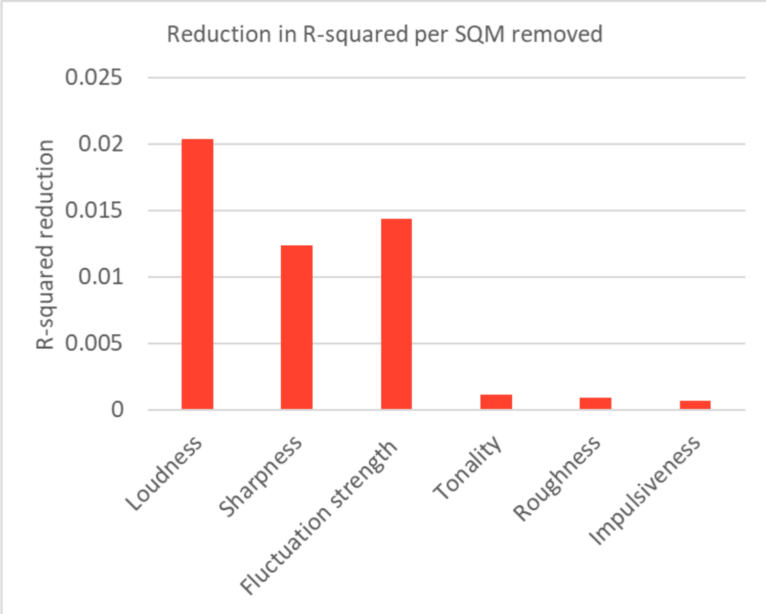

Figure 3: Reduction in R-squared value from SQM removal for subject-dependent intercept, fixed regression slope model

4. CONCLUSIONS

This research was an initial investigation into human response to UAV stimuli, including a multilevel linear regression analysis to illustrate grouped and subject-dependent trends between perceived annoyance, loudness, and pitch, and calculated SQMs. First, a simple linear regression was undergone to discover the key SQMs which best correlate to the perceived response values. It was found that loudness, sharpness, and fluctuation strength correlated strongly with perceived annoyance. Perceived loudness and pitch also correlated with perceived annoyance, indicating that if these variables could be controlled for, using methods such as increasing the distance between the UAV and the receiver, then negative responses to UAV operation may be reduced. It was found that the perceived annoyance, loudness, and pitch all had a logarithmic correlation with UAV distance, proving that distance is a key factor that should be taken into consideration when assessing the impact of UAV annoyance, not only due to acoustic characteristics, but the implications for non-acoustic characteristics as well. This could be investigated further using visual stimuli.

A multilevel linear regression method was used to analyse the subject-dependent variance between responses of perceived annoyance and the calculated SQMs for the UAV stimuli. It was found that loudness, sharpness and fluctuation strength were statistically significant predictor variables for perceived annoyance. Impulsiveness was not deemed significant in any of the models, and may not be an appropriate metric for predicting perceived annoyance.

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