DOI: 10.61782/fa.2025.0162

FORUM ACUSTICUM
EURONOISE 2025

AUDITORY-PERCEPTUAL AND EMOTIONAL MATCHING WITH PSYCHOACOUSTIC INDICATORS OF URBAN SOUNDSCAPES

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ABSTRACT

The perceptual classification of emotions, memories, preferences, and wishes is crucial for evaluating the sound quality of sonic environments. Over the years, several psychological taxonomies have developed, aiming to help categorise core emotions. When applied to auditory stimuli, some models simplify emotional dimensions to assess the sound quality of environments. However, aligning emotional taxonomies with psychoacoustic indicators requires careful attention, as individual interpretations can vary widely due to contextual factors such as socio-cultural influences, momentary attention, and the space use and function of the space in question. This study aims to align perceived emotional attributes with psychoacoustic indicators from sonic environments surrounding daycares and playgrounds, utilising data collected through soundwalks, interviews, and listening tests in Brazil, Germany, and the United Kingdom. It will associate emotional classification methods based on the core emotional dimensions proposed by Plutchik [1], Russell [2], and ISO/TS 12913-2 [3]. The psychoacoustical indicators under consideration are loudness, sharpness, roughness, fluctuation strength and tonality. The findings linking core emotions with psychoacoustic parameters for daycare centres and playground areas may identify key sound qualities to consider in these spaces, as well as potential soundscaping design and management strategies.

Keywords: *Semantic attributes, psychoacoustics, urban soundscape.*

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1. INTRODUCTION

Over the last fifteen years, the development of methods, instruments, and standards for investigating urban soundscapes has increased significantly. In 2018, ISO/TS 12913-2 [3] introduced some affective semantic attributes for classifying emotional responses, which were based on the work of Axelsson et al. [4], who simplified Russell's [2] semantic taxonomy. However, in recent years, the scientific community has highlighted some limitations to the suggested semantics [5].
This work aims to present an alternative semantic solution for the emotional content integrated into urban soundscape classification. The strategy combined the affective taxonomies of Plutchik [1] and Russell [2] while demonstrating the attributes matched with psychoacoustic indicators for each sound source category.

2. METHODS

This work investigated sonic environments containing daycares (kindergartens) and playgrounds, through selected perceptual and measured datasets of urban soundscapes, to match semantic attributes with psychoacoustic indicators. Datasets from Aachen, Germany [6-8]; Salford – Manchester, United Kingdom [9]; and Goiânia, Brazil [10] were used. The list provides only perceptual data. To ensure that the diversity of contextual and socio-cultural possibilities is adequately represented, the datasets comprise soundwalks, listening experiments, and interview responses from 301 participants (Table 1). Since the soundwalks and interviews employed open-ended questions for data collection, some responses provided additional information, which, after classification, increased the dataset scores by 39 observations. The final general matrix presented 340 responses from 298 participants. In the dataset of Salford–Manchester, besides the use of attributes from Plutchik [1], and the PAQs suggested in ISO/TS 12913-2 [3] were also collected. This data can aid in the interpretation of emotional tendencies and provide a basis for comparisons between taxonomies.

Table 1. Number of participants on each site and data collection method.

Point/City	Daycare			Playground		
Aachen	SW	LT	INT	SW	LT	INT
W1	19	0	1	19	0	1
W2	41	1	6	41	1	6
W4	-	-	-	12	0	0
A	-	-	-	22	0	0
L2	-	-	-	10	3	0
CA4	5	0	1	-	-	-
CA5	11	4	5	11	4	5
CA6	-	-	-	19	2	1
Salford						
PP	-	-	-	0	36	0
Goiânia						
UFG	0	0	11	-	-	-
Total	76	5	24	134	46	13

The central structure of the presented work followed the workflow outlined in Fig. 1, where efforts were applied to dataset preparation (Fig. 2) to construct matrices for the Principal Component Analysis (PCA). The PCA allowed for the reduction of attributes by combining Plutchik [1] and Russell [2] taxonomies through a Pearson correlation. Regarding the dataset preparation (Fig. 2), all datasets were initially compiled into a single matrix. Then, it was possible to verify if there was missing data, reverse the coding of subjective parameters if necessary, and eventually calculate psychoacoustic indicators (e.g., averages and percentiles) for the incomplete datasets using Artemis Suite. For psychoacoustic modelling, the following indicators were adopted: DIN 45631 for loudness, DIN 45692 for sharpness, and Artemis Suite ® hearing models for roughness, fluctuation strength, and tonality. Since the dataset had responses in English, German and Portuguese, it was necessary to translate the responses regarding sound sources and emotions into a common language. In this case, it was translated into the English language. Afterwards, the sound sources were classified into three categories: human, natural, and technological [4]. Emotional responses were sorted accordingly in the Plutchik [1] and Russell [2] taxonomies.

After the initial phase of dataset preparation, it was necessary to construct matrices for the statistical analysis. The dataset was divided into four matrices based on the reported and classified sound sources, as well as overall responses (Fig. 1), encompassing natural, human, and technological sound sources, as well as overall sonic environments. For each matrix, a Parallel Analysis [11] was conducted to determine the number of components supporting the PCA analysis. The PCA model employed Direct Oblimin rotation and assessed the Kaiser-Meyer-Olkin (KMO) and Bartlett's test of sphericity for model fitting. For each extracted component, selected attributes with loadings superior to 0.5 were identified [12]. These selected loadings formed a new parameter, which, through a Pearson correlation, was correlated with the psychoacoustic indicators, following the example of Axelsson et al. [4].

3. RESULTS

Table 2 shows the translated emotional responses in English, German and Portuguese, as well as the correspondence of the response to Plutchik's [1] and Russell's [2] taxonomies. Sometimes, participants could not express an evident emotion; however, they managed to describe a situation that evoked emotions, as indicated (grey colour) in their responses (Table 2). These situations depend on the semantic content and meaning. To help ensure the correct sorting of responses into taxonomies, it was necessary to observe the emotional tendency parameter. This criterion represents a median of other emotional attributes, e.g., Perceived Affective Qualities (PAQs) or the semantic attributes used in Dr Engel's thesis [6]. As a convention, the scales were converted to a scale of 1 to 5, where 1-2 indicated a positive tendency, three was neutral, and 4-5 indicated a negative tendency.

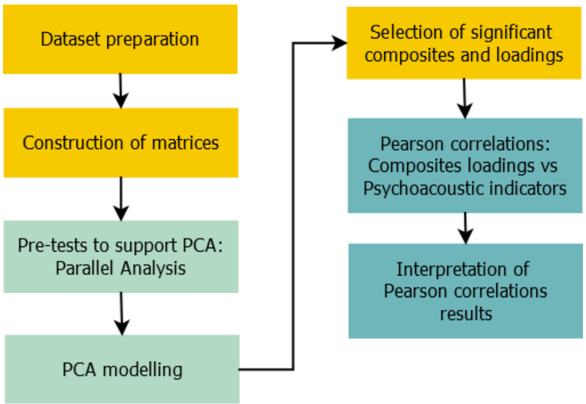

Figure 1. Workflow for emotional attributes matching with psychoacoustic indicators.

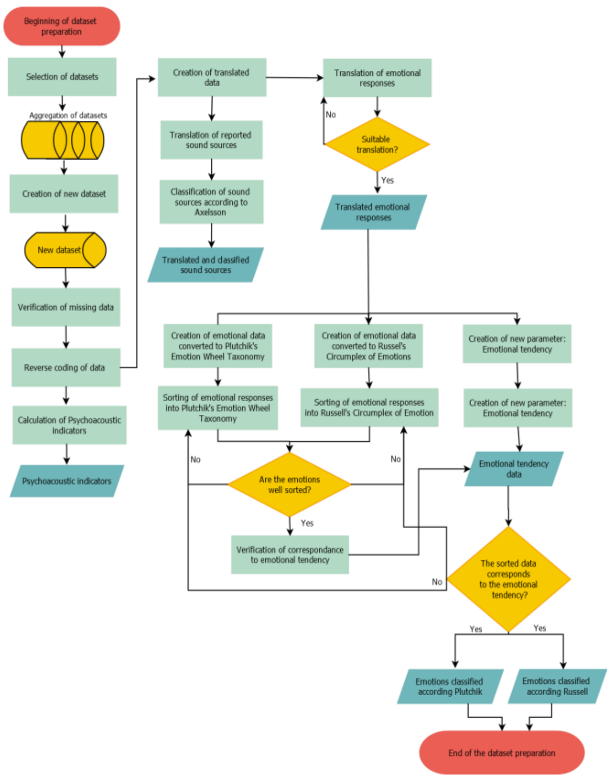

Figure 2. Flowchart of dataset preparation for PCA modelling.

Table 2. Reported responses related to emotions, translations and classifications.

English	German	Portuguese	Plutchik	Russell
acceptance	Akzeptanz	aceitação	acceptance	content
admiration	Bewunderung	admiração	acceptance	relaxed
aggressiveness	Aggressivität	agressividade	anger	nervous
amazement	Staunen	surpresa	joy	excited
anger	Wut	raiva	anger	stressed
annoyance	Ärger, nervlich	incômodo	annoyance	stressed
antecipation	Vorfreude	antecipação	interest	alert
anxiety	Bange, Sorge	ansiedade	apprehension	tense
apprehension	Besorgnis	apreensão	apprehension	tense
attention	Aufmerksamkeit	atenção	antecipation	alert
back to nature	Zurück zur Natur	de volta à natureza	serenity	relaxed
beautiful	Schön	lindo	acceptance	content
being like somewhere you live	Wo man lebt	ser como um lugar onde você mora	trust	content
busy	Beschäftigt	ocupado	distraction	excited
calm	Ruhe	calmo, calmaria	serenity	relaxed
caution	Vorsicht	cuidado	apprehension	tense
childhood	Kindheit	infância	joy	happy
			annoyance	nervous
church	Kirche	igreja	distraction	content
city	Stadt	cidade	distraction	excited
Closeness to nature	Naturverbundenheit	Proximidade com a natureza	serenity	relaxed
community	Gemeinschaft	comunidade	trust	content
contentment	Zufriedenheit	contentamento	joy	content
danger	Gefahr	perigo	apprehension	tense
discomfort	Unwohlsein	desconforto	apprehension	stressed
distraction	Ablenkung	distração	distraction	lethargic
Envy when the weather is nice	Neid bei schönem Wetter	Inveja quando o tempo está bom	joy	excited
fear	Angst	medo	fear	tense
feel good	Wohlfühlen	sentir-se bem	acceptance	content
happy	Glücklich	feliz	joy	happy
hate	Hass	detestar, ódio	disapproval	upset
free, freedom	Frei, Freiheit	livre	joy	content
fun	Spaß	diversão	joy	excited
good	Gut	bom	acceptance	content

graves	Gräber	sepulturas	sadness	sad
group feeling	Gruppengefühl	sentimento de grupo	trust	content
hate	Hass	ódio	disapproval	upset
healthy	Gesund	saudável	joy	content
holiday feelings	Urlaubsgefühle	sentimentos de férias	joy	happy
I like this park	Ich mag diesen Park	eu gosto deste parque	serenity	relaxed
interest	Interesse	Interesse	interest	excited
Iran Streets	Iranische Straßen	ruas do Irã	pensiveness	calm
irritation	Irritation	irritação, irritabilidade	annoyance	stressed
joy	Freude	alegria	joy	happy
lack of understanding	Unverständnis	falta de compreensão	distraction	lethargic
lively	Lebhaft	animado	distraction	excited
loud	Laut	alto	annoyance	stressed
love	Liebe	amor	joy	elated
nature	Natur	natureza	serenity	relaxed
negative	Negativ	negativo	disapproval	upset
neutral	Neutral	neutro	acceptance	content
noise	Lärm	Barulho	annoyance	stressed
not spesific, but similar to the one before	Nicht spezifisch, aber ähnlich wie zuvor	Não específico, mas semelhante ao anterior	acceptance	content
optimism	Optimismus	otimismo	optimism	content
park	Park	parque	serenity	relaxed
peaceful	Friedlich	pacífico, paz	serenity	relaxed
philosophy	Philosophie	filosofia	serenity	relaxed
playground give chills	Spielplatz sorgt für Gänsehaut	parque infantil dá arrepios	anger	stressed
positive	Positiv	positivo	optimism	content
quiet	Ruhe	quieto	serenity	relaxed
relaxation	Entspannung	relaxamento, relaxado	serenity	relaxed
restlessness	Unruhe	inquietação	boredom	lethargic
sadness	Traurigkeit	tristeza	sadness	sad
satisfaction	Zufriedenheit	satisfação	joy	content
serenity	Gelassenheit	serenidade	serenity	relaxed
spring feelings	Frühlingsgefühle	sentimentos relacionados à primavera	joy	excited
stress	Stress	estresse	fear	stressed
summer feelings	Sommergefühle	sentimentos relacionados ao verão	joy	happy
traffic	Verkehr	trânsito	annoyance	stressed

uncomfortable	Unangenehm	desconfortável	apprehension	stressed
wanna go home	Will nach Hause	quero ir para casa	annoyance	stressed
well-being	Wohlbefinden	bem-estar	joy	happy
wind instruments	Windmesser	instrumentos de sopro	annoyance	stressed
work	Arbeit	trabalho	disapproval	upset
			loathing	tense

Legend: AP – activation-pleasant, AU – activation-unpleasant, DP – deactivation-unpleasant, DU – deactivation-unpleasant. Grey colour – report that depends on the emotional context.

3.1 Principal Component Analysis

Before calculating the PCA models, a parallel analysis was used to estimate a reliable number of extracted components for each model. Four PCA models were calculated, which extracted components related to emotions associated with human, natural, and technological sounds, as well as the overall sonic environment, using attributes from Plutchik's [1] and Russell's [2] taxonomies. The model for the overall sonic environment extracted four components, which the extraction sum of squared loading explained, accounting for 48.5% of the model variance with a KMO of 0.076, $\chi^2(91) = 674.982$, and a p-value of < 0.000. The PCA model of emotions associated with human sounds extracted three components, explaining 36.95% of the model with a KMO of 0.089, χ^2 (105) = 458.028, and a p-value of <0.000, while the model associated with natural sounds presented an explanation of 68% and had a KMO of 0.242, χ^2 (21) = 233.055, and a p-value of <0.000. The PCA model of emotions related to technological sounds explained 56.7% of the variance and yielded a KMO of 0.073, $\chi^2(171) = 1190.782$, and a p-value of < 0.000. The components are presented in Table 3, and only the attributes with loading values over 0.5, indicated in grey colour, were considered for the Pearson correlation step, which enables the matching of semantic attributes with psychoacoustic indicators.

3.2 Pearson Correlation

The loadings of the components extracted in the PCA models were correlated with the averages and percentiles (P1, P5, P10, P50, P90, P95, and P99) of the following psychoacoustic indicators: loudness, sharpness, roughness (hearing model), fluctuation strength, and tonality (hearing model) using Pearson correlation. The significant results are presented in Tables 4 – 7.

Table 3. Components extracted in the PCA models for emotions related to human, natural, technological sound sources, and overall sonic environments. Loadings greater than 0.5 are indicated in grey.

Att.	1OV	1H	1N	1T	2OV	2H	2N	2T	3OV	3H	3N	3T	4OV	4T	5T	6T
SER	-	-	-	0.191	-	-	-	0.259	-	-	-	-0.103	-	-0.758	-0.318	0.079
JOY	-0.175	-0.315	0.788	0.105	-0.161	-0.247	-0.064	0.074	0.863	-0.127	-0.181	-0.017	0.049	-0.070	0.056	-0.133
TRU	0.224	-	0.111	-	0.069	-	-0.378	-	-0.128	-	-0.109	-	0.394	-	-	-
ACC	0.416	-	-	0.153	0.269	-	-	0.210	0.032	-	-	0.821	-0.058	0.056	-0.035	-0.015
FEA	-	0.343	-	-0.434	-	0.108	-	-0.087	-	0.018	-	0.005	-	0.106	-0.059	0.741
APP	-0.012	0.030	-	-0.024	-0.047	0.313	-	0.228	-0.030	0.773	-	-0.136	-0.011	0.242	-0.079	0.254
DIS	-	-0.454	0.266	0.392	-	0.788	0.664	-0.019	-	-0.246	0.016	0.238	-	0.171	-0.066	0.125
DSP	-0.018	-	-	0.230	-0.068	-	-	0.435	-0.044	-	-	-0.237	-0.017	0.221	-0.021	-0.340
PSV	-	-	-	0.108	-	-	-	0.121	-	-	-	-0.037	-	-0.186	0.803	0.091
LOA	-	-0.035	-	0.165	-	-0.049	-	0.475	-	0.016	-	-0.277	-	0.379	-0.096	-0.135
BDM	-	-	-	0.605	-	-	-	-0.633	-	-	-	-0.130	-	0.094	-0.058	0.014
ANG	-	0.285	-	-0.296	-	0.053	-	-0.109	-	-0.213	-	0.037	-	-0.003	-0.007	-0.234
ANO	-	0.723	-	-0.377	-	0.216	-	-0.145	-	-0.146	-	0.050	-	-0.004	-0.010	-0.598
ANT	-	-0.051	-	0.072	-	-0.072	-	0.050	-	0.023	-	-0.012	-	-0.048	0.038	-0.086
INT	-0.615	-	-	-	0.740	-	-	-	-0.115	-	-	-	0.004	-	-	-
OPT	0.632	-	-	-	0.415	-	-	-	0.052	-	-	-	-0.105	-	-	-
ALT	-0.229	-	-	-	0.296	-	-	-	-0.126	-	-	-	-0.006	-	-	-
EXC	-0.590	-0.445	0.581	-	0.651	0.649	0.671	-	0.049	-0.468	-0.078	-	0.014	-	-	-
ELA	-0.075	-	-	-	-0.137	-	-	-	0.633	-	-	-	0.045	-	-	-
COT	0.829	-0.294	0.465	0.221	0.521	-0.465	-0.660	0.216	0.074	0.081	-0.170	0.874	-0.015	0.086	-0.047	0.016
RLX	-0.034	-0.131	-0.907	0.147	-0.292	-0.194	0.186	0.228	-0.371	0.075	-0.327	-0.095	0.768	-0.713	-0.320	0.095
LTH	-0.039	-	-	0.699	-0.155	-	-	-0.641	-0.109	-	-	-0.074	-0.047	0.133	-0.073	0.052
SAD	-	-0.035	-	0.108	-	-0.049	-	0.121	-	0.016	-	-0.037	-	-0.186	0.803	0.091
STR	-0.082	0.883	-0.022	-0.914	-0.351	0.301	-0.063	-0.256	-0,362	-0.011	0.990	0.059	-0.736	0.111	-0.073	0.038
NRV	-	0.209	-	-	-	0.022	-	-	-	-0.248	-	-	-	-	-	-
TNS	-	-0.183	-	0.207	-	0.484	-	0.515	-	0.682	-	-0.261	-	0.453	-0.128	0.214

Legend: Attributes (Att) Overall (OV), Human (H), Natural (N), Technological (T), serenity (SER), joy (JOY), trust (TRU), acceptance (ACC), fear (FEA), apprehension (APP), interest (INT), distraction (DIS), disapproval (DSP), pensiveness (PSV), loathing (LOA), boredom (BDM), anger (ANG), annoyance (ANO), anticipation (ANT), optimism (OPT), AP-alert (ALT), AP-excited (EXC), AP-elated (ELA), DP-contented (COT), DP-relaxed (RLX), DU-lethargic (LTH), DU-sad (SAD), AU-stressed (STR), AU-nervous (NRV), AU-tense (TNS).

Table 4. Semantic matching of emotions related to the overall sonic environment and psychoacoustic indicators, * p-value<0.05 and ** p-value <0.01.

Components	Att.	Loading	Psychoacoustic indicators	Pearson coefficient
1OV	COT	0.829	N1	-0.397*
	EXC	-0.59	T1	-0.416*
	OPT	0.632	T10	-0.426*
	INT	-0.615	T50	-0.459*
			T90	-0.391*
			T95	-0.391*
2OV	COT	0.521	T1	0.404*
	EXC	0.651	T10	0.412*
	INT	0.74	T50	0.428*
			T95	0.395*
3OV	JOY	0.863	FS Avg	0.373*
	ELA	0.633		
4OV	RLX	0.768	FS5	0.343*
			FS10	0.37*
			FS50	0.384*
	STR	-0.736	T1	0.414**
			T5	0.341*
			T10	0.326*
			T99	-0.343*

Table 5. Semantic matching of emotions related to human sound and psychoacoustic indicators, * p-value<0.05, and ** p-value <0.01.

Components	Att.	Loading	Psychoacoustic indicators	Pearson coefficient
1H	STR	0.883	N90	-0.826**
			N95	-0.863**
	ANO	0.723	N99	-0.844**
			FS90	0.644*
2H	DIS	0.788	NS	NS
	EXC	0.649		
3H	APP	0.773	FS90	0.999*
	TNS	0.682	FS95	1.000*
			FS99	1.000**

Table 6. Semantic matching of emotions related to natural sound and psychoacoustic indicators, * p-value <0.05 and ** p-value <0.01.

Components	Att.	Loading	Psychoacoustic indicators	Pearson coefficient
1N	RLX	-0.907	N1	0.368**
			N5	0.459**
			N10	0.406**
			N50	0.364**
	EXC	0.581	N90	0.294*
			N95	0.264*
			N99	0.281*
			N Avg	0.395**
	JOY	0.788	FS1	0.353**
			FS5	0.342**
			FS10	0.341**
			FS Avg	0.351**
2N	EXC	0.671	T Avg	0.436*
	COT	-0.66		
3N	DIS	0.664	FS90	0.999*
	STR	0.990	FS95	1.000*
			FS99	1.000**

Table 7. Semantic matching of emotions related to technological sound and psychoacoustic indicators, * p-value <0.05 and ** p-value <0.01

Components	Att.	Loading	Psychoacoustic indicators	Pearson coefficient
1T	STR	-0.914	NS	NS
	LTH	0.699		
	BDM	0.605		
2T	LTH	-0.641	N Avg	0.813**
			S1	-0.531*
	TNS	0.515	S5	-0.54*
			FS50	0.665**
	BDM	-0.633	FS90	0.524*
			FS95	0.678**
			FS Avg	0.714**
3T	ACC	0.874	NS	NS
4T	COT	0.821	NS	NS
	SER	-0.758		

	RLX	-0.713		
5T	PSV	0.803	NS	NS
	SAD	0.803		
6T	FEA	0.741	N50	-0.349*
			N90	-0.346*
			N95	-0.346*
	ANO	-0.598	R50	-0.476**
			R90	-0.42*
			R95	-0.39*
			R99	-0.374*

4. DISCUSSION

As observed in the descriptive analysis, emotional responses had higher significance when they concerned technological sounds, followed by the overall sonic environment, natural sounds, and human sounds. Regarding the emotions associated with technological sounds (Tab.7), two components matched with psychoacoustic indicators significantly. In the 2T component, when there were fewer reports of 'lethargic' (loading=-0.641) and 'boredom' (loading=-0.633) associated emotions, there was an increase of 'tense' (loading=0.515) reports. These emotions were moderately correlated with negative S1 and S5; however, they showed a strong positive correlation with NAvg and a moderate positive correlation with FS Avg, FS50, FS90, and FS95 when the children were playing in playgrounds and equipment was producing screeching sounds [6]. In the 6T component, it was highlighted that greater 'fear' (loading=0.741) was associated with emotions, exhibiting negative moderate correlations with N50, N90, and N95 indicators. In contrast, fewer emotions associated with 'annoyance' (loading=-0.598) occurred when the sonic characteristics presented negative moderate correlations with R50, R90, R95, and R99 values.

Emotions associated with natural sounds (Tab. 6) showed three components with significant results when matched with psychoacoustic indicators. In the 1N component, when reports were less associated with 'relaxed' (loading = -0.907), there were a superior number of reports of 'excited' (loading=0.581) and 'joy' (loading=0.788). This occurred when there was a positive weak (N90, N95, N99) to moderate (N1, N5, N10, N50, N Avg, FS1, FS5, FS10, FS Avg) correlation, possibly due to the vocalisations of random birds. The 2N component showed that when emotions related to 'excited' (loading=0.671) were predominant, there were fewer emotions associated with 'contented' (loading = -0.66). This happens when there is a moderate positive correlation with T Avg, also due to the birds' vocalisations. The 3N component highlights that 'distraction' (loading=0.664) is proportionally associated with reports that participants were 'stressed' (loading = 0.990), and were strongly positively correlated to FS90, FS95 and FS99, which can occur when there are constant sounds of rustling leaves and wind sounds.

In the associations of emotions with human sounds, two components correlated significantly with the psychoacoustic indicators. The 1H component shows that emotions were reported with the meaning that they were 'stressed' (loading =0.883) and 'annoyed' (loading=0.723). These were strongly negatively correlated with N90, N95, and N99, and moderately positively correlated with FS90, possibly when children were producing a significant quantity of vocalisations but with different amplitudes. While in the 3H component, the emotions 'apprehension' (loading=0.773) and reports classified as 'tense' (0.682) also showed proportionality and were strongly positively correlated to FS90, FS95 and FS99, also related to kids' communication.

The overall sonic environment-associated emotions showed that four components matched significantly with the psychoacoustic indicators. The 1OV component demonstrated the feelings of being 'contended' (loading= 0.829) and 'optimism' (loading=0.632) to stand proportionally inverted to the emotions of being 'excited' (loading=-0.59) and having 'interest' (loading=-0.615). This tendency also occurs in the negatively moderated correlations with N1, T1, T10, T50, T90, and T95. The 2OV component shows that when excluding the attribute 'optimism', the characteristics of being 'contented' (loading = 0.521), 'excited' (loading = 0.651), and 'interest' (loading = 0.74) exhibited proportionality and showed a moderate positive correlation with T1, T10, T50, and T95. The 3OV component highlights that emotions of 'joy' (loading= 0.863) and being 'elated' (loading=0.633) are positively moderately correlated with FS Avg. The 4V component shows that being 'relaxed' (loading=0.768) and 'stressed' (loading=-0.736) oppose each other, presenting a moderately positive correlation with T1, T5, and T10, and a moderately negative correlation with T99.

5. CONCLUSIONS

This work aimed to associate Plutchik's [1] and Russell's [2] affective taxonomies for the semantic classification of emotions in urban soundscapes. The newly formed semantics were tested by matching traditional psychoacoustic indicators used in soundscape studies. The selected areas contained daycares and playgrounds in Aachen, Germany; Salford, United Kingdom; and Goiânia, Brazil.

The association of taxonomies revealed strong correlations between emotions related to technological sounds when analysing the combination of attributes 'lethargic', boredom', and 'tense'. These were correlated with S1, S5, NAvg, FSAvg, FS50, FS90, and FS95 for sounds produced the playground equipment.

Natural sounds, such as rustling leaves and wind, showed a strong correlation between the attributes 'distraction' and 'stressed' when associated with FS 90, FS 95, and FS 99. Human sounds, such as children's interactions, showed strong correlations between the reports of 'stressed' and 'annoyed' with N90, N95, N99, and FS90. Additionally, the attributes 'apprehension' and 'tense' correlated with FS 90, FS 95, and FS 99.

The presented results contribute to the further development of the affective attributes related to the sonic environment. Moreover, they demonstrate alternative semantic classifications through psychoacoustic matching, providing a basis for further investigations into soundscapes.

6. ACKNOWLEDGMENTS

The authors would like to thank the students who contributed to the completion of this work through their valuable assistance. Dr. Engel gratefully acknowledges the Head Genuit Stiftung for awarding a travel grant that enabled her participation in Forum Acusticum–Euronoise 2025.

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