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Research Paper

Urban soundscape categorization based on individual recognition, perception, and assessment of sound environments

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HIGHLIGHTS

- Regardless of the source, loud sounds can produce negative psychological effects.
- Sounds generated by human behaviors can foster psychological stability.
- Even noise sources like traffic can positively affect urban soundscape perception in specific context.
- Appropriate human activities can be encouraged for relaxing soundscapes.
- Our soundscape prediction model can be implemented in urban design and planning.

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ABSTRACT

This study proposes soundscape recognition models by clustering people based on differences in sound source perceptions. We investigated the effect of sound source identification differences on urban soundscape perception by categorizing people's environmental sound recognition in outdoor environments. Virtual reality technology employing audio-visual stimuli collected in various urban environments replicated actual environments. Fifty participants' subjective responses regarding sound source identification, perceived affective quality (8 typical (ISO scale) and 116 extensive attributes (Swedish rating scale)), and overall quality were surveyed. Their categorizations by sound source identification were divided into three clusters: Cluster 1–Attentive to traffic noise and other noises, Cluster 2–Less attentive to the sound environment, and Cluster 3–Attentive to natural and human sounds. Even in identical spaces, participants identified different sound sources, as each cluster focused on different sounds. The soundscape perceptual components were derived differently for each cluster; Cluster 2 extracted additional perception dimensions, i.e., tranquil and relaxed soundscapes. The results showed that each sound source that received an attentive reaction had a positive effect on soundscape perception, showing that appropriate human activities can be encouraged to improve relaxation via soundscape enhancements. The overall quality assessment by cluster revealed similar results, but the resulting indicators' effects varied. The study's different soundscape recognition models for each cluster, based on the relationship between soundscape indicators and descriptors, present a new perspective for interpreting urban soundscape perception and can also be used effectively in urban planning design.

1. Introduction

Research on the negative health effects of noise in urban environments has established the importance of sound in sustainable urban development (Recio, Linares, Banegas, & Díaz, 2016; Stansfeld, Haines, & Brown, 2000). As sound is a resource that satisfies human needs and wants, the soundscape was introduced as an acoustic standard to interpret perceptions of sound environments (Kang & Schulte-Fortkamp, 2018; Schafer, 1993). The International Organization for Standardization (ISO) 12913-1 (2014) defines soundscape as an "acoustic

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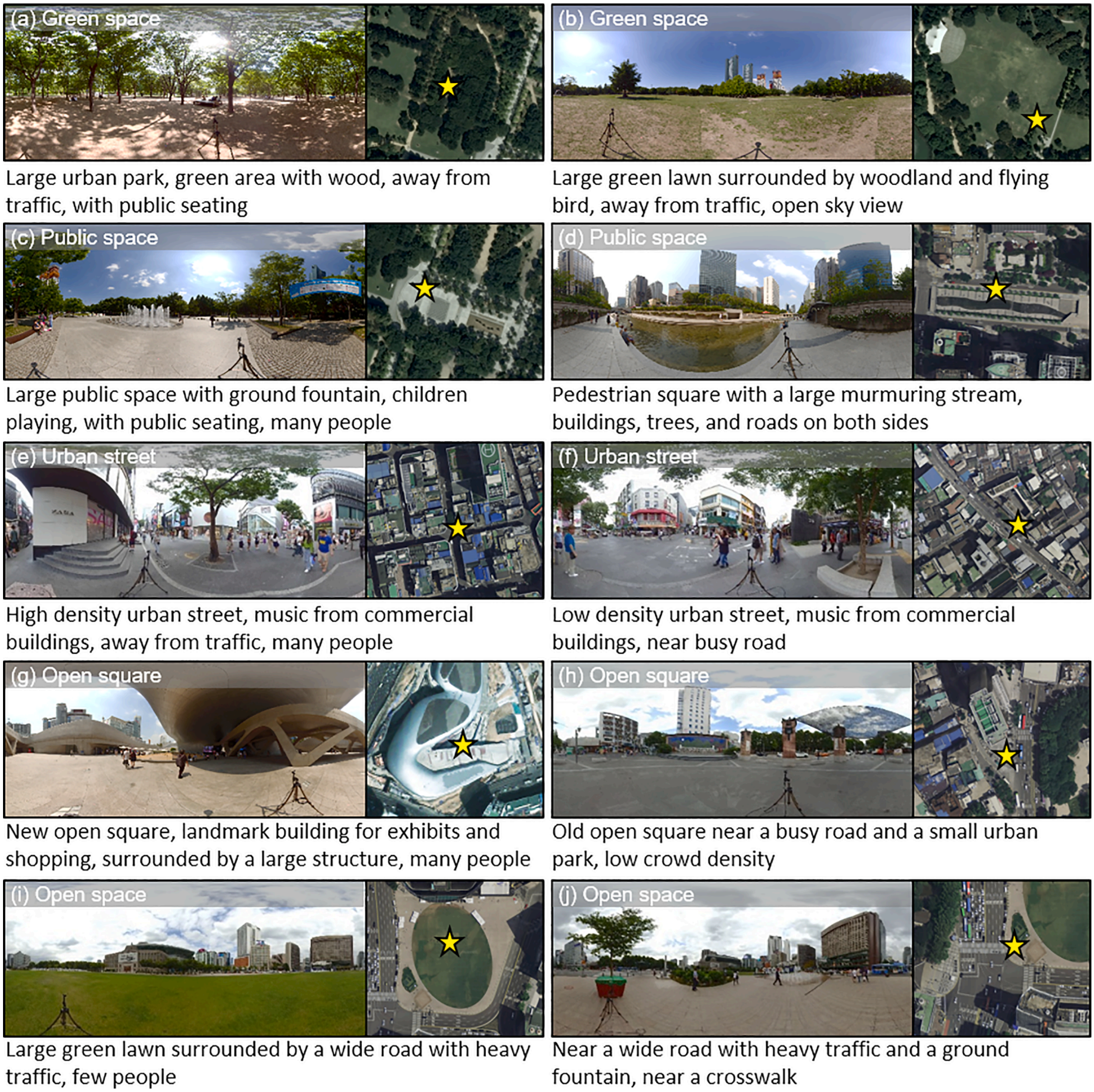

Fig. 1. Panoramic Views and Locations of the 10 Assessment Sites.

environment as perceived or experienced and/or understood by a person or people, in context." Many studies have used various urban environments (parks, commercial streets, and open spaces) to examine the relationship between soundscape indicators (acoustical, psychophysiological, design, or remedial indices) and descriptors (perceived affective quality, appropriateness, etc.) (Aletta, Kang, & Axelsson, 2016; Jeon & Jo, 2020; Zhao, Zhang, Meng, & Kang, 2018). Others proposed perception models applicable to city planning stages using various assessment tools (questionnaires, narrative interviews, etc.) (Davies et al., 2013; Hong & Jeon, 2015).

Sound sources provide important information on soundscape interpretations (Lavandier & Defréville, 2006; Nilsson, Botteldooren, & De Coensel, 2007) and can be detected and/or identified (Oldoni et al., 2013). To detect a sound source, individuals can simply note its presence or absence, while identification involves sound recognition and creating meaning based on perception, experience, knowledge, and familiarity. This meaning plays an important role in evaluating soundscape quality, making it significant for soundscape design (Dubois, Guastavino, & Raimbault, 2006; Raimbault & Dubois, 2005; Siedenburg & McAdams, 2017). A detected sound can be ignored or focused on, depending on an auditory attention mechanism called the cocktail-party effect (Arons, 1992). However, quantifying attention for sound sources is challenging. Fiebig's (2012) early experiments showed that some assessments can be made by evaluating the dominance of sound sources and that the resulting attention differences can change the overall quality of the sound (Botteldooren, Boes, Oldoni, & De Consel, 2012). Attention is an essential prerequisite for assigning meaning to sounds and leads to sound source identification (Botteldooren & De Coensel, 2009). Pérez-Martínez, Torija, and Ruiz (2018) assessed the relationship between dominant sound sources and soundscape quality, while Oldoni et al. (2013) used objective indicators (computational complexity and biological plausibility) to propose an auditory attention model. Nevertheless, few studies of urban environments have profoundly examined the subjective aspects of the effect of changes in sound source identification

Table 1
Acoustic parameters based on the soundscape sessions' acoustic recordings.

Site	L_{Aeq} [dB]	$L_{A10\text{-}A90}$ [dB]	$L_{Ceq\text{-}Aeq}$ [dB]	Loudness [sone]	Sharpness [acum]
(a)	69.1	7.0	18.5	33.89	1.02
(b)	72.5	17.6	19.4	36.94	0.67
(c)	80.6	14.7	7.1	60.82	1.48
(d)	63.3	4.1	3.6	22.09	1.13
(e)	64.7	4.7	7.2	25.76	1.18
(f)	78.5	11.6	17.7	58.57	1.00
(g)	73.2	5.3	3.7	38.81	1.10
(h)	54.8	6.5	16.8	14.72	1.14
(i)	58.9	10.4	20.3	18.47	0.79
(j)	62.3	4.7	9.3	22.87	1.19

expressed by the relationship between attention mechanisms and soundscape assessment.

The semantic differential method, a psychological measurement tool, is widely used to evaluate human emotional perceptions (Osgood, 1952), revealing the overall human perception of an evaluated object. Most previous studies presented various attributes related to the evaluated objects and applied principal component analysis to the subjective evaluation results to derive measures of human perceptions (Wold, Esbensen, & Geladi, 1987). Many urban environment studies have used semantic differential tests to interpret human perceptions of soundscapes (Ma, Wong, & Mak, 2018). Specifically, Axelsson, Nilsson, and Berglund (2010) derived the perceptual dimensions of pleasantness, eventfulness, and familiarity based on 116 extensive attributes, and suggested eight typical attributes: pleasant, unpleasant, eventful, uneventful, exciting, monotonous, chaotic, and calm. In a follow-up study, Cain, Jennings, and Poxon (2013) proposed a calmness-vibrancy model, complementing the pleasantness-eventfulness model, that consists of a 45-degree rotation of the latter. Other studies proposed various perceptual components, and those derived from the attribute collections also appeared to vary according to experimental design (Davies, Bruce, & Murphy, 2014; Hall, Irwin, Edmondson-Jones, Phillips, & Poxon, 2013; Jeon & Jo, 2020; Takada, Fujisawa, Obata, & Iwamiya, 2010; Yu, Kang, & Ma, 2016). Thus, the more diverse and broad the collection, the more in-depth the soundscape perception interpretation. However, since ISO 12913-2 (2018), researchers have mainly employed the eight typical attributes without examining their effectiveness through comparisons with other collections.

Stakeholders and practitioners (architects, engineers, and planners) must categorize soundscapes to efficiently design and manage urban soundscapes. Early attempts classified soundscapes based on physical characteristics. For example, Brambilla, Gallo, and Zambon (2013) categorized a park using objective acoustic indicators, while Jeon, Hong, and Lee (2013) classified urban environments into four types (designed soundscape, noisy soundscape, natural landmark, and urban open space) based on acoustic and non-acoustic data (visual images, day lighting, etc.). Later studies assessed subjective responses to soundscape classifications. Torija, Ruiz, and Ramos-Ridao (2013, 2014) proposed a methodology to automatically classify urban soundscapes based on 15 typological criteria and subjective evaluation responses. Jeon and Hong (2015) categorized various urban parks into three types according to sound source dominance, and compared the relationship between soundscape indicators and descriptors for each park. Jeon et al.'s (2018) follow-up study extended this to parks in various countries, and classified soundscapes into three types based on sound sources and the perceived affective quality evaluation results.

As previous studies have revealed, a categorization methodology serves to characterize soundscapes by focusing on the function of each space, thus allowing the grouping of places that exhibit similar soundscape qualities. However, few studies have categorized personal characteristics, focusing on people and not space. Most studies compared responses according to basic demographic variables (gender and age) (Li, Liu, & Haklay, 2018; Yang & Kang, 2005; Yu & Kang, 2005). Prior to classifying spaces, one must categorize the characteristics of the people who actually operate the spaces and examine each categorization type by focusing on sound source identification, an essential factor for sound environment analysis. By categorizing people according to attention differences and examining the cluster differences in soundscape perception, we can provide a new method for interpreting soundscape categorizations that centers on people rather than space. Thus, we can improve our understanding of soundscape perception differences. This study categorized attention groups according to various urban environment sound source identification results and compared soundscape perception differences between clusters. We established the following research questions:

How are groups classified according to sound source identification?
Are there differences in soundscape perceptions for each attention cluster?
Are perceptual components derived from typical (ISO 12913-2) and extensive attributes (Swedish rating scale)?
How is the relationship between soundscape indicators (acoustic parameters and sound source identification) and descriptors (perceived affective and overall quality) different for each cluster?

To bridge the aforementioned gaps, this study aimed to propose new soundscape recognition models for each cluster by examining and classifying the differences in individuals' characteristics and sound source identifications that affect sound environment perceptions.

2. Methods

2.1. Site selection

To investigate the effect on soundscape perception of sound recognition differences in an urban environment, we selected 10 evaluation sites in Seoul's Gangbuk area. Fig. 1 presents the selected sites' appearance, functions, and contextual characteristics, and each site contained relatively different auditory and visual elements: (a) and (b) correspond to the park function (Seoul Forest); (c) (Seoul Forest Plaza) and (d) are public spaces; (e) (Myeong-dong Street) and (f) (Insa-dong Street) are urban streets; (g) (Dongdaemun Design Plaza) and (h) are open squares; and (i) and (j) are open spaces (Seoul City Hall Plaza).

2.2. Audio-visual stimuli

2.2.1. Audio-visual recording

To collect audio-visual stimuli, we conducted measurements at 10 evaluation points between 10 am and 2 pm from May to July 2019. During this period, the average temperature was within the range 24.2–30.9 °C, and the weather was clear. For visual information, we used a six-channel 360 spherical camera (Insta 360 pro, Insta 360), and recorded in 8 k ultra-high definition, 30 fps resolution, and 95 Mbps. For auditory information, we used a four-channel ambisonic microphone (Soundfield SPS 200, Soundfield Ltd.) and a portable sound recorder (Mixpre-6, Sounddevices), with an A-format first-order (FOA) ambisonic setup. We measured L_{Aeq} using a 1/2-inch microphone (GRAS AE 46, GRAS Sound and Vibration) and a portable sound-level meter (AS-70, RION) for sound pressure level correction. Lastly, we measured both visual and auditory information at a 1.6 m height for three minutes, based on ISO 12913-2's (2018) recommendations.

Table 1 presents the physical characteristics at each evaluation point: (1) sound strength (A-weighted sound pressure level (L_{Aeq})), (2) spectral contents ($L_{Ceq\text{-}Aeq}$: difference between A-weight and C-weight SPL while showing the sound source's relative low-frequency characteristics), (3) temporal variations ($L_{A10\text{-}A90}$: difference between L_{A10} and L_{A90}-percentile sound pressure levels), and (4) psychoacoustics (Zwicker's loudness and sharpness). Loudness represents the sound's subjectively heard volume, having a high correlation with sound pressure levels and calculated according to DIN 45631/A1 (2008), while sharpness can determine the influence of a sound's high frequency band. The spectral envelope can be evaluated (Fastl & Zwicker, 2006) and calculated according to DIN 45692 (2009). For the analysis, we used Pulse software version 22 (Brüel & Kjær). All evaluation point average L_{Aeq} values were very broad, between 54.8 and 80.6 dBA. Loudness showed a similar tendency to L_{Aeq}, $L_{A10-A90}$ and $L_{Ceq-Aeq}$ had a 4.1–17.6 dB and 3.6–20.3 dB distribution range, respectively, and sharpness tended to oppose $L_{Ceq-Aeq}$. Thus, the difference between the sound pressure level's maximum and minimum values was more than 10 dB, and sufficiently included a typical city's sound environment variations.

2.2.2. Virtual reality (VR) environment reproduction

To evaluate soundscape in a laboratory and ensure high ecological validity in our limited setting, we constructed a VR environment based on the collected audio-visual materials. Numerous studies have used VR in indoor environments (Jeon & Jo, 2019; Jeon, Jo, Kim, & Yang, 2019; Jo & Jeon, 2019) and have applied it to assess soundscapes (Liu & Kang, 2018; Sanchez, Van Renterghem, Sun, De Coensel, & Botteldooren, 2017; Sun et al., 2019). Furthermore, sufficient verification studies have examined VR's effectiveness in soundscape evaluation (Maffei, Massimiliano, Aniello, Gennaro, & Virginia, 2015; Puyana-Romero, Lopez-Segura, Maffei, Hernández-Molina, & Masullo, 2017). Specifically, Maffeiet, Masullo, Pascale, Ruggiero, and Romero (2016) revealed that VR has a sufficiently high congruency with real environment acoustic and visual stimuli recognition. Thus, VR technology can be an efficient tool to evaluate urban environment awareness.

We combined our recorded visual information through a post-process (Insta360stitcher, Insta360) and provided the completed video in a head-mounted display (VIVE Pro, HTC). For sound, we converted the A-format FOA to a B-format FOA using a Spatial Audio API (Google VR) built into the unity engine software, and then down-mixed it with a binaural track. To calibrate sound pressure levels, we employed a head and torso simulator (Type 4100, Brüel & Kjær) to record stereophonic sounds, reproduced with headphones. At the sites, we adjusted the sound pressure level using Adobe Audition (version 1.5, Adobe) to ensure that the sound source recorded with the calibration microphone was the same as the L_{Aeq}. An open-type headphone (HD-650, Sennheiser) provided the completed sound source.

2.3. Subjective assessments

2.3.1. Questionnaire

To investigate changes in soundscape recognition based on sound source identification, we constructed a questionnaire containing various indicators (predicting descriptors) and descriptors (evaluating how humans perceive space) (Aletta et al., 2016), according to ISO 12913-2's (2018) Method A questionnaire and Axelsson et al. (2010). The final questionnaire assessed sound source identification, perceived affective quality, and overall quality.

For sound source identification, using a Likert scale ranging from 1 (*not at all*) to 5 (*dominates the space*) to score the responses to the questions: "To what extent do you currently hear the following four sound types: traffic noise (cars, buses, trains, airplanes, etc.), human sounds (conversations, laughter, children playing, footsteps, etc.), natural sounds (birds, water, wind, etc.), and other noises (sirens, construction, industry, etc.)?" Researchers vary in the sound source taxonomy they use for urban acoustic environments, but these taxonomies can generally be classified based on human activity (Brown, Kang, & Gjestland, 2011) or people, nature, and manmade structures (Bones, Cox, & Davies, 2018). In our study, we used questionnaire items on sound source identification based on Brown et al.'s (2011) taxonomy as data collection methods in Annex C of ISO 12913-2.

Two attribute collections were used to evaluate perceived affective quality. The first collection contained eight typical unidirectional attributes based on ISO 12913-2 (2018). The participants were asked to score their responses to the questionnaire using another five-point Likert scale (1 = *strongly disagree* to 5 = *strongly agree*): "To what extent do you agree or disagree that the surrounding sound environment is pleasant, chaotic, vibrant, uneventful, calm, annoying, eventful, or monotonous?" The second collection offered more in-depth interpretations of soundscape perceptions using Axelsson et al.'s (2010) 116 extensive unidirectional attributes (see Appendix A) that 50 relevant experts, through rigorous empirical selection procedures, selected as suitable for evaluating soundscapes. The participants answered the above question using a 100-mm visual analog scale (0 = *no match at all* to 100 = *perfect match*). The 8 typical unidirectional attributes in ISO 12913–2 are closely related to 116 extensive unidirectional attributes, which were proposed based on the Pleasantness – Eventfulness Model derived from the research findings of Axelsson et al. (2010).

Finally, overall quality assessed both overall impressions and appropriateness through the following questions: "Overall, how would you describe the surrounding sound environment?" (1 = *very bad* to 5 = *very good*) and "Overall, to what extent is the surrounding sound environment appropriate for the location?" (1 = *not at all* to 5 = *perfectly*). Language experts and researchers in the soundscape field helped with the English to Korean translation. To convey to the subject as accurately as possible the meaning of the original English word, and to preserve the meaning of English words as much as possible, all questionnaires were written with simultaneous parallel Korean and English statements.

2.3.2. Procedure

Recruited through university online advertising, 50 individuals participated in this study (male: 25, female: 25), 20–41 years in age (mean age: 23.82, standard deviation: 3.06). To reduce group response variations, we targeted undergraduate and graduate students who were attending the same university and who were familiar with the 10 sites, as they periodically passed through them when commuting to their university in Gangbuk. All participants had normal hearing, evaluated using an audiometer (AA-77, Rion). Prior to the experiment, we informed participants about the purpose and theory of the study to ensure that the questionnaire items were fully understood (Aletta et al., 2019). In particular, when instructing participants regarding the questionnaire structure, we asked them to identify sound source identification based on sound source dominance. This was based on a previous research finding that attentive response to sound source can be assessed by the perceived dominance of the sound source (Fiebig, 2012). As the participants might not have been familiar with VR devices, we conducted a simple training session, allowing them to adapt to the evaluation environment. As an additional ethical procedure, the individuals provided written consent to participate in the experiment, and to ensure anonymity, they were asked to use their IDs or nicknames. The evaluation stimuli followed the order of sites (a) to (j) and audio-visual stimulation was provided repeatedly if requested. The participants could freely move their heads to look around from a fixed location in the VR environment, and head-tracked binaural was provided. To reduce the physical discomfort of long-term experiments, the duration did not exceed 1 h and sufficient rest time was provided upon participant request.

All participants responded to the source identification, perceived affective quality (typical attributes), and overall quality questions for each evaluation point, resulting in 500 data sets (50 participants × 10 sites) for each evaluation item. We evaluated the 116 perceived affective qualities by randomly dividing the participants into two groups of 25 to ensure we complied with the allocated evaluation time in a VR environment. As each participant responded to 5 of the 10 sites, we collected 25 responses for each location. To ensure response consistency, we randomly selected 24 words as additional responses that overlapped with the 116, and these same 24 words were evaluated for all participants. Thus, 140 extensive attributes were evaluated for each location and we obtained 250 data sets (25 participants (2 groups) × 10 sites). To

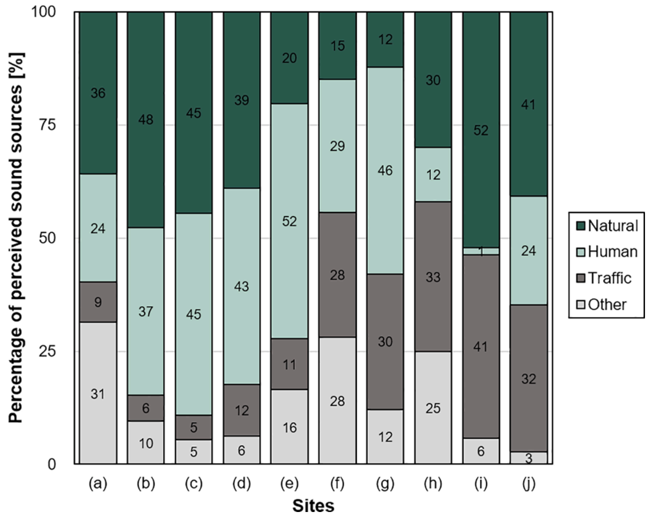

Fig. 2. Dominant Sound Source Types in Different Sites.

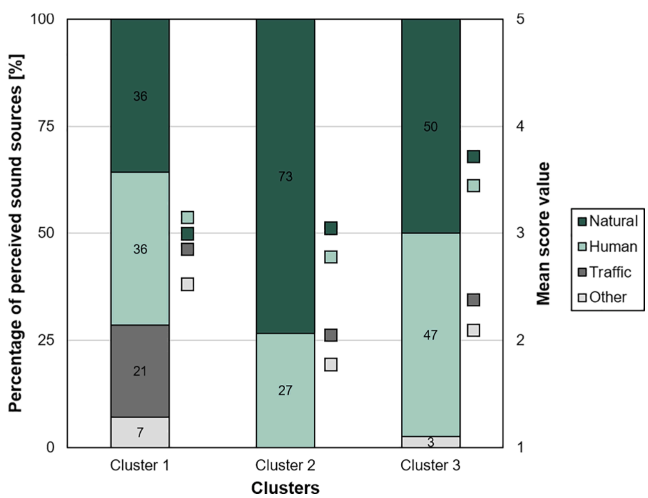

Fig. 3. Perceived Sound Source Types by Sound Source Attention Group.

remove scaling order effects (Gescheider, 2013), we provided the 140 attributes containing duplicate vocabulary in random order. Not only did the subjects not evaluate adjectives in the same order, but the attribute evaluation order was also not identically arranged between each evaluation point.

2.4. Statistical analysis

We performed the following analysis using SPSS (version 25, IBM) and R language (version 3.5.1, R Development Core Team). First, we performed a cluster analysis to classify the participants according to sound source identification. To compare soundscape recognition for each cluster, we performed a principal component analysis (PCA) for the 8 typical and 116 extensive attributes, respectively, and extracted the main perceptual components. Second, we examined the relationship between soundscape indicators (acoustic parameters and sound source identification) and descriptors (main perceptual components and overall quality) through Pearson's correlation analyses for each cluster. Finally, we presented a soundscape recognition model through multiple linear regression analyses for each attention cluster and compared indicators' different effects on descriptors.

3. Results

3.1. Group categorizations

3.1.1. Perceived sound source dominance

Fig. 2 shows the recognized sound source evaluation results for each site. The percentages of perceived sound sources were calculated as follows. First, in response to the given question on sound source identification, we calculated the total number of responses of 3, 4, and 5 on the 5-point Likert scale (i.e., 3 = *Moderately*, 4 = *A lot*, and 5 = *Dominates completely*). We then calculated the percentage of a given response among the total number of responses. In other words, the figure shows the percentage of each response for the individual sound source type out of all responses of "the sound source dominates completely." Sites (a) through (e) had traffic noise percentages of less than 10%, while human and natural sounds were perceived at higher rates of up to 52% and 48%, respectively. Contrariwise, sites (f) through (j) had traffic sounds perceived at up to 41% due to the prominent roadsides. Most human sounds were perceived at lower than 29%, except in (g). Additionally, in sites (i) and (j), natural sounds were perceived at a 40% minimum, depending on the influence of the nearby fountain on the participants. As noted, depending on the space's function and context, each site's identified sound sources appeared differently and the sounds that the participants responded to also varied.

Pearson's correlation coefficient (r) analyses revealed different relationships depending on sound source types. Traffic noise showed a weak positive relationship with $L_{Ceq\text{-}Aeq}$ ($r = 0.15$, $p < 0.05$), affecting the sound environment's low-frequency characteristics. Conversely, human sounds had a strong positive relationship with L_{Aeq} ($r = 0.57$, $p < 0.01$) and loudness ($r = 0.52$, $p < 0.05$), and a negative relationship with $L_{Ceq\text{-}Aeq}$ ($r = -0.49$, $p < 0.01$). These sounds had a great influence on the recognition of loudness in urban soundscapes and were recognized differently from the city center's general low frequencies (fan noises). This frequency characteristic emerged from the negative relationship between sharpness and $L_{Ceq\text{-}Aeq}$ ($r = 0.36$, $p < 0.01$). Therefore, human sounds are an important cognitive factor exhibiting relatively high frequency characteristics and helping individuals recognize space relatively. For natural sounds, $L_{A10\text{-}A90}$ ($r = 0.32$, $p < 0.01$) showed the highest positive relationship and had the greatest effect on soundscape fluctuation characteristics. L_{Aeq} ($r = 0.16$, $p < 0.05$) and loudness ($r = 0.14$, $p < 0.05$) had a weak positive relationship. Other noise had a positive relationship with $L_{Ceq\text{-}Aeq}$ ($r = 0.32$, $p < 0.01$), similar to traffic noise, and a weak positive relationship with L_{Aeq} ($r = 0.17$, $p < 0.01$) and loudness ($r = 0.23$, $p < 0.01$), affecting low-frequency characteristics and sound intensity.

3.1.2. Clustering based on sound source identification

Previous studies have used various clustering algorithms, including hierarchical cluster analysis, *K*-means, and partitioning around medoids, to spatially classify soundscapes (Jeon & Hong, 2015; Zambon, Benocci, Angelini, Brambilla, & Gallo, 2014). We used *K*-means clustering, which is known to be effective and applicable to various data types, to classify participants based on sound source identification. We used four independent sound sources as independent variables and the classification data employed the average response of each participant's sound source identifications for the 10 locations. Since we had four independent variables, we devised a Minkowski index suitable for data with two dimensions or higher to objectively measure the similarities between responses. In *K*-means clustering, the number of clusters must be determined in advance, and since the clustering result varies by value, we used the NbClust package (Charrad, Ghazzali, Boiteau, & Niknafs, 2014), provided by the R language, to set the optimal number of clusters (set to 3 through 26 indices: Appendix B). Thus, Cluster 1 was classified into 15 people, Cluster 2 into 16 people, and Cluster 3 into 19 people.

Fig. 3 demonstrates each divided cluster's perceived sound source

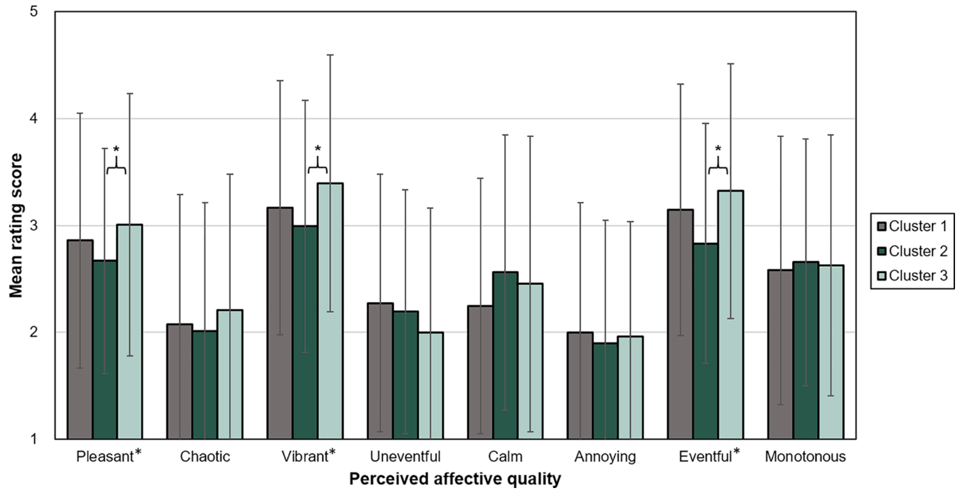

Fig. 4. Perceived Affective Quality Mean Rating Scores for Different Sound Source Identification Groups.

Table 2
PCA's rotated component matrices using typical soundscape attributes.

Component	Supportive				Detrimental				Tranquil
Cluster	*1 (49)*	*2 (26)*	*3 (43)*	*All (43)*	*1 (22)*	*2 (26)*	*3 (28)*	*All (26)*	*2 (29)*
Pleasant	**0.65**	**0.91**	**0.78**	**0.76**	−0.48	−0.03	−0.26	−0.27	0.07
Vibrant	**0.85**	**0.80**	**0.89**	**0.89**	−0.30	0.21	0.14	0.08	−0.38
Uneventful	**−0.86**	−0.24	**−0.70**	**−0.74**	−0.01	−0.03	−0.33	−0.27	**0.85**
Calm	**−0.76**	−0.18	−0.56	**−0.60**	−0.21	−0.38	**−0.62**	−0.54	**0.75**
Eventful	**0.88**	**0.71**	**0.87**	**0.85**	−0.07	0.42	0.26	0.25	−0.38
Monotonous	**−0.78**	−0.01	**−0.61**	**−0.60**	−0.21	−0.15	−0.45	−0.42	**0.84**
Chaotic	0.39	0.19	0.25	0.25	**0.75**	**0.89**	**0.82**	**0.83**	−0.24
Annoying	0.02	**0.07**	−0.08	−0.07	**0.88**	**0.94**	**0.83**	**0.86**	−0.10

Note. Numbers in parentheses represent explained variance.

results. The total group's average response was 2.47 for traffic noise, 3.19 for human sounds, 3.34 for natural sounds, and 2.18 for other noise. ANOVA was employed to determine whether the mean difference in responses between clusters was significant, revealing a statistically significant difference for all sound source types: traffic noise ($F(2{,}497) = 18.12$, $p < 0.01$), human sounds ($F(2{,}497) = 13.20$, $p < 0.01$), natural sounds ($F(2{,}497) = 14.34$, $p < 0.01$), and other noise ($F(2{,}497) = 13.77$, $p < 0.01$). Cluster 1 recognized the sound environment by considering various sound sources simultaneously, and was more attentive to traffic (mean: 2.92) and other noises (mean: 2.58). Cluster 2 mostly recognized natural and human sounds, but was generally less attentive to the sound environment, revealing lower than average responses for all sound source types. Cluster 3 primarily responded attentively to natural (mean: 3.77) and human sounds (mean: 3.50), recognizing the sound environment through these types. The participants identified different sound sources even in identical spaces, as each cluster focused on different sounds.

3.2. Perceived affective quality

3.2.1. Typical attributes (ISO scale)

Fig. 4 compares the response averages for each cluster regarding the eight typical attributes. The ANOVAs revealed statistically significant results: pleasant ($F(2{,}497) = 3.64$, $p < 0.05$), vibrant ($F(2{,}497) = 5.00$, $p < 0.01$), and eventful ($F(2{,}497) = 7.77$, $p < 0.01$). Additionally, post-hoc comparison results (Scheffé method) found a significant difference between Clusters 2 and 3 in positive expressions of space ($p < 0.05$). Overall, Cluster 3 evaluated the same urban environment more positively than other clusters.

To extract the main perceptual components according to differences in attention, we performed a PCA on the typical attribute results (Table 2). We applied a varimax rotation and selected factors with eigenvalues greater than 1. The Kaiser-Meyer-Olkin (KMO) test (sampling adequacy) showed that all clusters (All) were at an appropriate level of 0.75 or more. Barlett's sphericity test confirmed the response data's suitability for PCA analysis: all clusters (χ^2 (28) = 2079.77, $p < 0.01$), Cluster 1 (χ^2 (28) = 654.86, $p < 0.01$), Cluster 2 (χ^2 (28) = 692.49, $p < 0.01$), and Cluster 3 (χ^2 (28) = 806.64, $p < 0.01$). The typical perceptual components appeared differently for each cluster. The entire group (All), Cluster 1, and Cluster 3 were classified by Component 1, involving positive attributes (vibrant, eventful, and pleasant) and supportive soundscapes, and Component 2, comprising negative attributes (annoying and chaotic) and detrimental soundscapes (Aletta et al., 2019). However, Cluster 2 revealed a different important perceptual component: tranquil soundscapes (Component 3), constituting calm, uneventful, and monotonous attributes. Its explanatory power was 29%, higher than for detrimental soundscapes.

3.2.2. Extensive attributes

To analyze and compare the differences in urban soundscape perceptions for each cluster, a PCA was conducted on the 116 extensive attribute evaluation results (Appendix A and Fig. 5). We examined internal consistency through Pearson's correlation analysis of the 24 overlapping vocabulary responses, finding very high correlations of 0.64–0.81 (average 0.74). Varimax rotation was applied identically as for the typical attributes and the KMO measure was at an appropriate level of 0.75 or more for all. Bartlett's test of sphericity was also clear ($p < 0.05$). When the eigenvalue criterion is set at 1, 13–21 components are derived, depending on the cluster, and components with a 5% or less explanatory power are excluded. We divided the component-loading value for each attribute into 0.5–0.7 and 0.7 or higher, and analyzed the perceptual components of the attributes showing a value of 0.7 or

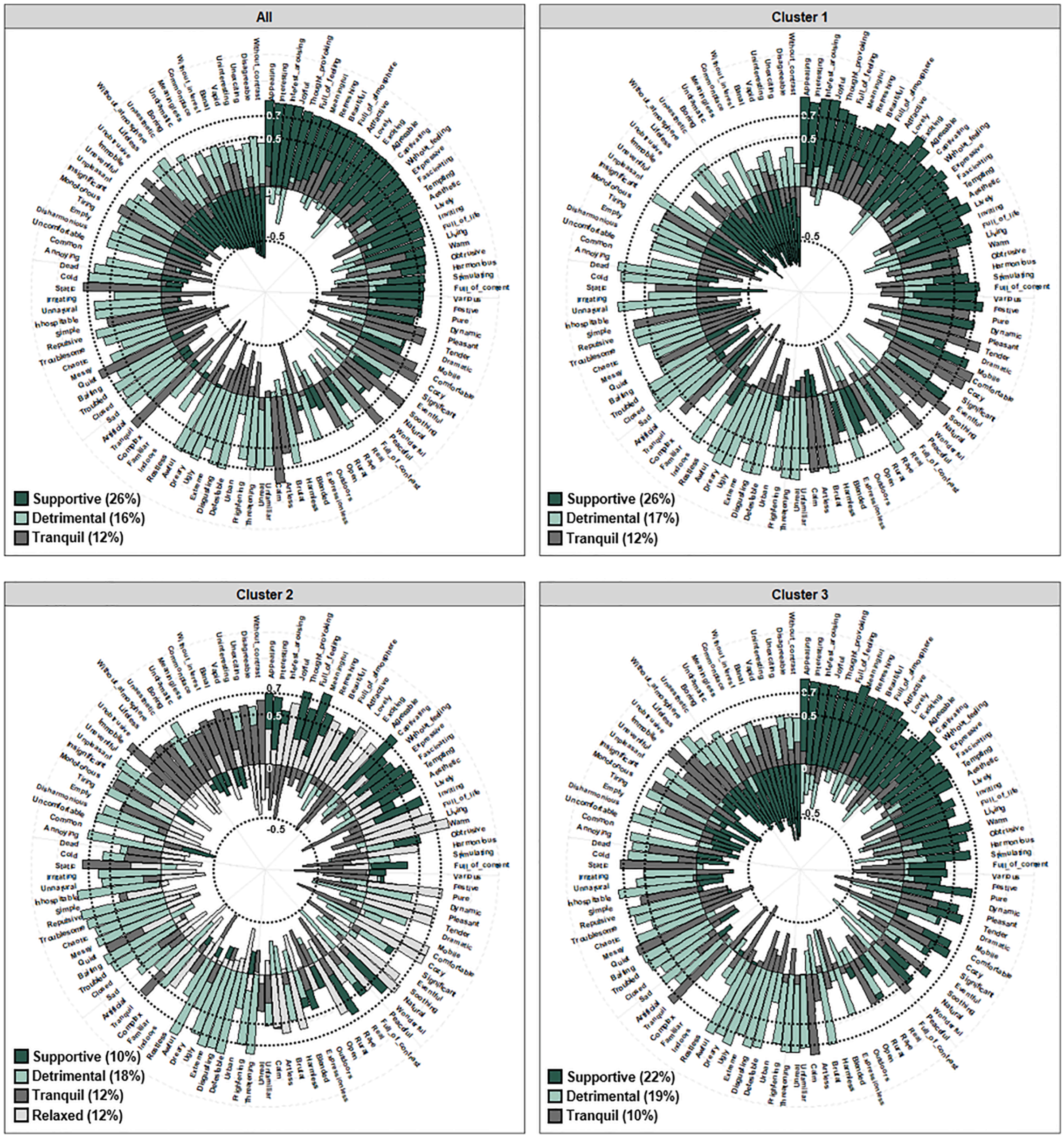

Fig. 5. Principal Component Analysis of 116 Semantic Differential Tests by Sound Source Identification Group.

higher (Axelsson et al., 2010). The selected perception components had a 50% explanatory power average for each cluster.

The entire group (All), Cluster 1, and Cluster 3 contained three perceptual components: (1) supportive soundscapes, involving positive attributes (appealing, interesting, exciting, attractive, and lively) (explanatory power: 22–26%), (2) detrimental soundscapes, representing negative attributes (dreary, detestable, ugly, and inhospitable) (explanatory power: 16–19%), and (3) tranquil soundscapes, comprising calm, tranquil, quiet, and static attributes (explanatory power: 10–12%).

Cluster 2 categorized a fourth perceptual component, relaxed soundscapes (warm, cozy, comfortable, and natural), and showed different explanatory power levels for each component. Detrimental soundscape was the highest (18%), while supportive soundscape was the lowest (10%). Overall, extensive attributes allow for more in-depth interpretations of urban environment perceptions, but as a limitation, their PCA results' overall explanatory power was approximately 50% or less than the typical attributes (70–80%).

3.3. Overall soundscape quality

3.3.1. Soundscape quality assessment according to different attention groups

Fig. 6 compares the overall soundscape quality evaluation results for each cluster, based on sound source identifications in various urban environments. Except for sites (f) and (h), the results were mostly positive. A strong positive linear relationship emerged between overall impression and appropriateness ($r = 0.50$, $p < 0.01$). After performing a two-way ANOVA to verify the statistical significance between soundscape quality responses and cluster differences, we found no significant difference in overall impression by cluster ($F(2,470) = 0.91$, $p = 0.40$) and a significant difference by site changes ($F(9,470) = 27.41$, $p < 0.01$). A significant interaction ($F(18,470) = 2.34$, $p < 0.01$) also emerged between site and cluster effects. To identify the nature of these interactions, we analyzed the simple main effects for each variable. Fig. 6 displays the places showing statistically significant differences. The overall impression for sites (b) ($F(2, 470) = 3.53$, $p < 0.05$), (d) ($F(2, 470) = 4.64$, $p < 0.05$), (g) ($F(2, 470) = 3.85$, $p < 0.05$), and (h) (F(2,

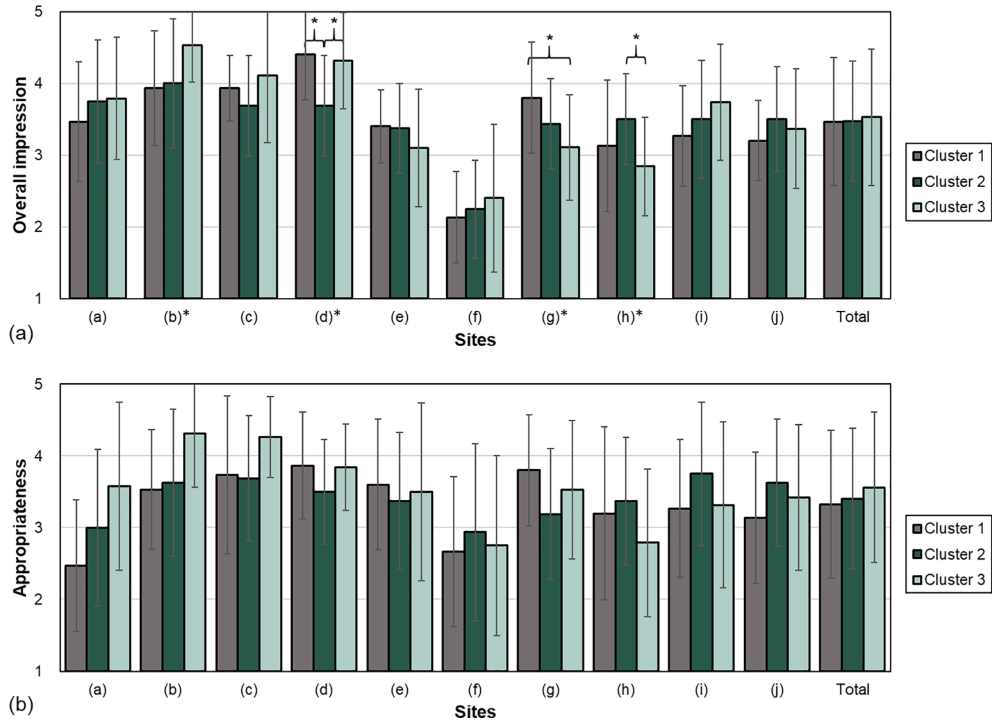

Fig. 6. Overall Soundscape Quality Mean Rating Scores for Different Sound Source Identification Groups by Assessment Site.

Table 3
Pearson's correlations between physical characteristics and sound source identification by group (* $p < 0.05$, ** $p < 0.01$).

Group	Sound sources	L_{Aeq}		$L_{A10\text{-}A90}$		$L_{Ceq\text{-}Aeq}$		Loudness		Sharpness	
Cluster 1	*Traffic*	−0.06		−0.16		0.06		0.01		0.05	
	Human	0.57	**	0.09		−0.45	**	0.53	**	0.29	*
	Natural	0.18		0.05		0.35	**	0.14		−0.02	
	Other	0.13		−0.12		0.13		0.20		0.11	
Cluster 2	*Traffic*	0.02		−0.09		0.21		0.13		−0.05	
	Human	0.61	**	0.05		−0.48	**	0.58	**	0.37	**
	Natural	0.25	*	0.40	**	0.14		0.23	*	−0.08	
	Other	0.23	*	0.06		0.37	**	0.06		0.31	**
Cluster 3	*Traffic*	−0.03		−0.14		0.15		0.08		−0.08	
	Human	0.56	**	−0.03		−0.57	**	0.49	**	0.41	**
	Natural	0.04		0.30	**	0.08		0.01		0.02	
	Other	0.18		0.12		0.44	**	0.23	*	−0.18	
All	*Traffic*	−0.03		−0.12		0.15	*	0.06		−0.05	
	Human	0.57	**	0.03		−0.49	**	0.52	**	0.36	**
	Natural	0.16	*	0.34	**	0.09		0.14	*	0.01	
	Other	0.17	**	0.03		0.32	**	0.23	**	−0.08	

470) = 3.57, $p < 0.05$) were all statistically significantly different. Following the Scheffé post hoc, Cluster 2's overall impression was 0.66 higher than Cluster 3′s at site (h). As Cluster 2 is less attentive to sound (Fig. 3), a relatively quiet site (h) was positively evaluated.

As with overall impression, a two-way ANOVA with sites and clusters as independent appropriateness variables revealed no difference by cluster ($F(2,470) = 2.72$, $p = 0.07$) and significant differences by site changes ($F(9,470) = 6.67$, $p < 0.01$). Since there was a significant interaction between sites and clusters ($F(18,470) = 1.74$, $p < 0.05$), we analyzed the simple main effect, but unlike for overall impression, differences in appropriateness responses between clusters at each site were not significant. Thus, when evaluating the overall soundscape quality of urban environments, the causes affecting each evaluation factor may vary, but varying attention levels to sound sources do not significantly affect overall perceptions of space.

3.3.2. *Soundscape perception models according to different attention groups*

We first examined the relationship between acoustic parameters and sound source identification by cluster through Pearson's correlation analyses. Table 3 shows that human sounds have relatively high frequency characteristics, making them a determining factor for physical (space) sound environments. Natural sounds of the total group revealed a positive relationship with $L_{A10\text{-}A90}$ ($r = 0.34$, $p < 0.01$), designating them as a determining factor of temporal variations in sound environments. Conversely, traffic and other noises (ventilation and air conditioning systems) showed a negative relationship with $L_{Ceq\text{-}Aeq}$. Thus, they are a determining factor of low frequency characteristics.

Pearson's correlations were analyzed to investigate the relationship between soundscape indicators (acoustic parameters, sound sources) and descriptors (perceived affective quality and overall quality) by cluster (Table 4 and Appendix C). When observing the entire group (All), human sounds showed a strong positive relationship with supportive

Table 4
Pearson’s correlations between soundscape indicators and descriptors, derived from typical (T) and extensive (E) semantic differential tests, by sound source identification group.

Indicators			Acoustic parameters										Sound sources							
Parameters			L_{Aeq}		$L_{A10\text{-}A90}$		$L_{Ceq\text{-}Aeq}$		*Loudness*		*Sharpness*		*Traffic*		*Human*		*Natural*		*Other*	
Semantic attributes		Cluster	T	E	T	E	T	E	T	E	T	E	T	E	T	E	T	E	T	E
Perceived affective quality	*Supportive*	*1*	**0.48**	**0.36**			**−0.51**		**0.44**	**0.34**	**0.43**	<u>0.23</u>			**0.68**	**0.51**				
		2	**0.38**				**−0.41**		**0.33**		**0.32**		<u>−0.16</u>		**0.55**		**0.21**			
		3	**0.55**				**−0.54**	**−0.30**	**0.50**		**0.45**	<u>0.24</u>		<u>−0.22</u>	**0.63**					<u>−0.22</u>
		All	**0.51**	**0.18**			**−0.54**	**−0.25**	**0.46**	<u>0.14</u>	**0.45**	**0.20**		<u>−0.15</u>	**0.66**	**0.23**	**0.16**	<u>0.14</u>		
	Detrimental	*1*	**0.25**				<u>0.16</u>		**0.34**				**0.24**			<u>−0.24</u>	**−0.35**		**0.33**	
		2	**0.32**	<u>0.25</u>					**0.38**	<u>0.28</u>			**0.38**		**0.27**				**0.55**	**0.42**
		3	**0.21**					**0.29**	**0.28**		<u>0.17</u>		**0.46**		<u>0.17</u>		**−0.37**		**0.30**	<u>0.25</u>
		All	**0.28**					**0.23**	**0.36**		<u>0.10</u>	<u>−0.15</u>	**0.39**		**0.18**		**−0.26**		**0.38**	**0.20**
	Tranquil	*1*																		
		2	**−0.40**	**−0.34**			**0.40**		**−0.42**	**−0.32**	**−0.42**		**−0.22**		**−0.41**	**−0.30**				
		3		**−0.34**		<u>−0.25</u>				**−0.36**										
		All		**−0.32**		**−0.18**				**−0.35**						**−0.22**				**−0.21**
	Relaxed	*1*																		
		2						**−0.32**				**0.33**				**0.29**				
		3																		
		All																		
Overall quality	*Overall impression*	*1*					**−0.34**	**−0.30**					**−0.32**	**−0.45**	**0.27**	<u>0.25</u>	**0.35**	**0.35**	**−0.26**	
		2		**−0.25**					**−0.21**	**−0.31**			**−0.48**	**−0.47**		<u>−0.23</u>	**0.24**	**0.30**	**−0.49**	**−0.55**
		3			**0.24**	<u>0.21</u>							**−0.45**	**−0.41**			**0.40**	**0.49**	**−0.35**	**−0.45**
		All			<u>0.10</u>		**−0.13**	<u>−0.15</u>	<u>−0.11</u>				**−0.40**	**−0.42**			**0.33**	**0.39**	**−0.35**	**−0.39**
	Appropriateness	*1*					**−0.31**	<u>−0.29</u>							**0.23**	**0.31**	<u>0.20</u>		**−0.22**	<u>−0.27</u>
		2																	**−0.27**	**−0.29**
		3	**0.20**		**0.20**								**−0.30**	**−0.33**	<u>0.16</u>		**0.30**	**0.45**	**−0.24**	**−0.33**
		All			<u>0.10</u>		**−0.16**	<u>−0.16</u>					**−0.18**	**−0.17**	**0.15**	<u>0.13</u>	**0.22**	**0.28**	**−0.24**	**−0.29**

Notes. <u>Underline</u> means $p < 0.05$. **Bold** means $p < 0.01$

Table 5
Standardized regression coefficients (β) from multiple linear regression (MLR) analysis of soundscape descriptors, derived from typical (T) and extensive (E) semantic differential tests using soundscape indicators by sound source identification group.

Indicators					Acoustic parameters								Sound sources							
Parameters		Cluster (R^2)			L_{Aeq}		$L_{A10\text{-}A90}$		$L_{Ceq\text{-}Aeq}$		*Sharpness*		*Traffic*		*Human*		*Natural*		*Other*	
Semantic attributes			T	E	T	E	T	E	T	E	T	E	T	E	T	E	T	E	T	E
Perceived affective quality	*Supportive*	*1*	*59*	*35*		$\underline{0.39}$		$\underline{-0.49}$	**−0.37**				**0.16**		**0.39**	**0.43**			$\underline{0.17}$	
		2	*39*	-											**0.42**		$\underline{0.15}$			
		3	*57*	*23*	**0.43**	0.40			$\underline{-0.22}$	$\underline{-0.47}$					**0.24**	**−0.43**	$\underline{0.14}$			
		All	*58*	*12*	**0.21**				**−0.33**		$\underline{0.09}$		$\underline{0.09}$		**0.34**		**0.15**	$\underline{0.14}$		
	Detrimental	*1*	*34*	-	**0.44**				**0.37**								**−0.39**			
		2	*37*	*22*															**0.46**	
		3	*40*	-	**0.41**						$\underline{0.19}$		**0.36**				**−0.22**			
		All	*34*	*8*	**0.34**				**0.20**		**0.14**		**0.27**				**−0.21**		**0.14**	$\underline{0.18}$
	Tranquil	*1*	-	-																
		2	*37*	-					$\underline{0.33}$				**−0.26**							
		3	-	-																
		All	-	*15*		**−0.32**														
	Relaxed	*1*	-	-																
		2	-	*24*												$\underline{0.38}$				
		3	-	-																
		All	-	-																
Overall quality	*Overall impression*	*1*	*42*	*39*	**−0.47**		$\underline{0.31}$		**−0.66**		**−0.27**		**−0.22**	**−0.36**	$\underline{0.24}$		**0.33**	$\underline{0.29}$		
		2	*35*	*47*									**−0.27**				$\underline{0.17}$	**0.27**	**−0.40**	**−0.50**
		3	*38*	*43*					$\underline{-0.27}$		**−0.26**		**−0.29**	$\underline{-0.19}$			**0.27**	**0.32**	$\underline{-0.18}$	$\underline{-0.23}$
		All	*31*	*33*	**−0.24**		**0.20**		**$\underline{-0.32}$**	$\underline{-0.27}$	**−0.19**		**−0.27**	**−0.24**			**0.24**	**0.29**	$\underline{-0.11}$	$\underline{-0.14}$
	Appropriateness	*1*	*23*	*23*	**−0.40**		$\underline{0.38}$		**$\underline{-0.61}$**							$\underline{0.33}$	$\underline{0.19}$			
		2	*12*	*24*										$\underline{0.33}$					**−0.29**	$\underline{-0.37}$
		3	*22*	*34*						$\underline{-0.47}$			**−0.15**				**0.25**	**0.33**		
		All	*14*	*18*	**−0.21**	$\underline{-0.22}$	**0.25**	$\underline{0.28}$	**$\underline{-0.28}$**	**$\underline{-0.35}$**					$\underline{0.16}$		**0.16**	**0.22**		

Notes. Underline means $p < 0.05$, **Bold** means $p < 0.01$.

Table 6
Summary of previous research on semantic differential tests for soundscape perception.

Sites	Country	Method	SPL (dBA)	Adjectives (N)	Measure (Scale)	Participants (N)	Age	Component/Factors	References
9 urban environments	Korea	Lab	57.2–79.4	20	Unipolar measure (5)	30	22–29	Pleasantness, Eventfulness/ Overall quality, Regularity, Spatial impression, Naturalness	Jeon & Jo (2020)
100 general outdoor Environment	UK	Lab	53.3–64.3	38 (19 pairs)	Bipolar measure (11)	25	25–42	Calmness/Relaxation, Dynamics/ Vibrancy, Communication	Sudarsono, Lam, & Davies (2016)
Urban shopping Streets	China	Field	55.0–80.0	36 (18 pairs)	Bipolar measure (7)	493	20–40	Preference, Communication, Loudness, Playfulness, Richness	Yu et al. (2016)
4 general outdoor environments	UK	Field, Lab	62.0–73.0	38 (19 pairs)	Bipolar measure (11)	18/14/14	17–40	Calmness/Relaxation, Dynamics, Communication, Spatially, Naturality, Meaningfulness	Sudarsono, Lam, & Davies (2017)
4 urban environments	UK	Lab	–	38 (19 pairs)	Bipolar measure (11)	15	–	Relaxation/Calmness, Dynamics/ Vibrancy, Communication, Spatiality	Davies et al. (2014)4
41 urban environments	Spain	Field	39.3–87.1	30 (15 pairs)	Bipolar measure (11)	570	–	–	Torija et al. (2013)
8 urban environments	UK	Lab	62.0–85.2	10 (5 pairs)	Bipolar measure (9)	22/9/9	–	Calmness, Vibrancy	Cain et al. (2013)
219 urban environments	UK	Lab	–	6	Bipolar measure (9)	5	21–40	Emotional valence, Arousal	Hall et al. (2013)
Urban environment (Photo montage)	Korea	Lab	55.0–70.0	24 (12 pairs)	Bipolar measure (7)	20	23–34	Overall quality, Pleasantness, Acoustic comfort, Spatial impression	Hong & Jeon (2013)
2 urban environments	UK	Field	–	–	–	–	–	Calmness, Vibrancy	Davies et al. (2013)
10 urban environments	Korea	Field	52.2–75.5	24 (12 pairs)	Bipolar measure (7)	300	25–42	Comfort/Loudness/Temporal variation, Spatial sensation	Jeon et al. (2011)
36 environmental noises (indoor-outdoor)	Japan	Lab	–	26 (13 pairs)	Bipolar measure (7)	20	–	Emotion, Clearness, Powerfulness	Takada et al. (2010)
2 public spaces	UK	Field	60.2–67.4	38 (18 pairs)	Bipolar measure (7)	491	–	Relaxation, Communication, Spatiality, Dynamics	Kang and Zhang (2010)
16 urban environments	Korea	Field	54.0–78.0	20 (10 pairs)	Bipolar measure (7)	15	20–30	Comfort/Loudness/Pitch sensation, Temporal variation, Characteristics	Jeon, Lee, You, & Kang (2010)
10 urban environments	UK, Sweden	Lab	43.0–79.0	116	Visual analog scale (0–100)	100	19–54	Pleasantness, Eventfulness, Familiarity	Axelsson et al. (2010)
9 urban environments	Spain	Lab	–	36 (18 pairs)	Bipolar measure (7)	311	18–34	Emotional evaluation, Strength, Activity, Clarity	Guillén & Barrio (2007)

soundscapes, while traffic and other noises had a positive relationship with detrimental soundscapes. Further, natural sounds had a weak positive relationship with supportive soundscapes and a negative relationship with detrimental soundscapes. Clusters 1 and 3 showed similar tendencies with no significant differences from the entire cluster (All) regarding the relationship between perceived affective qualities and soundscape indicators. However, only in Cluster 1 was the overall quality positive for human sounds and overall impression, and only in Cluster 3 did appropriateness show a negative relationship with traffic noise. The positive effect of natural sounds was also greater in Cluster 3. Cluster 2 generally differed from Clusters 1 and 3, but human and natural sounds showed similar results, a positive tendency for supportive soundscapes. However, since human sounds and traffic noise have a negative relationship with tranquil soundscapes, human sounds are not necessarily a positive factor.

We also performed a multiple linear regression analysis to examine indicators' actual contributions to the descriptors for each cluster (Table 5 and Appendix C). For comprehension purposes, Table 5 only shows cases where the derived model's R^2 was statistically significant. In Cluster 1 (attentive to traffic and other noises), human sounds had a positive effect on soundscape recognition. In Cluster 3, equal human and natural sound evaluations, the latter sounds had a positive effect on affective quality, with natural sounds having the highest contributions in terms of overall impressions of quality and appropriateness, making the effect of these sounds very important. Traffic and other noises, which had some positive effects on perceived affective quality in Cluster 1, showed negative contributions to overall impressions in Cluster 3. Lastly, Cluster 2 revealed some similarities and differences with Cluster 3, recognizing and perceiving the positive contributions of human and natural sounds (supportive soundscape prediction model). Since Cluster 2 responds less attentively to all sound sources and prefers a quiet environment, noise sources (other noise) can cause more negative emotions and form a detrimental soundscape. For overall quality, traffic and other noises had a negative effect.

4. Discussion

4.1. Soundscape indicators and descriptors

By investigating the relationship between soundscape indicators and descriptors, we derived a new soundscape prediction model. Natural sounds reduced negative emotions and increased positive emotions (Hong & Jeon, 2013; Ren, Kang, Zhu, & Wang, 2018). Furthermore, affective quality and soundscape indicators, similar to overall quality, revealed a positive linear relationship between overall quality and natural sounds and a negative relationship with traffic and other noise. Interestingly, relaxed soundscapes had a positive relationship with human sounds. Thus, although Cluster 2 individuals are less attentive, the human and natural sounds in which they are interested do affect them positively. Therefore, appropriately inducing human sounds in urban environments is important for soundscape design (Meng & Kang, 2015; Jo & Jeon, 2020a, 2020b). Jo and Jeon (2020a, 2020b)

Table 7
PCA's rotated component matrices using 116 semantic soundscape expressions.

Attributes	All			Cluster 1			Cluster 2				Cluster 3		
	1	2	3	1	2	3	1	2	3	4	1	2	3
Aesthetic	**0.67**	−0.06	0.23	**0.75**	0.13	0.11	−0.26	0.27	0.02	**0.65**	**0.66**	−0.21	0.13
Agreeable	**0.71**	−0.31	−0.01	**0.81**	−0.26	0.03	−0.13	**0.57**	−0.40	0.25	**0.66**	−0.38	−0.17
Annoying	−0.25	**0.55**	−0.48	−0.05	0.46	−0.43	**0.73**	−0.26	−0.12	−0.16	−0.40	**0.66**	−0.29
Appealing	**0.81**	−0.10	0.19	**0.84**	0.22	0.18	−0.17	0.33	−0.23	**0.67**	**0.80**	−0.37	0.12
Artificial	−0.10	**0.50**	−0.33	0.01	**0.52**	−0.49	0.40	**−0.51**	−0.05	0.00	−0.07	**0.58**	−0.07
Artless	0.11	−0.16	**0.54**	−0.21	0.08	**0.68**	−0.27	**0.56**	0.22	0.03	0.23	−0.38	0.26
Attractive	**0.72**	−0.07	0.22	**0.68**	0.25	0.22	−0.33	0.22	−0.07	**0.57**	**0.79**	−0.25	0.03
Awful	−0.04	**0.71**	−0.21	0.01	**0.75**	0.02	**0.78**	−0.05	0.01	−0.15	−0.04	**0.77**	−0.12
Baiting	−0.12	**0.61**	−0.35	−0.09	**0.52**	−0.21	**0.76**	−0.07	−0.12	−0.08	−0.18	**0.73**	−0.28
Banal	**−0.55**	0.44	0.28	**−0.73**	0.34	0.19	0.41	−0.01	**0.58**	−0.17	−0.49	0.41	0.42
Beautiful	**0.73**	−0.12	0.39	**0.75**	−0.01	0.32	−0.24	**0.56**	0.09	**0.56**	**0.79**	−0.28	0.23
Blended	0.17	0.13	−0.49	0.38	0.08	−0.45	0.27	−0.34	−0.34	0.36	−0.04	0.11	−0.39
Boring	**−0.51**	**0.53**	0.06	**−0.73**	0.33	0.04	**0.63**	−0.05	0.42	−0.11	−0.48	**0.53**	0.13
Brutal	0.14	**0.65**	−0.06	0.07	**0.74**	−0.02	0.46	−0.04	0.11	0.07	0.24	**0.68**	−0.07
Calm	0.10	−0.05	**0.82**	−0.26	0.11	**0.71**	−0.32	**0.50**	**0.51**	0.20	0.35	−0.23	**0.76**
Captivating	**0.70**	0.10	0.17	**0.67**	0.21	0.00	−0.15	0.08	0.03	**0.76**	**0.81**	−0.04	0.10
Chaotic	−0.14	0.46	**−0.63**	0.11	**0.52**	−0.46	**0.72**	−0.27	−0.33	−0.07	−0.39	**0.51**	**−0.52**
Closed	−0.11	**0.66**	0.08	−0.39	**0.72**	0.10	**0.50**	−0.31	0.25	0.19	0.07	**0.62**	0.08
Cold	−0.21	**0.70**	−0.05	−0.04	**0.73**	−0.12	**0.56**	−0.39	0.36	0.16	−0.31	**0.66**	0.17
Comfortable	0.43	−0.33	**0.61**	0.21	−0.09	**0.84**	−0.43	**0.75**	0.07	0.01	**0.60**	−0.46	0.32
Common	−0.27	−0.16	−0.12	−0.23	−0.37	−0.17	0.20	0.19	−0.18	**−0.50**	−0.33	−0.13	0.03
Commonplace	**−0.55**	0.40	0.18	**−0.72**	0.25	0.10	0.47	0.18	**0.52**	−0.14	**−0.60**	0.37	0.27
Complex	−0.06	0.32	**−0.65**	0.24	0.35	**−0.59**	0.49	−0.39	−0.34	0.05	−0.32	0.39	**−0.52**
Cozy	0.41	−0.20	**0.67**	0.06	−0.01	**0.80**	−0.31	**0.75**	0.15	0.14	**0.63**	−0.36	0.43
Dead	−0.25	**0.66**	0.13	−0.20	**0.77**	0.08	0.40	−0.22	0.33	−0.04	−0.25	**0.63**	0.46
Detestable	0.01	**0.72**	−0.27	0.07	**0.78**	−0.19	**0.79**	−0.13	−0.02	−0.05	−0.01	**0.74**	−0.16
Disagreeable	**−0.66**	0.48	−0.07	**−0.72**	0.37	−0.11	**0.55**	−0.48	0.37	−0.06	**−0.72**	0.44	0.14
Disgusting	0.00	**0.70**	−0.28	0.04	**0.78**	−0.10	**0.76**	−0.10	−0.04	−0.02	−0.03	**0.75**	−0.21
Disharmonious	−0.31	**0.58**	−0.35	−0.21	0.47	**−0.53**	**0.65**	−0.34	0.09	0.10	−0.42	**0.63**	−0.11
Dramatic	0.43	0.40	−0.23	0.48	0.37	−0.20	0.45	−0.06	−0.12	0.43	0.43	0.40	−0.26
Dreary	−0.02	**0.70**	0.01	−0.02	**0.81**	0.07	0.46	−0.03	0.19	0.02	−0.02	**0.74**	0.10
Dynamic	0.46	−0.05	**−0.55**	**0.70**	−0.11	−0.33	0.44	−0.10	**−0.52**	0.23	0.30	−0.12	**−0.66**
Empty	−0.33	**0.53**	0.29	**−0.52**	**0.55**	0.18	0.32	−0.16	**0.50**	0.16	−0.27	0.46	0.41
Eventful	0.37	0.05	−0.33	**0.70**	0.13	−0.01	0.09	−0.19	**−0.50**	0.08	0.17	0.13	−0.31
Exciting	**0.71**	−0.17	−0.16	**0.86**	0.00	−0.07	−0.08	0.32	**−0.52**	0.30	**0.60**	−0.27	−0.28
Expressionless	0.19	0.49	0.05	0.01	**0.67**	−0.02	0.21	−0.01	0.21	0.40	0.30	0.46	−0.05
Expressive	**0.68**	0.03	−0.02	**0.78**	0.12	0.04	−0.01	0.12	−0.30	**0.57**	**0.64**	−0.03	−0.07
Extreme	−0.01	**0.57**	−0.48	0.09	**0.52**	**−0.52**	**0.78**	−0.08	−0.21	0.01	−0.10	**0.66**	−0.38
Familiar	−0.06	−0.17	−0.02	−0.02	−0.46	−0.08	0.15	0.42	−0.09	−0.18	−0.16	−0.15	−0.01
Fascinating	**0.68**	0.11	0.20	**0.73**	0.20	0.24	−0.14	0.26	0.00	**0.64**	**0.68**	0.04	0.07
Festive	**0.52**	0.07	−0.29	**0.76**	0.16	−0.05	0.12	0.08	−0.44	0.15	0.36	0.10	−0.35
Frightening	0.04	**0.60**	−0.10	0.21	**0.70**	0.03	**0.67**	0.16	0.02	−0.22	0.09	**0.66**	0.08
Full of atmosphere	**0.73**	−0.02	0.10	**0.80**	0.08	0.17	−0.06	0.49	−0.07	0.36	**0.77**	−0.07	−0.07
Full of content	**0.53**	0.07	−0.36	**0.72**	0.21	−0.21	0.02	−0.25	−0.46	0.37	0.39	0.05	−0.41
Full of contrast	0.31	0.44	−0.08	0.27	0.45	0.02	0.38	−0.20	0.14	**0.51**	0.39	0.40	−0.19
Full of feeling	**0.74**	0.01	0.10	**0.76**	0.16	0.18	−0.04	0.29	−0.17	**0.59**	**0.76**	−0.13	−0.01
Full of life	**0.63**	−0.20	0.03	**0.74**	−0.23	0.08	0.07	**0.59**	−0.19	0.35	**0.58**	−0.34	−0.17
Harmless	0.16	−0.22	0.38	−0.01	−0.04	0.48	−0.21	**0.55**	0.11	0.15	0.13	−0.42	0.16
Harmonious	**0.55**	−0.32	0.32	0.41	−0.07	**0.55**	−0.38	0.49	−0.36	0.34	**0.54**	−0.47	0.13
Immobile	−0.37	0.40	**0.57**	**−0.69**	0.33	0.38	−0.06	−0.12	**0.75**	0.16	−0.16	0.38	**0.67**
Indoors	−0.06	0.37	0.18	−0.14	**0.73**	0.20	−0.06	−0.15	0.20	0.01	−0.05	0.26	0.14
Inhospitable	−0.19	**0.65**	−0.29	−0.07	0.43	−0.43	**0.82**	−0.06	0.02	−0.04	−0.25	**0.76**	−0.02
Insignificant	−0.35	**0.57**	0.04	−0.29	**0.66**	0.07	**0.67**	0.20	0.16	−0.19	**−0.50**	**0.52**	0.29
Arousing interest	**0.79**	−0.07	0.02	**0.84**	0.20	−0.09	−0.14	0.39	−0.28	**0.51**	**0.77**	−0.24	−0.09
Interesting	**0.79**	−0.16	0.01	**0.80**	0.03	0.11	−0.28	0.14	−0.43	**0.64**	**0.78**	−0.29	−0.09
Inviting	**0.63**	0.12	0.07	**0.69**	0.25	−0.06	−0.05	0.15	−0.11	**0.65**	**0.61**	0.00	0.08
Irritating	−0.19	0.45	−0.48	−0.02	0.46	−0.42	**0.60**	−0.34	−0.23	−0.10	−0.36	**0.50**	−0.32
Joyful	**0.79**	−0.34	0.02	**0.84**	−0.16	0.12	−0.25	**0.60**	**−0.51**	0.22	**0.77**	−0.41	−0.17
Lifeless	−0.43	**0.57**	0.17	−0.46	**0.52**	0.08	0.20	−0.28	**0.56**	−0.01	−0.40	**0.67**	0.34
Lively	**0.66**	−0.24	−0.26	**0.82**	−0.21	−0.13	0.04	0.26	**−0.60**	0.39	**0.51**	−0.34	−0.33
Living	**0.60**	−0.33	−0.09	**0.71**	−0.36	−0.01	0.01	**0.68**	−0.32	0.24	0.48	−0.40	−0.36
Lovely	**0.72**	−0.04	0.28	**0.72**	0.02	0.36	−0.14	**0.63**	−0.07	**0.50**	**0.74**	−0.08	0.09
Meaningful	**0.74**	0.05	0.14	**0.65**	0.03	0.13	−0.09	0.15	−0.08	**0.77**	**0.84**	−0.01	−0.03
Meaningless	**−0.54**	0.45	0.04	**−0.58**	0.47	0.01	0.47	0.01	0.43	−0.22	**−0.60**	0.44	0.13
Messy	−0.13	**0.60**	**−0.53**	0.10	**0.53**	**−0.57**	**0.75**	−0.23	−0.11	−0.03	−0.29	**0.70**	−0.39
Mobile	0.43	−0.22	**−0.55**	**0.74**	−0.21	−0.32	0.23	0.04	**−0.66**	0.13	0.13	−0.28	**−0.63**
Monotonous	−0.34	0.14	**0.61**	**−0.65**	0.20	**0.50**	0.18	0.25	**0.66**	0.02	−0.18	−0.12	**0.62**
Natural	0.35	−0.45	0.37	0.23	−0.39	**0.60**	−0.33	**0.70**	−0.07	−0.03	0.39	**−0.57**	0.08
Obtrusive	**0.57**	0.24	−0.20	**0.55**	0.29	−0.15	0.26	−0.07	−0.31	**0.52**	**0.63**	0.20	−0.28
Open	0.23	−0.17	−0.02	0.35	−0.21	−0.06	−0.27	0.02	−0.21	0.25	0.14	−0.13	0.04
Outdoors	0.19	−0.28	−0.13	0.46	−0.46	−0.08	0.12	0.24	−0.37	0.00	0.01	−0.29	0.07
Peaceful	0.33	−0.27	**0.65**	0.16	−0.13	**0.72**	−0.48	**0.51**	0.20	0.17	0.48	−0.40	**0.55**
Pleasant	0.46	−0.37	**0.59**	0.42	−0.19	**0.64**	**−0.53**	**0.67**	0.18	0.16	**0.56**	**−0.50**	0.36

(*continued on next page*)

Table 7 (*continued*)

Attributes	All			Cluster 1			Cluster 2				Cluster 3		
	1	2	3	1	2	3	1	2	3	4	1	2	3
Pure	**0.52**	−0.16	0.49	0.24	−0.05	**0.64**	−0.26	<u>**0.72**</u>	−0.01	0.27	**0.67**	−0.24	0.22
Quiet	−0.12	0.08	<u>**0.77**</u>	**−0.57**	0.20	**0.52**	−0.23	0.31	**0.69**	0.07	0.23	−0.08	<u>**0.74**</u>
Rare	0.30	**0.53**	0.12	0.09	<u>**0.79**</u>	−0.09	0.07	−0.21	0.19	**0.61**	0.45	0.39	0.11
Real	0.31	−0.26	−0.17	0.46	−0.41	0.08	0.08	0.31	−0.43	−0.08	0.23	−0.19	−0.22
Refreshing	<u>**0.73**</u>	−0.08	0.23	**0.68**	0.05	0.35	−0.17	0.38	−0.19	**0.59**	<u>**0.77**</u>	−0.22	0.11
Repulsive	−0.15	**0.67**	−0.42	0.00	**0.65**	−0.37	<u>**0.81**</u>	−0.32	−0.04	0.01	−0.29	**0.69**	−0.27
Restless	−0.04	0.14	**−0.67**	0.27	−0.01	**−0.63**	0.41	−0.24	−0.48	−0.05	−0.31	0.29	**−0.59**
Rural	0.24	0.00	0.46	0.19	0.21	0.43	−0.14	**0.56**	0.12	0.17	0.23	−0.15	0.45
Sad	−0.10	<u>**0.70**</u>	0.03	−0.07	<u>**0.76**</u>	0.03	**0.55**	−0.11	0.17	0.07	−0.15	**0.69**	0.25
Significant	0.37	0.45	−0.02	0.26	0.49	0.13	0.38	−0.03	0.08	0.45	0.46	0.40	−0.15
Simple	−0.16	0.19	**0.54**	−0.41	0.17	**0.62**	0.17	0.35	0.42	0.09	−0.05	0.08	**0.56**
Soothing	0.36	−0.13	**0.69**	0.10	0.00	<u>**0.82**</u>	−0.29	**0.64**	0.30	0.14	**0.58**	−0.26	**0.50**
Static	−0.20	0.16	<u>**0.75**</u>	**−0.68**	0.31	0.39	−0.15	0.29	<u>**0.75**</u>	0.08	0.15	−0.07	<u>**0.73**</u>
Stimulating	**0.54**	0.18	−0.30	**0.62**	0.29	−0.27	0.20	−0.17	**−0.63**	0.06	**0.64**	0.22	−0.15
Tempting	**0.67**	0.22	0.06	**0.68**	0.43	0.04	−0.09	0.10	−0.02	**0.68**	<u>**0.70**</u>	0.14	−0.07
Tender	0.46	−0.12	**0.58**	0.22	0.10	<u>**0.80**</u>	−0.24	**0.67**	0.20	0.24	**0.62**	−0.28	0.27
Thought provoking	<u>**0.76**</u>	0.12	0.07	<u>**0.78**</u>	0.23	0.06	0.02	0.27	−0.10	<u>**0.73**</u>	<u>**0.75**</u>	−0.02	−0.04
Threatening	0.04	**0.66**	−0.33	0.12	<u>**0.77**</u>	−0.10	<u>**0.75**</u>	−0.03	−0.23	−0.18	−0.01	<u>**0.73**</u>	−0.25
Tiring	−0.33	**0.56**	−0.42	−0.23	0.49	**−0.55**	**0.68**	−0.33	−0.07	−0.08	−0.44	**0.64**	−0.15
Tranquil	−0.08	0.13	<u>**0.78**</u>	−0.39	0.36	**0.60**	−0.29	0.38	**0.66**	0.10	0.14	−0.06	<u>**0.76**</u>
Troubled	−0.11	<u>**0.70**</u>	−0.30	0.03	<u>**0.71**</u>	−0.40	<u>**0.73**</u>	−0.12	0.01	0.12	−0.29	<u>**0.71**</u>	−0.09
Troublesome	−0.15	**0.62**	−0.46	0.04	**0.64**	**−0.51**	<u>**0.78**</u>	−0.15	−0.15	−0.11	−0.31	**0.65**	−0.28
Ugly	−0.02	<u>**0.72**</u>	−0.20	0.09	<u>**0.78**</u>	−0.10	**0.69**	−0.08	−0.02	−0.20	−0.05	<u>**0.79**</u>	−0.05
Unaesthetic	**−0.50**	0.40	−0.14	**−0.61**	0.24	−0.21	**0.52**	−0.23	0.21	−0.09	**−0.53**	0.47	−0.07
Uncomfortable	−0.29	**0.58**	−0.47	−0.10	0.49	**−0.61**	<u>**0.70**</u>	−0.45	−0.13	−0.07	−0.40	**0.69**	−0.11
Undramatic	**−0.53**	−0.03	0.26	<u>**−0.73**</u>	−0.14	0.01	0.13	0.09	0.45	−0.16	−0.48	−0.16	0.39
Uneventful	−0.37	0.06	0.38	<u>**−0.78**</u>	−0.02	0.00	0.01	0.26	0.43	0.11	−0.25	−0.05	0.42
Unexciting	**−0.65**	0.42	0.10	<u>**−0.74**</u>	0.29	−0.15	0.29	−0.43	**0.57**	−0.14	**−0.56**	0.46	0.35
Unfamiliar	0.06	**0.65**	−0.06	0.00	**0.63**	−0.20	0.48	−0.14	0.27	0.48	0.10	**0.69**	−0.01
Uninteresting	**−0.63**	0.37	−0.07	<u>**−0.72**</u>	0.17	−0.19	**0.52**	−0.14	0.34	−0.08	<u>**−0.72**</u>	0.38	0.06
Unnatural	−0.19	**0.65**	−0.16	−0.17	<u>**0.76**</u>	−0.20	**0.57**	−0.42	0.17	0.23	−0.25	**0.58**	0.03
Unobtrusive	−0.38	0.15	0.39	**−0.68**	−0.02	0.17	0.11	−0.03	**0.53**	0.17	−0.28	0.05	**0.50**
Unpleasant	−0.36	**0.53**	−0.48	−0.23	0.34	**−0.57**	<u>**0.74**</u>	−0.36	−0.07	−0.02	**−0.54**	**0.60**	−0.23
Unreal	0.04	**0.67**	0.12	−0.16	<u>**0.78**</u>	−0.06	0.19	0.08	0.34	0.32	0.11	<u>**0.73**</u>	0.09
Urban	0.01	0.18	−0.43	0.14	−0.10	−0.36	0.34	−0.43	−0.20	0.18	−0.07	0.28	−0.38
Vapid	**−0.57**	0.42	0.25	<u>**−0.70**</u>	0.37	0.14	0.43	0.17	**0.55**	−0.21	**−0.58**	0.36	0.38
Various	**0.52**	−0.04	−0.45	<u>**0.70**</u>	0.09	−0.22	0.01	−0.02	<u>**−0.72**</u>	0.16	0.41	0.04	−0.49
Warm	**0.58**	−0.17	0.40	0.44	−0.12	**0.56**	−0.09	<u>**0.82**</u>	0.01	0.23	**0.68**	−0.27	0.11
Without atmosphere	0.34	0.30	0.15	0.00	0.37	0.04	0.11	0.03	0.13	**0.63**	**0.50**	0.21	−0.03
Without contrast	−0.48	**0.60**	0.07	**−0.58**	**0.52**	−0.11	**0.51**	−0.31	**0.53**	0.07	−0.45	**0.57**	0.26
Without feeling	**−0.68**	0.41	0.02	<u>**−0.76**</u>	0.21	−0.29	0.36	−0.34	**0.60**	−0.12	**−0.68**	0.43	0.21
Without interest	<u>**0.70**</u>	−0.08	0.29	<u>**0.75**</u>	0.08	0.27	−0.24	0.31	−0.06	**0.56**	<u>**0.78**</u>	−0.20	0.25
Wonderful	**−0.55**	0.46	0.02	<u>**−0.74**</u>	0.23	−0.21	0.47	−0.29	**0.50**	0.03	−0.49	0.48	0.15

Notes. **Bold**: components matrices value > 0.5, <u>**Underline and Bold**</u>: components matrices value > 0.7.

discovered that appropriate human sounds in a certain space can exert a positive influence, while Meng and Kang (2015) reported that in commercial areas or urban streets, crowd density beyond the range of 0.10–0.25 persons/m^2 decreases comfort due to the increased loudness. However, additional research is required because there has been insufficient research to date on the appropriate level of human sounds in urban environments. Meanwhile, as Table 4 shows, human sounds have both positive and negative effects on soundscape perception, and preferences can be assessed in different ways depending on the sound contents. Therefore, it is necessary to conduct additional research on the differences in soundscape perception based on the contents of human sounds (Steele, Bild, Tarlao, Martín, Izquierdo-Cubero, & Guastavino, 2016).

In Cluster 1, sound sources known to increase annoyance (traffic and other noise) made positive contributions to supportive soundscapes, contrary to previous findings (Ndrepepa & Twardella, 2011; Nilsson et al., 2007). Thus, even noise sources can potentially exert a positive effect on urban soundscape perception depending on the level of attention to the sound source. Meanwhile, the noise source can have a positive effect through temporal variation because the soundscape attributes that determine supportive soundscapes include dynamic-related attributes (vibrant and eventful) as well as pleasant attributes. However, traffic noise had a negative effect on overall quality, while human and natural sounds had a positive effect (Jeon & Jo, 2020). Hence, the effect of sound source perception on sound environments, emotional responses, and overall quality may vary. Accordingly, soundscape quality perception must involve non-acoustic (visual, experience, sociocultural background, etc.) and acoustic indicators (sound source and acoustic parameters) (Jeon, Lee, Hong, & Cabrera, 2011). As in Cluster 1, reacting attentively to sound sources positively affected Cluster 3, but the influencing sources differed for each cluster. Therefore, even in identical urban environments, individual characteristics (interest in and sensitivity to sound/noise) can have different effects on space perception. Further, for Cluster 2, human sounds positively contributed to relaxed emotions, rendering them important for sound environment recognition. It can also be seen that the psychological state (e.g., comfort) of people in the space is an important judgment factor (Jo & Jeon, 2020a, 2020b).

4.2. Comparisons between attribute collections

We used 8 typical and 116 extensive attributes to interpret sound environment perceptions, and their overall quality and soundscape indicators did not differ significantly (Tables 4 and 5). However, extensive attributes present a higher R^2 for most overall quality prediction models, making them more useful for predicting urban environment perceptions. Contrariwise, perceived affective quality showed the opposite, as the R^2 for typical attributes (0.37–0.58) was higher than for extensive

Table 8
Twenty-six index values with different methods for determining optimal cluster numbers.

Index	Year	Authors	Number of clusters			*N*	Index value
			2	3	4		
Maximum/Minimum index value							
CH	1974	Calinski and Harabasz	16.3	17.5	15.3	**3**	17.5
Dunn	1974	Dunni	0.1	0.2	0.1	**3**	0.2
McClain	1975	McClain and Rao	0.8	1.2	2.1	**2**	0.8
Cindex	1976	Hubert and Levin	0.4	0.3	0.3	**4**	0.3
DB	1979	Davies and Bouldin	1.7	1.4	1.4	**3**	1.4
Ptbiserial	1980	Millian	0.3	0.5	0.4	**3**	0.5
CCC	1983	Sarle	17.9	11.6	8.7	**2**	17.9
Silhouette	1987	Rowsseeuw and Lai	0.2	0.3	0.2	**3**	0.3
KL	1988	Krzanowski and Lai	0.9	8.8	0.1	**3**	8.8
SDindex	2000	Halkidi et al.	3.7	3.0	3.2	**3**	3.0
SDbw	2001	Halkidi and Vazirgiannis	1.3	1.0	0.5	**4**	0.5
Maximum difference between index hierarchy levels							
Ball	1965	Ball and Hall	16.5	8.5	5.5	**3**	8.0
Friedman	1967	Friedman and Bubin	311.5	319.5	381.0	**4**	61.5
Scott	1971	Scott and Symons	298.0	333.3	360.6	**3**	35.2
Hartigan	1975	Hartigan	14.4	6.9	10.2	**3**	7.5
Ratkowsky	1978	Ratkowsky and Lance	0.3	0.4	0.4	**3**	0.4
TrCovW	1985	Milligan and Cooper	82.0	39.3	24.5	**3**	42.7
Etc.							
Rubin	1967	Friedman and Rubin	50.2	65.3	74.8	**3**	−5.5
Beale	1969	Beale	33.0	25.4	22.1	**3**	4.4
Marriot	1969	Marriot	−0.9	−0.7	−0.5	**2**	−0.9
Frey	1972	Frey and Van Groenewoud	8391.9	9337.1	9609.2	**3**	−673.1
Pseudot2	1973	Duda and Hart	−0.1	1.5	−0.4	**1**	None
Duda	1973	Duda and Hart	−12.6	−7.4	−4.7	**2**	−12.6
TraceW	1985	Miligan and Cooper	1.6	1.5	1.3	**2**	1.6
Hubert	1985	Hubgert and Arobie	0.0	0.0	0.0	**0**	0.0
Dindex	2000	Lebart et al.	0.7	0.6	0.6	**0**	0.0

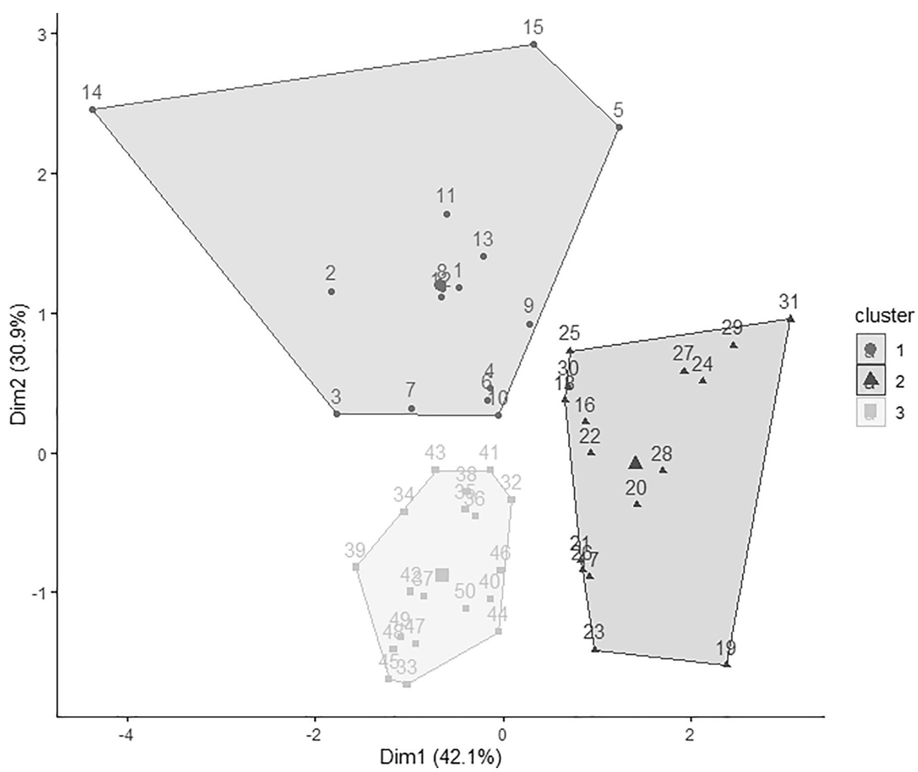

Fig. 7. Two-dimensional scattering plot for different cluster based on principal component analysis of sound source identification.

attributes (0.8–0.35), indicating a higher usefulness in terms of predicting emotional responses.

One meaningful finding is that when classifying people according to the proposed methods, additional tranquil soundscapes can be discovered (Cluster 2). Interestingly, when using extensive attributes, although less explanatory than typical attributes, we can discover additional emotional responses during in-depth analyses. For example, relaxation being related to the positive effect of human sounds (Cluster

2-typical attributes) was only noticed when using extensive attributes. Additionally, the predictive model for relaxation ($R^2 = 0.24$) had the highest explanatory power, compared to other perceived affective quality models ($R^2 = 0.22$), supporting the high utilization value of extensive attributes.

4.3. Comparisons with previous research

The soundscape perceptual components derived from the semantic differential test results (PCA analysis) can be classified into (1) physical characteristics (loudness, temporal variation, spatiality (impression/sensation), and regularity), (2) meaning (meaningfulness and communication), and (3) emotional characteristics (pleasantness, eventfulness, and calmness/relaxation; Table 6). Most components related to emotional characteristics focus on positive soundscape roles. Compared to previous studies, this study included not only positive emotional responses to soundscapes, but also negative responses as important components. Some studies have attempted to investigate the negative effects of detrimental soundscape; for example, Aletta, Oberman, and Kang (2018) examined the negative health effects thereof. Research has also attempted to evaluate the negative attributes of soundscape and to investigate the cause based on Grounded Theory (Liu & Kang, 2016; Schulte-Fortkamp, Volz, & Jakob, 2008). However, most previous studies have simply observed correlations, and featured discrepancies related to applicability for urban soundscape design. We proposed various recognition models based on each person's perceptual characteristics (attention to sound source) to interpret emotional responses to space from various aspects. Additionally, our prediction model, an evaluation of positive and negative soundscape contributions, can be effectively implemented in urban design and planning. For example, in a space containing many individuals with Cluster 3 tendencies, designs/planning should appropriately provide natural sounds, control traffic and other noise, and use a masking effect through birdsong or water sounds. However, since the masking effect of natural sound may appear differently depending on the context of the sound environment, further research is necessary to examine ways to utilize the masking sound of natural sound in an urban environment.

4.4. Limitations and future research

First, our small sample limits the generalizability of our results. Since the study participants were in their 20 s, to ensure generalizability, future work should include a wider age range and greater demographic variation. Second, as a multisensory approach is important for soundscape studies (Jeon & Jo, 2020; Yu, Behm, Bill, & Kang, 2017), future research should investigate the effects of visual elements (audio-visual interactions). Third, when grouping participants, researchers should consider more non-acoustic factors (personality, preferences, and psychological wellbeing), besides sound source identification, to further analyze the effect of personal characteristics on soundscape recognition (Lindborg & Friberg, 2015; Yang & Kang, 2005). In addition to the process of clustering, non-acoustic factors are essential when interpreting soundscape perception. Because the range of non-acoustic factors is great, further research is required. Fourth, this study comprises a soundscape evaluation based on a short-term experience. Thus, it is necessary to examine the difference in perception clusters over a long period through a repeated-longitudinal design. Lastly, future studies could compare differences between various cluster methods (mean-shift clustering and density-based spatial clustering of applications with noise) when classifying participants. In addition to the sound-source identification, it is possible to classify participants based on various indices of soundscape perception (preference, appropriateness, etc.).

5. Conclusion

We classified individuals based on their recognition of sound environments and investigated the effect of sound source identification differences on soundscape perception. We derived various main typical perceptual components for soundscapes, using typical and extensive attributes for each cluster, and examined the relationship between soundscape indicators and descriptors. Finally, we proposed a soundscape recognition model for each cluster. As we also considered the negative, rather than the traditional method of emphasizing only the positive soundscape aspects, our model can be effectively applied to urban planning, because if a soundscape's negative effects can be understood and controlled, a better urban environment can be provided. Consequently, the model proposed in this study can help urban designers and practitioners to more accurately assess and predict the human perception of sound within the urban context.

Our new discoveries emerged from our focus on human perceptions of sound environments, instead of the function of space.

1) By categorizing clusters based on responses to sound source identification, we obtained three clusters. Cluster 1 recognized the sound environment by considering various sound sources simultaneously, and reacted more attentively to traffic and other noises. Cluster 2 was a less attentive group and Cluster 3 reacted attentively to natural and human sounds.
2) By using typical and extensive attributes, we derived tranquil and relaxed soundscapes, respectively, as additional perceptual components in Cluster 2. Accordingly, extensive attributes revealed a low explanatory power, but a higher cognition interpretation capacity than typical attributes. We also found that these perception dimensions are related to the positive effects (psychological stability) of certain human sounds in certain cases. Therefore, appropriate human activities can be encouraged when planning urban designs.
3) Average overall quality did not differ by attention clusters. However, we did find different sound source influences. Even in the case of sounds classified as noise (traffic and other noise), a person who reacts attentively to the sound (Cluster 1) may consider it positive for soundscape recognition. However, traffic noise makes a very low level of contribution to the positive effect on supportive soundscape. Furthermore, from the perspective of overall quality, its negative effect is greater than its positive effect. Therefore, further research is required to examine whether attentive response to traffic noise can lead to a significant level of positive effect from a long-term perspective.

The findings not only present a new perspective for interpreting soundscape perception in an urban environment, but can also be used effectively to predict individuals' spatial perceptions in urban design and planning.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Cluster attributes

See Table 7

Appendix B. Cluster analysis

As shown in Table 8, 11 indices determine the optimal number of clusters based on the maximum or minimum value, and 6 indices establish the optimal number of clusters based on the maximum difference between hierarchical levels. The number of clusters was chosen based on a total of 26 indices, such as 9 indices for determining the optimal number of clusters based on different criteria. As a result, we decided to classify the number of clusters into three, recommended by 15 out of 26 indices. Therefore, the maximum iteration was performed 100 times to remove the local optima (Steinley, 2003) that may occur when clustering through the *K*-means clustering method (Fig. 7).

Appendix C. Statistical analysis

In-text Table 4 shows the results derived from the typical and extensive attributes. We excluded the results that were not statistically significant. We calculated the factor scores to represent the main perceptual components, derived from the perceived affective quality results, as one quantified value. A factor score is the value of multiple variables belonging to one factor converted to one score and calculated through regression analysis (Var, 1998). A regression model was derived with acoustic parameters and sound sources as independent variables, and perceived affective quality and overall quality as dependent variables. We classified recognition models based on typical and extensive attributes.

In addition, to examine multicollinearity between the independent variables, we calculated the tolerance, variance inflation ratio (VIF), and variance proportion of each independent variable. The correlation coefficient between L_{Aeq} and loudness was higher than 0.8, which violated meso-collinearity, thus excluding loudness from the model. All independent variables' tolerance, except for loudness, was greater than 0.1 and VIF was lower than 10. Since the regression coefficients of two or more independent variables did not show a high variance proportion of 0.5 or more simultaneously, there are no multicollinearity problems (Myers, 1990; Myers, Well, & Lorch, 2010).

Appendix D. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.landurbplan.2021.104241.

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