

Article

Landscape Perception in Cultural and Creative Industrial Parks: Integrating User-Generated Content (UGC) and Electrodermal Activity Insights

Xuefei Wang ¹, Baoyao Zhu ¹, Zhiqi Chen ¹, Dawei Ma ², Chuanhao Sun ¹, Mo Wang ^{1,3,*}  and Xing Jiang ^{1,*}

¹ College of Architecture and Urban Planning, Guangzhou University, Guangzhou 510006, China; saup_wxf@gzhu.edu.cn (X.W.); masterszhu@gmail.com (B.Z.); chanzk9210@163.com (Z.C.); sunch1110@outlook.com (C.S.)

² School of Management, Guangzhou University, Guangzhou 510091, China; kijiadavid@163.com

³ Architectural Design and Research Institute, Guangzhou University, Guangzhou 510091, China

* Correspondence: saupwangmo@gzhu.edu.cn (M.W.); jiangxing@gzhu.edu.cn (X.J.)

Abstract: As economic growth and societal shifts reshape urban environments, cultural and creative industrial parks are emerging as vital contributors to sustainable urban development. The design of these landscapes plays a pivotal role in enhancing user satisfaction, increasing spatial attractiveness, and promoting eco-friendly urban practices. This study examines visitor landscape perception preferences in the Textile and Garment Cultural and Creative Industrial Park, located in Haizhu District, Guangzhou, through a novel methodology combining user-generated content (UGC), deep learning models, outdoor electrodermal activity (EDA) measurements, and questionnaire surveys. The UGC-based landscape recognition model achieved an accuracy of 86.8% and was validated against user preferences captured through questionnaires. Results demonstrate that visitors prefer areas featuring cultural landmarks and natural elements, while spaces dominated by human activity and transportation infrastructure are less favored. Key landscape elements, such as signage, thematic sculptures, brand logos, and trees, were identified as highly preferred features within the park. While EDA experiments revealed significant variations in physiological responses across different spatial settings, no strong correlation was observed between EDA indicators and subjective questionnaire scores. This integrative approach enables a comprehensive, objective assessment of landscape perception, providing a data-driven, user-centered framework for improving landscape design in cultural and creative industrial parks.

Keywords: cultural and creative industrial park; landscape; perception preference; user-generated content; electrodermal activity



Citation: Wang, X.; Zhu, B.; Chen, Z.; Ma, D.; Sun, C.; Wang, M.; Jiang, X. Landscape Perception in Cultural and Creative Industrial Parks: Integrating User-Generated Content (UGC) and Electrodermal Activity Insights. *Sustainability* **2024**, *16*, 9228. <https://doi.org/10.3390/su16219228>

Academic Editor: Alejandro Javier Rescia Perazzo

Received: 11 September 2024

Revised: 18 October 2024

Accepted: 19 October 2024

Published: 24 October 2024



Copyright: © 2024 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

The Budapest Declaration recognizes heritage conservation as a tool for sustainable development in all societies through dialogue and mutual understanding [1]. Cultural and creative industrial parks, serving as benchmarks for the conservation and repurposing of historical industrial heritage, have emerged as vital components of modern urban landscapes. These parks, often situated on sites undergoing urban industrial renewal and de-industrialization, blend cultural preservation with economic innovation, significantly influencing urban society and the promotion of sustainable development of cultural and creative industries [2]. A key factor in their design is landscape preference, which reflects the degree to which individuals favor particular landscape features. This concept is critical in landscape planning, design, and management, as it elucidates the mechanisms of human–environment interactions, thereby providing theoretical foundations and methodological guidance for crafting more appealing and functional spaces [3].

User-generated content (UGC), particularly image data, offers a rich repository of information for landscape preference studies, surpassing traditional methods such as surveys [4], photo-guided interviews [5], and expert assessments [6,7]. UGC captures intuitive evaluations and preferences for landscapes, augmented by geospatial information that highlights areas of heightened interest [4]. These data are collected in the natural environment of users' daily lives, providing time-sensitive and authentic insights that capture social dynamics and popular trends [8]. Scholars have increasingly utilized UGC to assess landscape preferences. Research indicates that image-photo data can effectively substitute for real spatial scenes, offering timely and authentic insights into public preferences and social dynamics [9]. Scholars have leveraged UGC from platforms like Flickr to quantitatively assess the aesthetic value of tourist destinations [10] and gauge visitation rates for national protected areas [11]. Similarly, Facebook posts comprising text, images, and videos have been employed to delineate the geospatial distribution of social movements [12].

Recent advancements in electrodermal activity (EDA) measurement techniques have expanded their application across various disciplines, including psychology [13], medicine, sociology [14], and neuroscience. These methods are now employed in studies exploring the interaction between human senses and landscapes. Recent studies have demonstrated the efficacy of physiological measurements in various contexts. For instance, Chen et al. [15] utilized emotion map evaluations to measure environmental experiences in indoor and outdoor spaces, identifying environmental factors that evoke positive or negative emotions. Jukiewicz et al. [16] combined electrical and thermal skin measurements in a game format to assess emotional responses to visual stimuli. Additionally, Luo et al. [17] employed wearable sensors to track the physiological and emotional impacts of different residential open spaces on older adults, linking outdoor features to emotional responses.

Building on these theoretical foundations, this study employs a deep learning model derived from UGC image data alongside electrodermal activity experiments to explore landscape perceptual preferences within cultural and creative parks. The innovation lies in combining UGC-based landscape content recognition with real-world electrodermal activity measurements in the same setting, offering an experience-centered evaluation of perceptual preferences. This approach not only informs landscape optimization strategies for cultural and creative industrial parks but also introduces a precise and forward-looking perspective for sustainable urban landscape design, enhancing both the comfort and enjoyment of urban environments.

The paper is structured as follows: Section 2 introduces the study area and describes the research methodology in detail. Section 3 presents the constructed DL model and experimental results, which are analyzed separately from the evaluation questionnaire. Finally, in Section 4, the discussion focuses on the landscape elements and types with the strongest and weakest perceived preferences, as well as expectations for the future use of more useful and efficient methods or theories to study areas related to sustainable development.

2. Materials and Methods

Recognizing the limitations of traditional research methods' lack of generalizability and objectivity, this study uses the UGC-based DL model to fuse physiological experiments and combines them with the results of subjective questionnaires to further explore users' landscape perception preferences. Therefore, this method is expected to provide more comprehensive and reliable results than traditional studies. In this section, the model prediction data and experimental data generation process is detailed, including a description of the material acquisition and research methodology steps taken in order to lay the foundation for data analysis, as shown in the methodological flow chart (Figure 1).

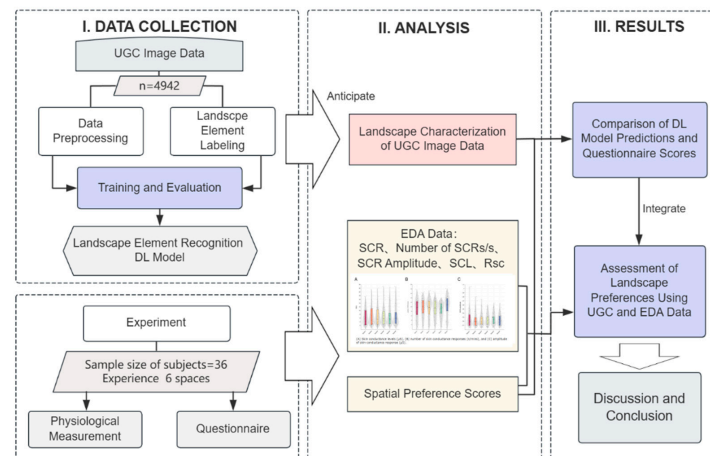


Figure 1. Framework.

2.1. Study Area

Guangzhou, characterized by a high resident population density of 2512 individuals per km² within its administrative districts, presents an optimal setting for UGC data analysis [18]. The city's dense population contributes to the extensive generation of UGC on social media platforms, encompassing a wide array of landscape and activity types, thereby providing a substantial and diverse data source for this study.

The TIT Textile and Garment Cultural and Creative Industrial Park, situated in the Haizhu District of Guangzhou, Guangdong Province, serves as the focal point of this research (Figure 2). Spanning 75,000 m², with a total building area of approximately 40,000 m², the park is strategically positioned along the city's new central axis and in proximity to the Guangzhou TV Tower. Its predecessor is the Guangzhou Textile Machinery Factory, which was established in 1956. It has developed into a vibrant cultural and creative center, guided by the theory of sustainable development. This transformation of abandoned industrial parks using the principles of sustainable development makes a significant contribution to the economy, society, and culture of the city, positioning the TIT Creative Park as an exemplary model for the conservation and utilization of industrial legacies.

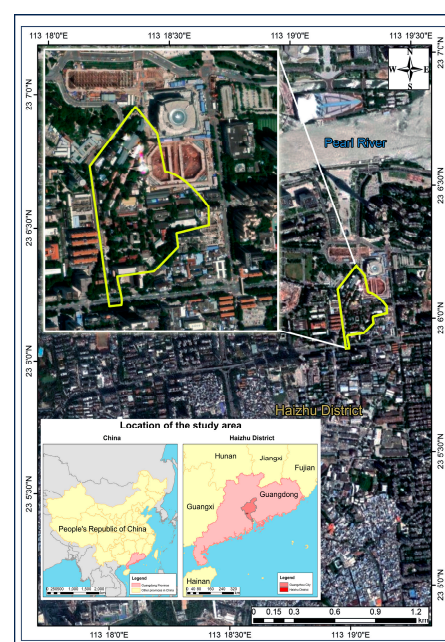


Figure 2. Location of the study area.

2.2. Deep Learning Model Construction

2.2.1. Data Sets: Collection, Pre-Processing, and Labeling

1. Data Acquisition and Sample Size

To obtain the image data, prominent social network platforms such as Volkswagen Dianping and Xiao Hongshu, supplemented by Sina Weibo, were selected as primary sources due to their substantial influence and rich data offerings pertinent to studying landscape perception preferences. Users frequently employ the keyword “TIT Creative Park” when sharing content related to the park; hence, this keyword was utilized for UGC data collection. Data posted by users from 1 July 2018 to 1 July 2023 were gathered to mitigate the impact of external factors such as the COVID-19 pandemic. The dataset was organized by posting date, landscape elements present in the images, and other relevant parameters. Only content from public smartphone user accounts was included, with stringent measures in place to protect user privacy and ensure anonymity, ensuring that the data collected were used only for research. There is now research that confirms that people tend to take photos of their preferred images [19,20]; indeed, some images may capture elements they find unappealing or wish to critique. To address this, we employed both manual and software-based filtering methods to remove images associated with negative user experiences. Following these criteria, a comprehensive image database comprising 4942 UGC photos was assembled, with all images uniformly saved in formats such as jpg, img, or png and restricted to sizes not exceeding 4 MB.

2. Data Preprocessing

The UGC image dataset underwent a rigorous preprocessing phase. Initially, images that were blurry, poorly lit, or irrelevant—such as those depicting portraits, food, or advertisements—were excluded to maintain data quality and relevance. Duplicate images from the same user were also removed. From the refined dataset, a random selection of 2942 UGC images, representing 60% of the total dataset, was made for constructing the Easy DL model.

3. Landscape Element Labeling

For landscape element extraction, the study employed Clarifai Computer Vision AI, a machine learning algorithm designed for image analysis. Utilizing the platform’s “Image Recognition” function, landscape elements within the UGC images were identified and assigned reliability scores. Only tags with reliability scores of 0.6 or higher were retained, ensuring high confidence in the accuracy of identified elements. Manual processing was then conducted to filter out infrequent or irrelevant labels (e.g., “old”, “shopping”, “storm”, “toy”) and to consolidate tags with similar meanings (e.g., “road”, “street”, “pavement”) into unified categories (e.g., “nature”, “leaf”, “environment”). This process ultimately yielded 20 principal landscape element tags. The final step involved categorizing these 20 landscape element labels into six overarching categories based on content attributes: architectural landscapes, natural landscapes, humanistic landscapes, landscape facilities, road traffic, and people (Table S1). This structured categorization facilitated a comprehensive analysis of the landscape elements within the UGC dataset, thereby supporting the development of the DL model.

2.2.2. Training and Evaluation

Baidu PaddlePaddle Easy DL is a deep learning-based AI model development platform that offers two automated modeling approaches: Auto Model Search, which utilizes transfer learning, and Auto DL, which employs a neural architecture search to automatically generate deep learning network structures. This study used the Auto DL method, constructing neural networks from scratch with reinforcement learning to automate the architecture design [21].

The model training process began with simple random sampling from the UGC photo dataset, comprising 60% of the total sample, amounting to 2942 images. Specific landscape

element labels were assigned to each photo through a combination of manual and intelligent labeling methods, ensuring each label appeared at least 40 times within the training set to maintain sufficient representation. The labeled UGC dataset was then divided into training, validation, and test sets in a 6:2:2 ratio. This distribution was designed to validate and evaluate the model thoroughly at each stage, enhancing its generalization capability on diverse location data. Utilizing this platform, the model for UGC image content recognition based on landscape element labeling was successfully trained through supervised learning.

The performance of the trained Easy DL model was assessed using standard machine learning evaluation metrics. The test set provided a quantitative measure of the model's performance, reflecting its ability to generalize and predict unseen data accurately [22]. The training, validation, and test sets contained 2026, 440, and 440 images, respectively, encompassing 20 landscape element labels. The model achieved an average precision (AP) of 87.24%. At a confidence threshold of 0.5, the precision (P) was 86.8%, and the recall (R) was 81.0%, resulting in an F1 score of 0.84 (Table S2). The total training duration was 286 min. Among the 20 labels, elements such as Canton Tower, transportation, people, sky, and seats demonstrated the highest recognition rates (AP > 95%), whereas vertical greenery and steps exhibited lower recognition performance (AP < 65%). These discrepancies in recognition effectiveness can be attributed to factors such as small sample sizes for certain labels, poor image clarity, and the high similarity among certain labels, which contributed to recognition challenges. Overall, the model displayed a high accuracy level, satisfying this study's comprehensive requirements for batch predictive recognition of UGC images. The robust performance and adaptability of the model suggest considerable potential for future applications, particularly in the realm of landscape content recognition from image data.

2.2.3. Deployment and Analysis

The EasyEdge platform of Easy DL offers diverse deployment options, including public cloud deployment, private server deployment, Universal Device-side SDK, and integrated hardware–software solutions. For this study, the public cloud deployment option was selected, utilizing Baidu's servers to host the customized image content recognition models. The local web address was accessed via the API interface provided by the server, enabling the batch processing of 2000 UGC images retained in the database.

The Easy DL model was employed to perform batch recognition on UGC photos, yielding recognition results for image contents. These results facilitated a detailed investigation into the characteristics of landscape types within TIT Creative Park and the public's preferences through statistical analysis, classification, and summarization techniques. The model was used to predict the landscape elements in the 2000 UGC images, returning multiple landscape element labels and the corresponding confidence scores for each prediction. Based on these results, the landscape composition of TIT Creative Park was analyzed to further elucidate public preferences for various landscape elements and types. This deployment approach not only supports efficient large-scale image content analysis but also enhances the understanding of landscape perception and preference, contributing valuable insights for optimizing the landscape design of cultural and creative industrial parks.

2.3. Experiment

2.3.1. Experimental Design

Existing research indicates that landscape preference assessments using student populations as study samples yield results highly comparable to those obtained from the general public [23]. Additionally, individuals aged 18 to 28 are the predominant users of social media networks and represent the primary audience for creative parks. Thus, this experiment targeted young students within this age group to ensure that the study accurately reflects their landscape preferences and facilitates efficient data acquisition.

To enhance the accuracy and representativeness of the physiological data collected, a total of 36 young students (aged 18 to 26) were recruited as participants for an outdoor experiment conducted in Guangzhou. The experiment utilized the ErgoLAB smart wearable finger sensor, a physiological monitoring device designed for finger placement, where a higher density of sweat glands enhances sensitivity to electrodermal signals. This device supports the stable and precise collection of various physiological indicators, even under physical activity conditions. The measurement range and accuracy of the Skin Conductance Response (SCR) monitor are detailed in Table S3.

To ensure the reliability of the collected data, participants were instructed to refrain from consuming food, medications, or beverages containing caffeine or other stimulants for at least 8 h before the experiment. Conducted in late June 2023, the experimental procedure required participants to engage with each of six distinct landscape spaces (as outlined in Table S4) for 6 min per space, with the entire experiment lasting 45 min per participant. Electrodermal activity data, alongside questionnaire responses reflecting participants' environmental experiences in these specific landscape spaces, were gathered. After excluding four datasets due to anomalies, a total of 32 complete datasets were retained for analysis.

The questionnaire sample predominantly consisted of participants aged 21–23 years (59.37%), followed by those aged 18–20 years (21.88%). A majority of the participants were female (68.75%), and most held a master's degree (71.88%) (Table S5). On average, participants completed the survey in approximately 5 min.

2.3.2. Physiological Measurement

The ErgoLAB cloud platform was employed to monitor the physiological signals of participants during their interactions with the landscape environments, extracting key physiological feature indicators to characterize their emotional perception states. EDA is widely recognized as one of the most sensitive indicators of emotional feedback, originating from the involuntary activation of sweat glands in the skin. EDA is closely associated with mood, arousal, and attention, making it the most prevalent measure in physiological response studies [24,25]. SCR specifically reflects physiological and psychological activation induced by external stimuli [26], serving as an indicator of short-term brain processes and as a localized marker of emotional arousal in response to novel or anisotropic events.

This analysis utilized several key metrics of electrodermal activity to assess physiological activation levels during landscape experiences, including mean SCR values, the number of SCRs, SCR amplitude, skin conductance level (SCL), and skin conductance rate (R_{sc}). These metrics were used to evaluate the physiological responses of participants to different landscape elements, and when combined with subjective questionnaire data, they provided a comprehensive analysis of perceptual preferences across various landscape spaces.

To account for individual differences in physiological signaling, R_{sc} was employed as a standardized indicator of skin conductance. Mean skin conductance was recorded in response to various visual stimuli (A_{sc}) across different landscape spaces, as well as mean skin conductance in a sedated state (A_{clam}). These indices were then utilized to calculate R_{sc} using the formula shown below:

$$R_{sc} = \frac{A_{sc} - A_{clam}}{A_{clam}} \quad (1)$$

2.4. Questionnaire

2.4.1. Questionnaire Design

The questionnaire employed in this study comprised two sections: the first gathered personal information from the participants, while the second evaluated their experiences in the designated spaces, covering a total of 27 questions. To assess perceived preferences for landscape elements, a 5-point Likert scale was utilized, with participants rating their preferences on a scale ranging from “dislike very much” to “like very much”, corresponding to integer values from 1 to 5 [27]. This subjective evaluation framework

provided a structured method for quantifying perceived preferences across a range of landscape elements.

2.4.2. Reliability Testing

A total of 32 questionnaires were distributed, and all were recovered, achieving a 100% response rate with 32 valid questionnaires. The reliability of the questionnaire content was assessed using Statistical Products and Services Solution (SPSS) version 25.0. The Cronbach's alpha coefficient was calculated at 0.834, exceeding the threshold of 0.8, indicating a high level of internal consistency and reliability for the questionnaire used in this study. This strong reliability underscores the robustness of the subjective data collected for analyzing perceived landscape preferences.

3. Results and Discussion

3.1. Landscape Characterization of UGC Image Data

By filtering confidence scores and retaining between 1 and 10 landscape element labels per image, a total of 15,620 labeled data points were obtained, averaging approximately 7.81 labels per image. The perceptual recognition frequencies of the 20 landscape elements were then calculated by determining the proportion of each element within the overall dataset (Figure 3).

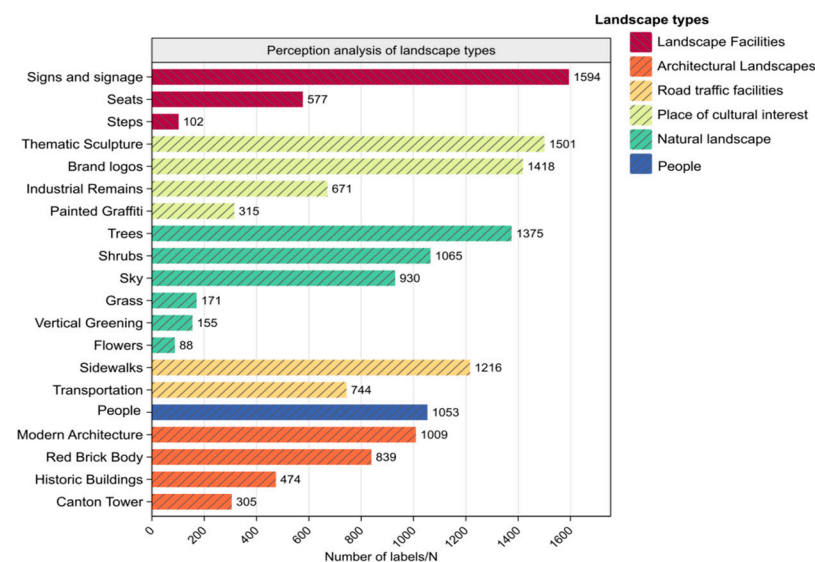


Figure 3. Perceived recognition frequency of each landscape element.

Analysis of the recognition frequency revealed that “signs and signage” had the highest frequency (1594 occurrences), indicating that it is the most prominent landscape element perceived within TIT Creative Park, reflecting a strong preference among visitors. This high recognition can be attributed to the presence of numerous notable enterprises in the park, where signs and signage play a crucial role in brand promotion and identity creation, serving as visually appealing symbols that attract visitors for photography and exploration. Similarly, the landscape element “themed sculptures” exhibited a high perception frequency (1501 occurrences). Themed sculptures, often featuring engaging cartoon imagery, enhance brand tangibility and foster emotional connections, thereby encouraging visitors to engage more deeply with the brand’s offerings.

Using the visualization binning function of SPSS 25.0, the perceptual intensity of each landscape element was categorized into statistical grades of strong, average, and weak perception using equal spacing classification (Table S6). The analysis identified that elements such as logos and signage (10.20%), themed sculptures (9.61%), branding logos (9.08%), trees (8.80%), sidewalks (7.78%), and shrubs (6.82%) exhibited stronger

perceptual intensity, collectively accounting for 65.50% of all landscape labeling data. In contrast, elements like historical buildings (3.03%), graffiti (2.02%), Canton Tower (1.95%), grass (1.09%), vertical greening (0.99%), steps (0.77%), and flowers (0.56%) had weaker perceived intensities, each below 3.32%. Field observations suggested that while TIT Creative Park has been re-planned and maintained with a foundation in the 1990s textile industry, the integration and visibility of historical structures, such as old factories and red-brick buildings, remain suboptimal. Many historical buildings are overshadowed by newer, modern constructions, diminishing their prominence to visitors.

At the landscape-type level, the perceived intensity ranked from strongest to weakest as follows: humanistic landscape (25.00%), natural landscape (24.23%), architectural landscape (16.82%), landscape facilities (14.67%), road transportation facilities (12.55%), and people (6.74%) (Table S7). These findings align with the environmental characteristics of TIT Creative Campus, reflecting compatibility with the qualities of similar landscape types (Figure 4).

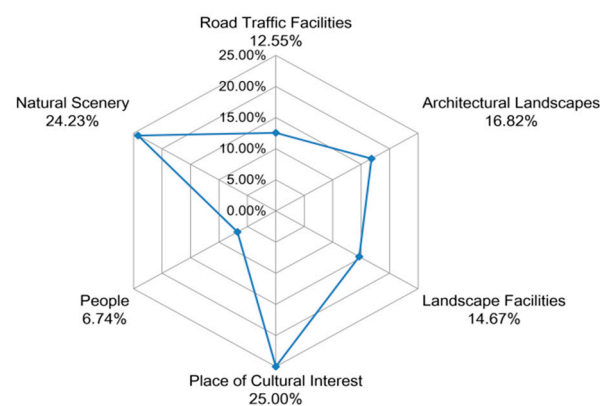


Figure 4. Landscape type perception analysis.

3.2. Skin Conductance Response

The preprocessing of experimental data was conducted using the ErgoLAB platform, involving signal noise reduction, data filtering, and segmentation to enhance the quality of physiological signals and ensure precise analysis. An independent sample *t*-test was performed on the indices, revealing statistically significant differences across all mean values ($p < 0.05$). The physiological signals of subjects varied significantly when experiencing different spaces, suggesting that changes in landscape types and elements can substantially influence psychological and emotional states.

As detailed in Table S8, Space 6 exhibited the highest mean *Rsc* at 0.586, whereas Space 1 recorded the lowest mean *Rsc* at 0.322. Space 5 demonstrated the largest SCR amplitude (0.304), while Space 3 had the smallest amplitude (0.282). The highest rate of change of skin electricity was observed in Space 1 (0.371), with the lowest in Space 5 (0.291). Overall, subjects exhibited the most soothing and relaxing emotional responses in Space 5, characterized by lower physiological arousal, while Space 1 elicited more stimulating emotional responses, indicated by higher physiological activation.

Figure 5 illustrates the median SCL across the six landscape spaces, ranging approximately from 4 to 6 μ S, with Space 6 showing the highest SCL value (7.31) and Space 1 the lowest (6.05). The median frequency of skin conductance responses across the spaces ranged from 9 to 11 times per minute, with minimal variation between spaces. Space 5 displayed a more centralized distribution of SCRs, with a median of 9.42 and a mean of 8.53, whereas Space 6 had the highest number of SCRs at 10.24. Additionally, the median SCR amplitude ranged from 0.15 to 0.25, with Space 1 showing a wider distribution of values and Space 4 displaying a more centralized distribution. Space 5 exhibited the largest SCR amplitude (0.25), while Space 6 recorded the smallest amplitude (0.23). These results underscore the nuanced emotional and physiological responses elicited by different landscape

spaces, highlighting the significant impact of landscape elements on individual well-being and emotional states.

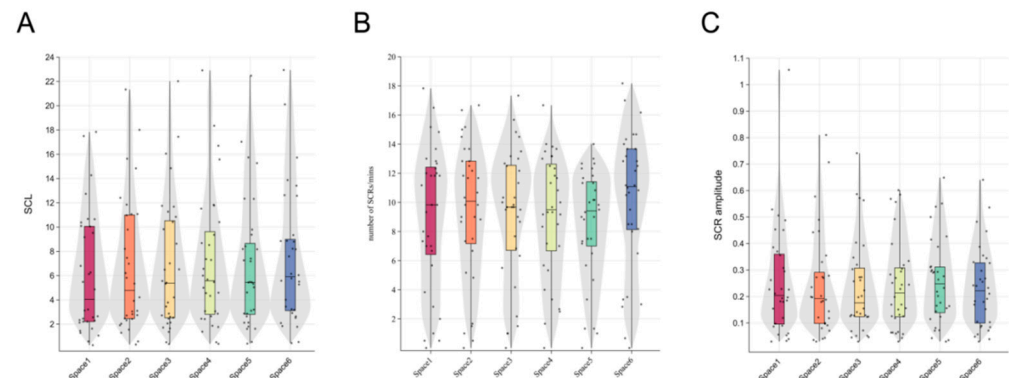


Figure 5. (A) Skin conductance levels (μS), (B) number of skin conductance responses (n/min), and (C) amplitude of skin conductance response (μS).

3.3. Evaluation Questionnaire

As illustrated in Figure 6, the combined evaluations of the experiential spaces revealed that, excluding outliers, Space 6 (mean rating: 3.69) and Space 2 (mean rating: 3.47) received the highest ratings. Spaces 1 (2.91), 4 (3.16), and 6 (3.06) displayed a more concentrated range of ratings, with medians closely aligning with their respective means. Space 3 received the lowest overall rating (2.41). The questionnaire results indicate that Space 5 was the most favored of the six experiential spaces, followed in descending order by Spaces 2, 4, 6, and 1. Space 3 was the least preferred among the participants. These findings provide valuable insights into the subjective preferences of young users regarding various landscape spaces, highlighting the differential appeal of specific environments within the study.

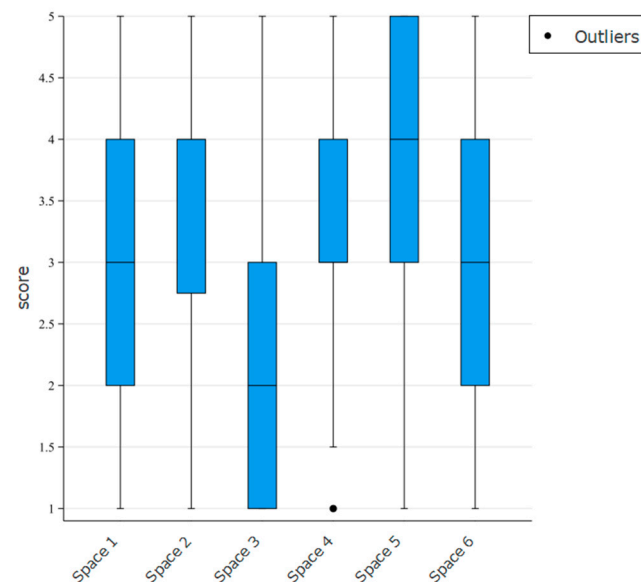


Figure 6. Spatial preference scores for each landscape.

3.4. Comparison of DL Model Predictions and Questionnaire Scores

Comparative analysis of normalized data from the DL model and questionnaire scores (Table S9) revealed both differences and consistencies across landscape types. A notable divergence was observed between architectural and humanistic landscapes: the DL model indicated the highest perceived preference intensity for humanistic landscapes,

whereas the questionnaire responses favored architectural landscapes. This discrepancy may be attributed to the differing criteria between the DL model's automated recognition process and human subjective evaluation. Consistencies were found in the other four landscape types, particularly in the "People" category, where both the normalized values of the DL model and the questionnaire scores were zero. Furthermore, the values for road transportation facilities, landscape facilities, and natural landscapes were relatively similar, suggesting a high degree of agreement between the DL model predictions and questionnaire evaluations.

Pearson correlation analysis (Table S10) revealed a moderate positive correlation between the number of SCRs and questionnaire scores, indicating that SCR intensity and amplitude increased in landscapes with higher subjective preference ratings. Conversely, a weak negative correlation was found between the number of SCRs per minute and questionnaire scores, suggesting a slight reduction in SCR frequency in spaces with higher perceived preference. Additionally, weak positive correlations were observed between SCL, Rsc, and questionnaire scores, implying that SCL and Rsc values tended to increase slightly in less preferred landscape spaces. Overall, the correlations between various electrodermal indicators and questionnaire scores were weak, with most results not reaching statistical significance. This finding suggests that the associations between physiological responses and subjective preferences in different landscape spaces are complex and may be influenced by additional factors, highlighting the multifaceted nature of landscape perception.

3.5. Assessment of Landscape Preferences Using UGC and EDA Data

The aim of this study was to develop a landscape content recognition model based on UGC image data combined with galvanic skin response experiments to assess landscape preference perception among visitors to cultural and creative industrial parks. The findings partially validate the proposed hypotheses and yield additional insights.

The analysis of TIT Creative Park and the behavior of users posting UGC images indicate that the park's nature as an incubator for innovative and creative industries supports a landscape rich in brand elements, such as logos and IP imagery, which are prominently displayed to promote brand identity. Visitors to TIT Creative Park frequently photograph and share images of humanistic landscapes, including themed sculptures and brand logos, which are visually engaging and artistic, underscoring the creative park's character and diversity. Notably, signs and directional signage exhibited the highest perceived intensity (10.20%) among landscape elements, not only serving navigational purposes but also contributing to the park's distinctive atmosphere, thereby enhancing the user experience. The design language of these elements captures attention and conveys the unique charm of the park. Furthermore, natural landscapes showed high perceived intensity (24.23%) in the model, aligning with TIT Creative Park's eco-friendly ethos. The integration of trees and shrubs not only improves air quality but also fosters a healthy and inviting environment for work and leisure, reflecting visitors' preference for natural settings.

Conversely, landscape types such as road transportation facilities (12.55%) and people (6.74%) exhibited lower perceived preference intensities. This may be attributed to poorly designed sidewalks and parking areas, which can cause negative emotions due to the disruption from vehicular traffic, as supported by prior research [28]. Additionally, elements such as vertical greening, steps, and flowers were rated low in perceived intensity, likely due to inadequate maintenance, which diminishes their aesthetic appeal and potential for engagement [29]. Historical buildings also registered weak perceived intensity (3.03%), possibly because of insufficient maintenance and utilization, with a focus on modern and business-oriented elements overshadowing the appeal of traditional architecture.

According to the DL model results, humanistic and natural landscapes emerged as the most preferred landscape types, while road transportation facilities and people were less favored. Among the 20 landscape elements, signs and signage, themed sculptures, brand logos, and trees ranked highest in preference, whereas grass, vertical greening, steps,

and flowers ranked lowest. Comparisons between the model outcomes and questionnaire scores revealed substantial consistency, suggesting that natural and humanistic landscapes elicit positive emotions and affective responses, corroborating findings by Koivisto and Grassini [30] and Cassatella et al. [31].

However, contrary to expectations, no significant correlation was observed between EDA metrics and subjective preference scores. Although significant variability was noted in skin conductance data across the six different landscape spaces, the correlations between these physiological metrics and subjective questionnaire scores were generally weak or moderate, indicating the complexity of the relationship between physiological responses and subjective preferences in landscape spaces. This relationship may be influenced by other factors such as auditory, visual, or olfactory stimuli [32–34]. Notably, five electrodermal indicators from Space 5 ranked highest, suggesting that EDA measurements can partially reflect positive emotional responses to certain landscape spaces. However, for landscape spaces eliciting negative responses, the relationship between physiological responses and subjective evaluations remains difficult to elucidate.

4. Conclusions

This study proposed a landscape content recognition model integrating UGC with galvanic skin response experiments to assess landscape preference perceptions among visitors to cultural and creative industrial parks. The findings demonstrated partial validation of the proposed hypotheses, highlighting significant insights into how specific landscape elements influence user experiences. The analysis revealed that TIT Creative Park's emphasis on brand elements, such as logos, themed sculptures, and signage, aligns with the park's function as a hub for creative industries, where humanistic and visually engaging features are highly favored by visitors. The study identified that humanistic and natural landscapes evoke the highest perceived preference, reflecting the park's focus on aesthetics and eco-friendly initiatives. In contrast, elements like road transportation facilities and people showed lower preference levels, likely due to design inefficiencies and disruptions from vehicular traffic.

The study found a high level of consistency between the objective outputs of the deep learning model and the subjective questionnaire scores, indicating that humanistic and natural landscapes consistently elicit positive emotional responses. However, no significant correlation was detected between EDA metrics and subjective preference scores, suggesting a complex relationship between physiological responses and perceived preferences, possibly influenced by additional environmental factors such as sound, light, or smell. Therefore, these influencing factors should be further explored when promoting the optimal design of the park to ensure that the aesthetic value and the need for sustainable development are simultaneously met in the landscape design process.

This study has several limitations that warrant consideration. The UGC data sourced from social media reflects the behaviors and perspectives of specific social groups, particularly those that are more active online and younger demographics. Individual differences, including gender, place of origin, and social power dynamics, may significantly influence landscape preferences, potentially skewing the results. Future research should explore methodologies that incorporate the social and demographic characteristics of social media users to better understand these influences.

Furthermore, the outdoor electrodermal activity experiments did not fully account for external environmental variables such as noise and light, which may have impacted the physiological responses of participants. Future studies should incorporate more diverse measurement methods, such as with the help of AI [35], virtual reality technology [36,37], and EEG [38] or expand the sample size and prolong the experimental time to minimize the interference of external factors [39–42]. This approach would aim to elucidate the underlying correlation mechanisms more accurately, thereby enhancing the validity and applicability of the findings in broader contexts.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/su16219228/s1>, Table S1. Classification of Landscape Element Types; Table S2. Labeled AP values for each landscape element.; Table S3. Measurement parameters and device specifications; Table S4. Landscape Space Overview; Table S5. Descriptive statistics for questionnaire worker sample; Table S6. Grading of landscape elements based on perceptual intensity statistics; Table S7. Mean values of physiological indices of EDA; Table S8. Perceived Intensity Statistics for Six Landscape Types; Table S9. Model Prediction and Questionnaire Score Data; Table S10. Pearson correlation analysis of questionnaire scores with various physiological indicators.

Author Contributions: Conceptualization, X.W. and B.Z.; methodology, X.W., B.Z. and M.W.; software, B.Z., Z.C. and C.S.; validation, Z.C., D.M. and X.J.; formal analysis, X.W., D.M. and X.J.; investigation, B.Z., Z.C. and C.S.; resources, X.W. D.M., M.W. and X.J.; data curation, B.Z. and X.W.; writing—original draft preparation, B.Z. and C.S.; writing—review and editing, X.W. and M.W.; visualization, B.Z. and C.S.; supervision, X.W., M.W. and X.J.; project administration, X.W. and M.W.; funding acquisition, X.W. and X.J. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Philosophical and Science Foundation of Guangdong Province, grant numbers GD23XS033 and GD23XLN18.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Ethics Committee of the College of Architecture and Urban Planning, Guangzhou University.

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The study did not report any publicly archived datasets.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Jokilehto, J. Reflection on historic urban landscapes as a tool for conservation. *World Herit. Pap.* **2010**, *27*, 53.
2. Sun, M.; Chen, C. Renovation of industrial heritage sites and sustainable urban regeneration in post-industrial Shanghai. *J. Urban Aff.* **2023**, *45*, 729–752. [[CrossRef](#)]
3. Hersperger, A.M.; Grădinaru, S.R.; Pierri Daunt, A.B.; Imhof, C.S.; Fan, P. Landscape ecological concepts in planning: Review of recent developments. *Landsc. Ecol.* **2021**, *36*, 2329–2345. [[CrossRef](#)] [[PubMed](#)]
4. Qin, X.; Fang, M.; Yang, D.; Wangari, V.W. Quantitative evaluation of attraction intensity of highway landscape visual elements based on dynamic perception. *Environ. Impact Assess. Rev.* **2023**, *100*, 107081. [[CrossRef](#)]
5. Zhang, C.; Yao, Y.; Li, M. Research on crowd behavioral preference under the perspective of environmental perception—Taking Hohhot city park as an example. *Urban Archit.* **2022**, *19*, 77–83. [[CrossRef](#)]
6. Daniel, T.C. Whither scenic beauty? Visual landscape quality assessment in the 21st century. *Landsc. Urban Plan.* **2001**, *54*, 267–281. [[CrossRef](#)]
7. Wang, X.; Tang, P.; He, Y.; Woolley, H.; Hu, X.; Yang, L.; Luo, J. The correlation between children’s outdoor activities and community space characteristics: A case study utilizing SOPARC and KDE methods in Chengdu, China. *Cities* **2024**, *150*, 105002. [[CrossRef](#)]
8. Lee, J.-S.; Sangwon, P. A cross-cultural anatomy of destination image: An application of mixed-methods of UGC and survey. *Tour. Manag.* **2023**, *98*, 104746. [[CrossRef](#)]
9. Hu, Y.; Gao, S.; Janowicz, K.; Yu, B.; Li, W.; Prasad, S. Extracting and understanding urban areas of interest using geotagged photos. *Comput. Environ. Urban Syst.* **2015**, *54*, 240–254. [[CrossRef](#)]
10. Figueroa-Alfaro, R.W.; Tang, Z. Evaluating the aesthetic value of cultural ecosystem services by mapping geotagged photographs from social media data on Panoramio and Flickr. *J. Environ. Plan. Manag.* **2017**, *60*, 266–281. [[CrossRef](#)]
11. Schirpke, U.; Tasser, E.; Ebner, M.; Tappeiner, U. What can geotagged photographs tell us about cultural ecosystem services of lakes? *Ecosyst. Serv.* **2021**, *51*, 101354. [[CrossRef](#)]
12. Conover, M.D.; Davis, C.; Ferrara, E.; McKelvey, K.; Menczer, F.; Flammini, A. The Geospatial Characteristics of a Social Movement Communication Network. *PLoS ONE* **2013**, *8*, e55957. [[CrossRef](#)] [[PubMed](#)]
13. Grings, W.W. Cognitive factors in electrodermal conditioning. *Psychol. Bull.* **1973**, *79*, 200. [[CrossRef](#)] [[PubMed](#)]
14. Li, S.; Sung, B.; Lin, Y.; Mitas, O. Electrodermal activity measure: A methodological review. *Ann. Tour. Res.* **2022**, *96*, 103460. [[CrossRef](#)]
15. Chen, Z.; Shultz, S.; Liu, Y. Built environment experience assessment and design via bio-feedback. *Time Archit.* **2017**, *5*, 24–28.

16. Jukiewicz, M.; Łupkowski, P.; Majchrowski, R.; Marcinkowska, J.; Ratajczyk, D. Electrodermal and thermal measurement of users' emotional reaction for a visual stimuli. *Case Stud. Therm. Eng.* **2021**, *27*, 101303. [\[CrossRef\]](#)
17. Luo, W.; Chen, C.; Li, H.; Hou, Y. How do residential open spaces influence the older adults' emotions: A field experiment using wearable sensors. *Landsc. Urban Plan.* **2024**, *251*, 105152. [\[CrossRef\]](#)
18. Chen, Y.; Chang, K.-t.; Han, F.; Karacsonyi, D.; Qian, Q. Investigating urbanization and its spatial determinants in the central districts of Guangzhou, China. *Habitat Int.* **2016**, *51*, 59–69. [\[CrossRef\]](#)
19. Sun, M.; Chris, R.; Steve, P. Assessing tourists' perceptions and behaviour through photographic and blog analysis: The case of Chinese bloggers and New Zealand holidays. *Tour. Manag. Perspect.* **2014**, *12*, 125–133. [\[CrossRef\]](#)
20. de Tejada Granados, S.; Carlota; Muro, R.S.-T.; Romero, E.J.R. Exploring landscape preference through photo-based Q methodology. Madrid seen by suburban adolescents. *Int. Res. Geogr. Environ. Educ.* **2021**, *30*, 255–278. [\[CrossRef\]](#)
21. Voulodimos, A.; Doulamis, N.; Doulamis, A.; Protopapadakis, E. Deep Learning for Computer Vision: A Brief Review. *Comput. Intell. Neurosci.* **2018**, *2018*, 7068349. [\[CrossRef\]](#) [\[PubMed\]](#)
22. Jahani, A.; Fazel, A. Aesthetic Quality Modeling of Landscape in Urban Greenspace by Using Artificial Neural Network. *J. Nat. Environ.* **2016**, *69*, 951–963. [\[CrossRef\]](#)
23. Fu, E.; Zhou, J.; Yao, Z.; Li, X. Affective Experience Measurement in Outdoor Environment via Machine Visual Cognition. *Landsc. Archit. Front.* **2021**, *9*, 46–59. [\[CrossRef\]](#)
24. Schmidt, S.; Walach, H. Electrodermal activity (EDA): State-of-the-art measurement and techniques for parapsychological purposes. *J. Parapsychol.* **2000**, *64*, 139–163.
25. Christie, M.J. Electrodermal activity in the 1980s: A review. *J. R. Soc. Med.* **1981**, *74*, 616–622. [\[CrossRef\]](#)
26. Kreibig, S. Autonomic Nervous System Activity in Emotion: A Review. *Biol. Psychol.* **2010**, *84*, 394–421. [\[CrossRef\]](#)
27. Batterton, K.A.; Hale, K.N. The Likert Scale What It Is and How To Use It. *Phalanx* **2017**, *50*, 32–39.
28. Keil, A. Use and Perception of Post-Industrial Urban Landscapes in the Ruhr. In *Wild Urban Woodlands: New Perspectives for Urban Forestry*; Springer: Berlin/Heidelberg, Germany, 2005; pp. 117–130.
29. Huang, C.; Wei, F.; Qiu, S.; Cao, X.; Chen, L.; Xu, J.; Gao, J.; Lin, Q. Interpreting regenerated post-industrial lands as green spaces: Comparing public perceptions of postindustrial landscapes using human factor de-sign framework. *Ecol. Indic.* **2023**, *157*, 111282. [\[CrossRef\]](#)
30. Koivisto, M.; Grassini, S. Mental imagery of nature induces positive psychological effects. *Curr. Psychol.* **2023**, *42*, 30348–30363. [\[CrossRef\]](#)
31. Cassatella, C. Assessing Visual and Social Perceptionssocial perception of Landscape. In *Landscape Indicators: Assessing and Monitoring Landscape Quality*; Cassatella, C., Peano, A., Eds.; Springer Netherlands: Dordrecht, The Netherlands, 2011; pp. 105–140.
32. Yang, M.; Huang, J. Phasic and tonic electrodermal activity in emotional responses to acoustic environments. *J. Environ. Psychol.* **2024**, *96*, 102282. [\[CrossRef\]](#)
33. Cai, H.; Lin, Q.; Liu, H.; Li, X.; Xiao, H. Recognition of human mood, alertness and comfort under the influence of indoor lighting using physiological features. *Biomed. Signal Process. Control* **2024**, *89*, 105661. [\[CrossRef\]](#)
34. Møller, P.; Dijksterhuis, G. Differential human electrodermal responses to odours. *Neurosci. Lett.* **2003**, *346*, 129–132. [\[CrossRef\]](#) [\[PubMed\]](#)
35. Levering, A.; Marcos, D.; Tuia, D. On the relation between landscape beauty and land cover: A case study in the UK at Sentinel-2 resolution with interpretable AI. *ISPRS J. Photogramm. Remote Sens.* **2021**, *177*, 194–203. [\[CrossRef\]](#)
36. Karaca, E.; Çakar, T.; Karaca, M.; Gül, H.H.M. Designing restorative landscapes for students: A Kansei engineering approach enhanced by VR and EEG technologies. *Ain Shams Eng. J.* **2024**, *15*, 102901. [\[CrossRef\]](#)
37. Zhu, H.; Yang, F.; Bao, Z.; Nan, X. A study on the impact of Visible Green Index and vegetation structures on brain wave change in residential landscape. *Urban For. Urban Green.* **2021**, *64*, 127299. [\[CrossRef\]](#)
38. Jeon, J.Y.; Hyun, I.J.; Kounseok, L. Psycho-physiological restoration with audio-visual interactions through virtual reality simulations of soundscape and landscape experiences in urban, waterfront, and green environments. *Sustain. Cities Soc.* **2023**, *99*, 104929. [\[CrossRef\]](#)
39. Wang, M.; Zhong, X.; Yuan, H.; Zhang, D.; Cheng, L.; Zhang, J. Integrating carbon and water footprint into nature-based solution (NBS) for urban planning in a highly built-up area in Guangzhou, China. *Sci. Total Environ.* **2024**, *951*, 175505. [\[CrossRef\]](#)
40. Pearson, A.L.; Lin, Z.; Shortridge, A. Beauty is in the eye of the beholder: Moderate ability to predict perceptions of beauty, restorativeness, and naturalness, in imagery among 10,727 participants. *Landsc. Urban Plan.* **2024**, *243*, 104958. [\[CrossRef\]](#)
41. Dupont, L.; Antrop, M.; Van Eetvelde, V. Does landscape related expertise influence the visual perception of landscape photographs? Implications for participatory landscape planning and management. *Landsc. Urban Plan.* **2015**, *141*, 68–77. [\[CrossRef\]](#)
42. Lee, M.J.; Oh, W. Changes in Electroencephalographic Results and Heart Rate Variability after Exposure to Green Landscape Photographs Correlated with Color Temperature and Illumination Level. *J. People Plants Environ.* **2021**, *24*, 639–649. [\[CrossRef\]](#)

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.