Evaluating Urban Perception: Comparing Place Pulse 2.0 Dataset Results with Images of Varied Field of View

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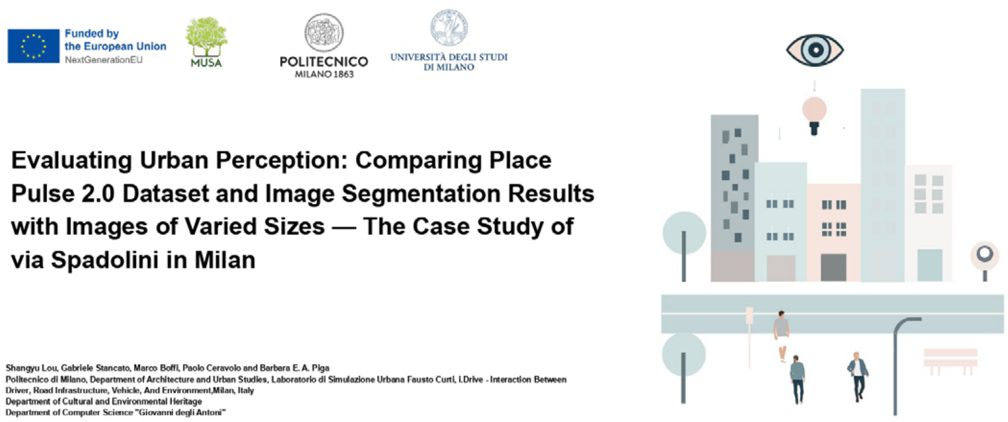
Abstract

Understanding urban perception is crucial for designing cities that en-hance human well-being. To address limited urban perception data, recent studies use large, crowdsourced datasets like Place Pulse 2.0 (PP2) for machine learning predictions. However, the accuracy of these datasets in representing real human perception is rarely examined. This study analyzes the representativeness of the PP2 dataset from a hu-man field of view (FOV) perspective. Focusing on a 400-meter segment of Spadolini Street in Milan, we compare perceived physical features, design qualities, and six urban perceptions between street view images of PP2 FOV and human FOV. Our results reveal the differences: hu-man FOV perceives more sky, roads, and sidewalks, but fewer trees and grass. In design qualities, human FOV perceives more openness but less greenness and enclosure. Beauty, liveliness, and depression scores decrease from human FOV to PP2 view, while safety and wealth scores increase. Human FOV shows more spots with high values for beauty and liveliness and fewer for wealth compared to the PP2 view. These findings underscore the importance of considering representation from a human perspective in urban studies, suggesting that the PP2 dataset may need refinement for accurate re-presentation. Further vali-dation and improved measurement techniques are essential to better align urban design with public perception and well-being.

Keywords
artificial intelligence, machine learning, place pulse, visual studies, in-motion experience



Evaluating Urban Perception: Comparing Place Pulse 2.0 Dataset Results with Images of Varied Field of View. Source: author's drawing.

doi.org/10.3280/oa-1180-c494

Introduction and background

Understanding how individuals perceive cities is essential for designing places that are rooted in the relationship between people and their envi-ronment. [B. Piga and Morello 2015, pp. 647]. This comprehension offers valuable guidance for urban planners and decision-makers in shap-ing urban landscapes, thereby enriching human well-being and the overall quality of life [Frank et al. 2010, pp. 924–933]. Studies indicate that the built environment influences people's perceptions while in mo-tion [Alfonzo 2005, pp. 808–836].

Some studies suggest that the dimensions of the sidewalk, the pres-ence of trees and the volume of traffic also impact the walking experi-ence [Dessing et al. 2016, pp. 48; Ferrer et al. 2015, pp. 141–160; Johansson et al. 2016, pp. 256–275] and improve mental and physical health [Basu and Sevtsuk 2022, pp. 1–19; Wang et al., 2019, pp. 90–102]. Ewing [Ewing, Handy 2009, pp. 65–84] observed that the per-ceived characteristics of space, such as en-closure and openness, im-pact reactions such as feelings of safety and curiosity while walking. Recent studies have used computer vision to analyze physical features, exploring their impact on perception [Helbich et al. 2019, pp. 107–117; B. E. A. Piga et al. 2021, pp. 13; Wang et al. 2019, pp. 90–102]. Additionally, formulas have been developed to objectively measure per-ceived space qualities using these features [Ma et al. 2021, pp. 110; Z. Zhang et al. 2021, pp. 18]. Machine learning and big data have introduced new methods to predict urban visual perception. The MIT Media Lab's Place Pulse 2.0 (PP2), a 2013 dataset, uniquely evaluates urban perception through images. This dataset comes from an online survey where 81,630 participants rated street view images on six urban attrib-utes: safety, liveliness, boredom, wealth, depression, and beauty. It comprises 110,988 images from 56 cities in 28 countries [Dubey et al. 2016, pp. 196–212]. Recently, an increasing number of researchers have used the PP2 dataset to develop machine learning models aimed at assessing visual perceptions of various large urban regions [Ji et al., 2021 pp. 10; Wei et al. 2022, pp. 112; F. Zhang et al. 2018, pp. 148–160]. However, it remains to be investigated whether the PP2 dataset accurately portrays the person-environment relationship [Dubey et al. 2016, pp. 196–212; Verma et al. 2019, pp. 852–857; Zhang et al. 2018, pp. 148–160]; without this investigation, there is a risk of bias in perception prediction processes. Addressing this issue is crucial for validating the dataset and subsequently supporting future studies based on machine learning approaches, which aim to identify reliable tools for understanding urban experiences.

In this context, the present study applies the PP2 dataset, in combination with image segmentation, to compare the results obtained from Street View Images (SVIs) of the same size as those in PP2 with pano-ramas generated from the same perspective but wider, i.e. encompass-ing the human Field of View (FOV), along a five-minutes' walk.

Method, Materials, and the case study application

To compare the PP2 dataset applied to rectangular SVIs and the same images enlarged to create panoramas depicting the FOV, we focused on three key elements: urban features, design qualities, and people's visual perception. The examination covers a 400-meter segment, rep-resenting a five-minute walk, to study person-environment interaction in a consistent urban setting. The path includes 21 observation points at 20-meter intervals [Hipp et al. 2022, pp. 537–565; Lu 2019, p. 191], allowing for a comparative analysis between the view size used in PP2 and the human FOV, considering views in both walking directions.

Materials include street segments extracted from OpenStreetMap using QGIS and SVIs obtained via the Google Street View API. These images match the size used in the PP2 dataset, i.e. 400*300 pixels with a 90° FOV [Beaucamp et al. 2022, pp. 33–40]. To replicate the human FOV, we extracted tiles from the API and stitched multiple images from dif-ferent angles to reduce SVI distortion, covering a virtual space of 160° horizontally and 120° vertically [Hipp et al. 2022, pp. 537–565] (fig. 1). Then, we used the Pyramid Scene Pars-ing Network (PSPNet) [Zhao et al. 2017] to classify and measure physical features (e.g., buildings, roads, sky) of these SVIs [B. E. A. Piga et al., 2021, pp. 13] (fig. 2). Next, to assess space design

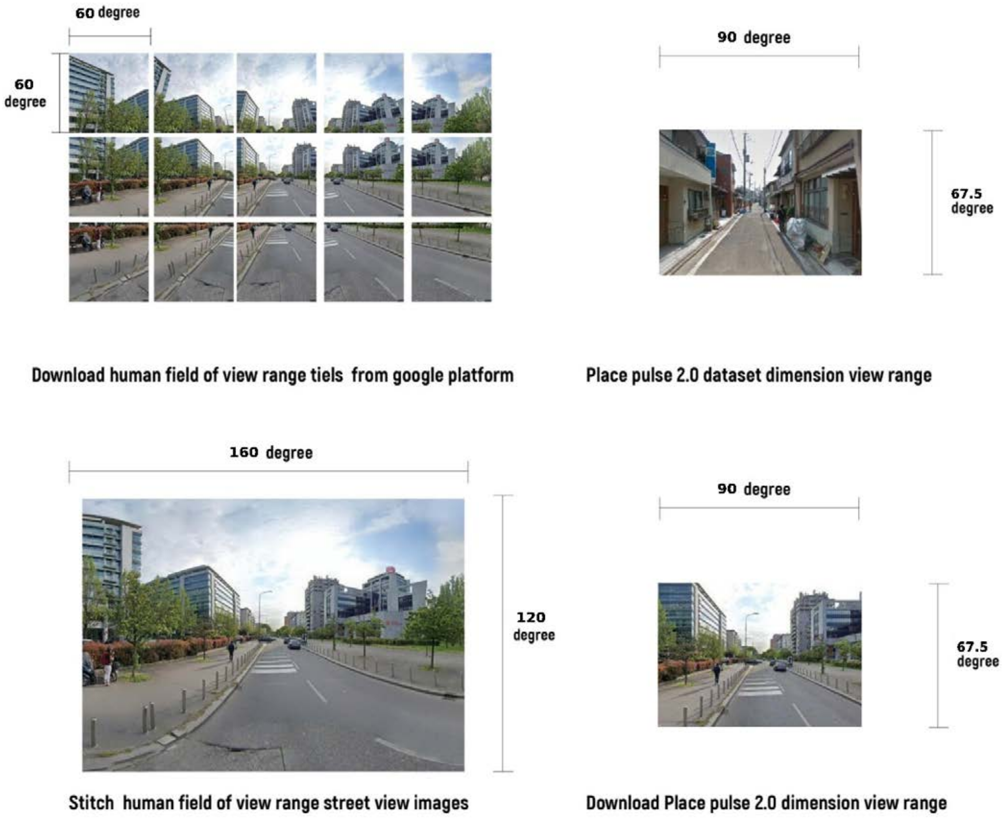


Fig. 1. The collection and process of Google Street View™ image collection. Source: author's drawing.

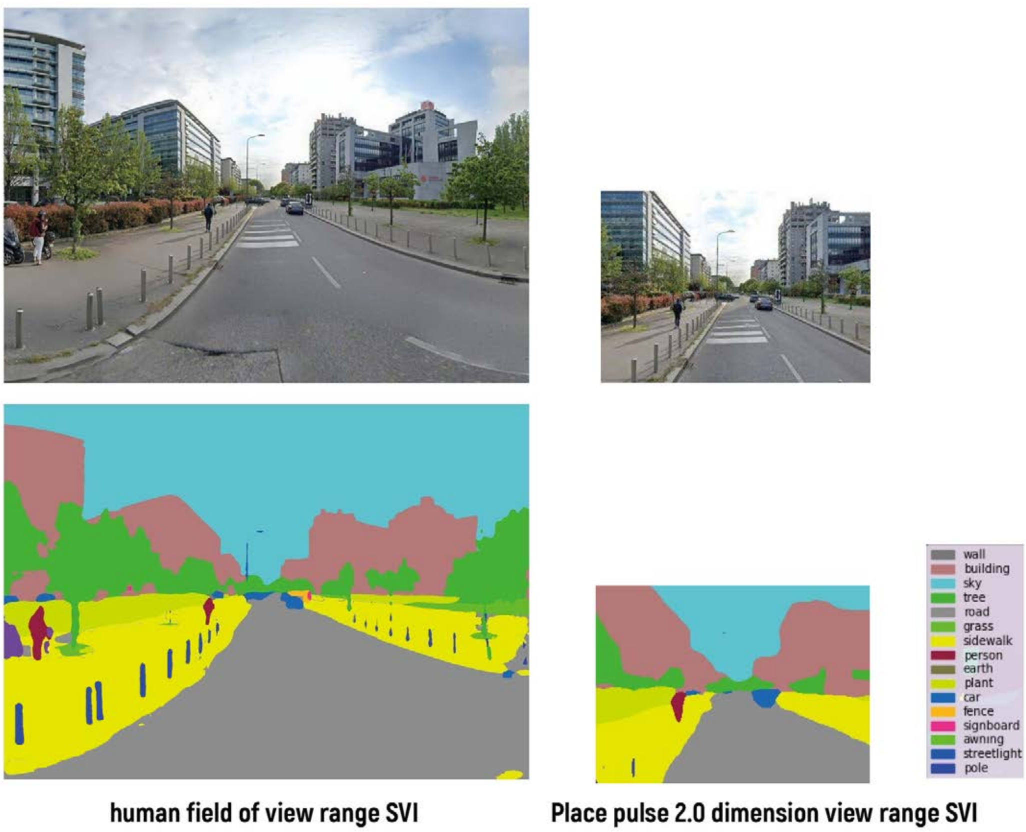


Fig. 2. PspNet semantic segmentation of SVIs: left shows Human FOV, right shows Place Pulse 2.0 view size. Source: author's drawing.

qualities, we applied formulas based on Ewing's indica-tors (Greenness, Openness, Imageability, Enclosure, Complexity) [Ewing and Handy 2009, pp. 65–84; Ma et al. 2021, pp. 110; Z. Zhang et al. 2021, pp. 18]. Additionally, we predicted scores based on SVIs using a trained model with the PP2 dataset by applying three machine learning algorithms – Random Forest, K-Nearest Neighbors, and Support Vector Machine and evaluate the best performance. The final step involved Pearson's correlation analysis to explore the relationship between visual perception and envi-ronmental characteristics, providing insight into the interplay between urban space features and people's perceptions.
The case study examines Spadolini Street in Milan (fig. 3), a redevelopment project initiated in the 2000s in southern Milan. Assuming the reliability of PP2, we evaluated whether considering different FOVs affects the results related to urban perception.

Fig. 3. Map of the city of Milan with the location of Spadolini Street (red rectangle). Source: author's drawing.

Results and Insights

After employing computer vision methods to examine the physical at-tributes at each location, we generated quantitative representations of these surroundings (fig .4). The com-parative analysis between PP2 views and human FOV revealed distinct disparities, while the results of the two directional views are similar. Specifically, the number of observation spots with middle-high and high percentages of grass and sidewalks is greater in the PP2 view compared to the human FOV, while the number of spots with middle-low and low percentages of buildings and trees is lower. Conversely, the number of observation spots with middle-high and high percentages of the sky is lower in the PP2 view. In summary, compared to the human field of vision, the PP2 view captures more buildings, trees, grass, and sidewalks but less sky. This result emphasizes the importance of understanding how different FOVs impact perceived environmental features.
To objectively assess the quality indicators of spatial design at the ob-servation sites we employ specific formulas [Ma et al. 2021, pp. 110; Z. Zhang et al. 2021, pp. 18] deriving from the concepts by Ewing [Ewing and Handy 2009, pp. 65–84] and leading to the creation of quantitative representations of the environmental characteristics (fig. 5). Differences are more pronounced when compar-ing the human FOV and PP2 view; however, the two directional views within each FOV are similar. The PP2 view has more observation spots with middle-high enclosure and high values (0.6-1) compared to human FOV, while spots with middle-low and low values (0-0.4) of imageability and greenness are fewer. Conversely, human FOV has more spots with middle-high and high values (0.6-1) of openness and fewer spots with

Fig. 4. Mapping physical features of observation spots on Spadolini Street. From left to right: buildings, sky, trees, grass, sidewalk, road. Source: author's drawing.

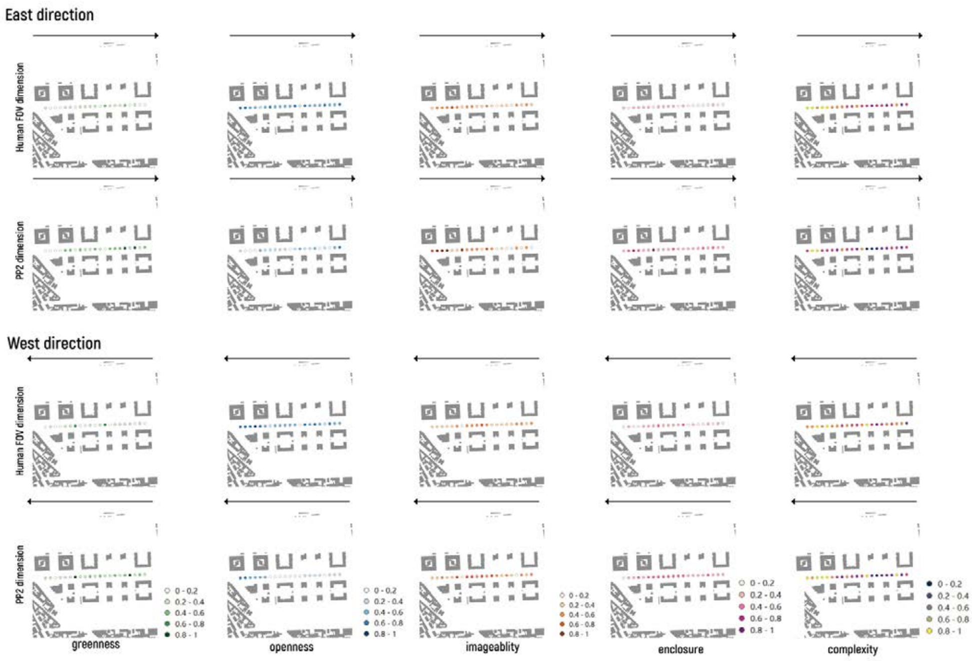


Fig. 5. Mapping the space design qualities of observation spots on Spadolini Street. From left to right: greenness, openness, imageability, enclosure, complexity. Elaboration by the author.

middle-low and low values (0-0.4) of complexity. In summary, compared to human FOV, the PP2 view perceives more enclosure, imageability, and greenness but less openness and complexity.

When comparing the human FOV and PP2 view, significant differences emerge in the average values of physical characteristics and the quality indices (fig. 6). Comparing the human FOV with the PP2 view reveals distinct differences, while the two directional views have similar values. The PP2 view shows a higher average proportion of perceived buildings, trees, grass, and plants than the hu-man FOV. In contrast, roads and sidewalks are less perceived in the PP2 view. Regarding design quality indices, the PP2 view is associated with higher perceived imageability, enclosure, and greenness, but lower levels of perceived openness and

complexity compared to the human FOV. These findings highlight significant differences in perceived envi-ronmental features influenced by the selected FOV, emphasizing the impor-tance of understanding the relationship between FOV and perceived environmental results. After completing the training phase of the machine learning algorithms, the results indicated that the SVM algorithm exhibited the lowest RMSE values in predicting the perception of beauty, boringness, liveliness, safety and depression scores (Table 1). thus, indicating higher preci-sion. Subsequently, we applied the trained SVM model to street view images of Spado-lini Street to derive the final prediction results (fig. 7).
Our results on subjective perception mapping reveal that perceptions associated with views in opposite directions show subtle differences. These differences are more pronounced when comparing the PP2 view and the human FOV. Specifically, the number of observation spots with middle-high and high values (score 6-10) for beauty and lively percep-tions is lower in the PP2 view compared to human FOV; the number of spots with low values (score 0-4) for safety is also lower. In contrast, the number of observation spots with middle-high and high values (score 6-10) for wealthy perception is higher in the PP2 view compared to human FOV.

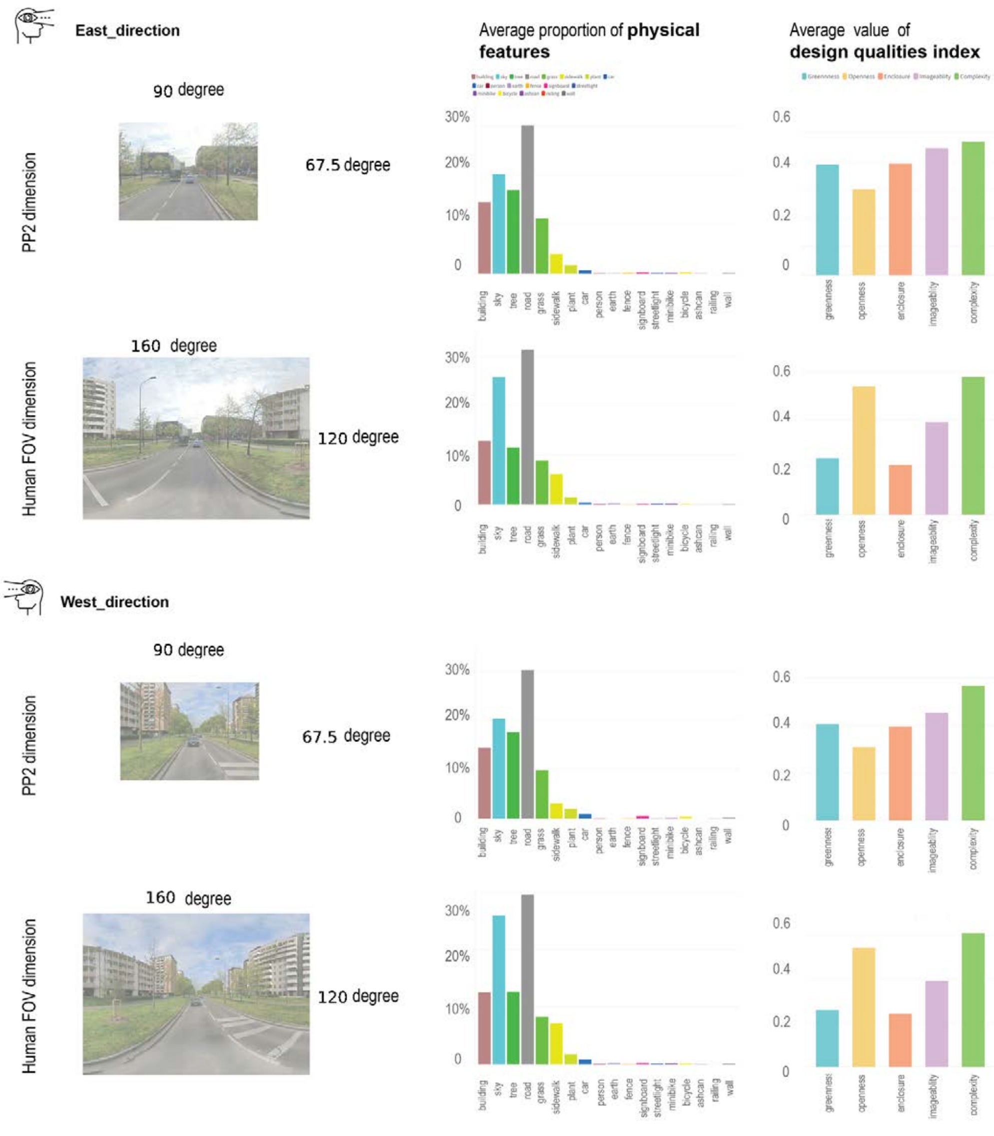


Fig. 6. Comparison of the average value of physical features and design qualities index in PP2 view and human FOV. Source: author's drawing.

Table 1. RMSE evaluation metric results. Asterisks mark the lowest values. SVM excels in predicting beauty, boredom, liveliness, safety and depression scores. Elaboration by the author.

Perception→	beautiful	lively	safe	wealthy	boring	depressing
Machine learning algorithm↓	***RMSE***					
SVM	1.467*	1.263*	1.149*	1.464*	1.405*	1.394*
RF	1.475	1.267	1.211	1.463	1.406	1.397
KNN	1.495	1.28	1.226	1.487	1.449	1.417

Fig. 7. Mapping of space 6-dimension visual perceptions of the observation spots in Spadolini street. From the left to the right: beauty, lively, safety, boring, depressing, wealthy. Elaboration by the author.

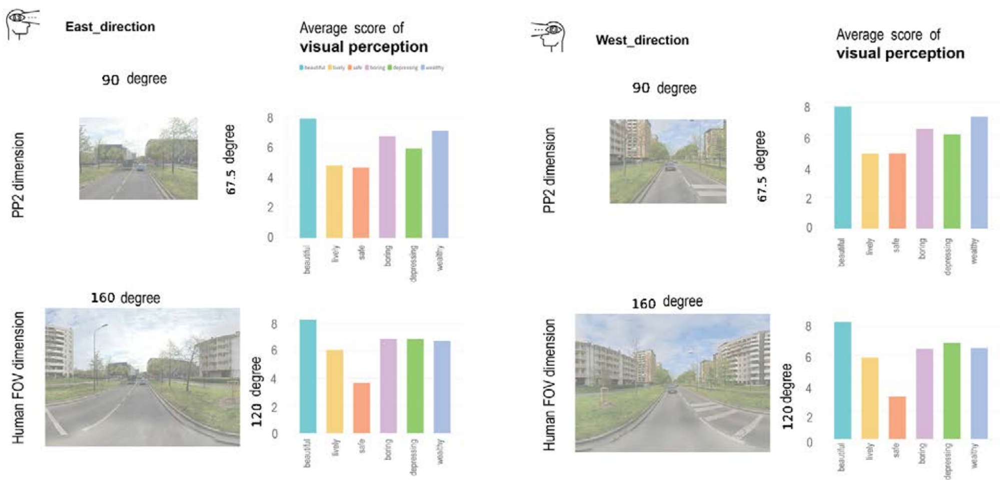


Fig. 8. The comparison of average scores of 6-dimensions perceptions in PP2 view and human FOV. Source: author's drawing.

The average score study shows (fig. 8) that the scores for beauty, liveliness, and depression decrease from human FOV to PP2 view, while scores for safety and wealth increase. This highlights the subtle but significant perceptual variations across different image sizes.
Upon computing the correlation matrix and comparing correlations between PP2 view and human FOV, we found there is a difference in correlation between PP2 view and Human FOV in both directions. Specifically, the perceived sidewalk shows a significant negative correlation with the perception of wealth in the Human FOV in both east and west directions. Additionally, the perceived minibike percentage shows a significant negative correlation with the perception of boredom. In contrast,in the PP2 view, there is no significant correlation between the perceived sidewalk and wealthy perception, nor between the perceived minibike percentage and boring perception in either direction. Furthermore, there is no significant correlation between perceived plant percentage and wealthy perception in the Human FOV, while in the PP2 view, there is a significant negative correlation between perceived plant per-

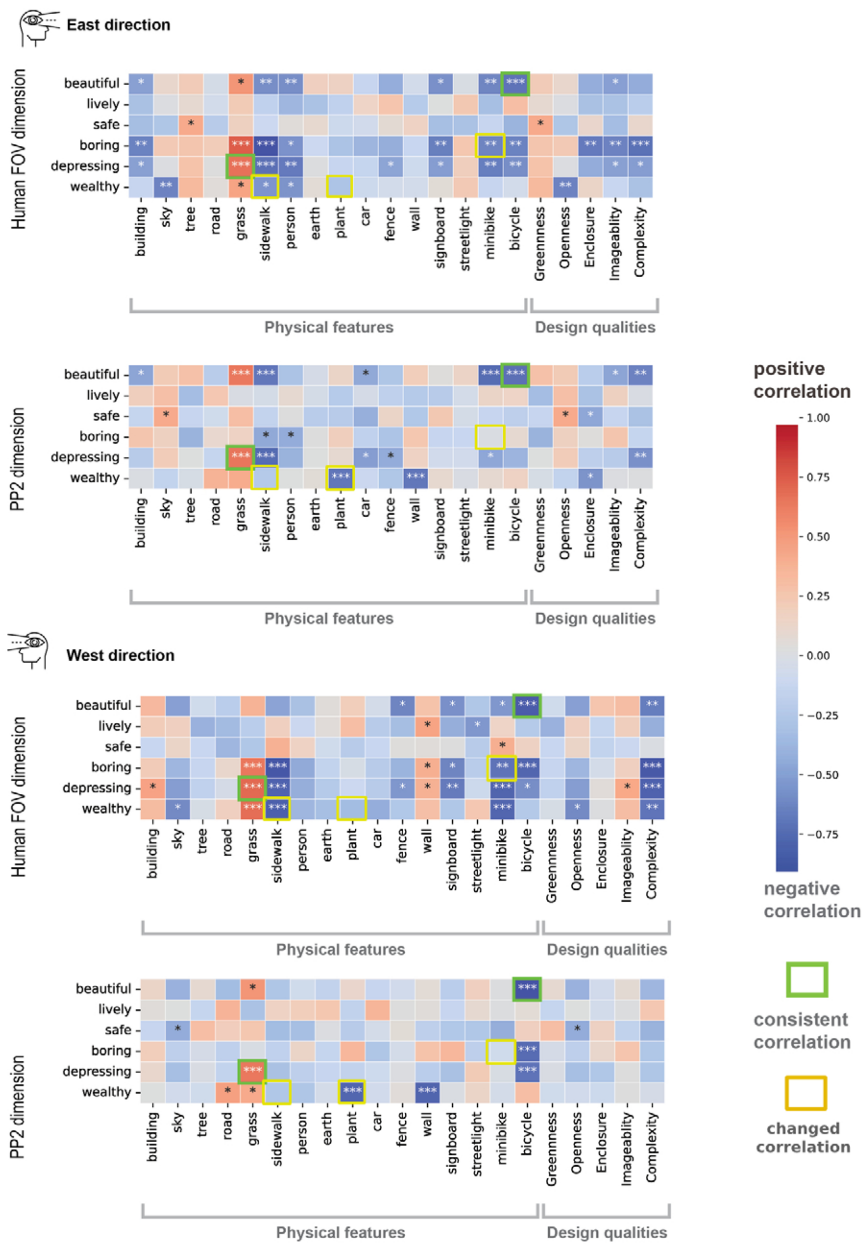


Fig. 9. Pearson correlation analysis of environmental features and visual perception in both walking directions. Green indicates consistent correlations across all FOVs comparing PP2 and human FOV. Source: author's drawing.

centage and wealthy perception in both directions. Furthermore, the relationships (positive/negative) for the opposing directional views remain consistent, though notable distinctions exist. The findings show a consistent positive correlation between perceptions of depression and the presence of grass. Additionally, the perception of beauty negatively correlates with the perceived number of bicycles, which includes a bike-sharing docking station (fig. 9).

Discussion and conclusions

The present study compares the result of the quantitative assessment of perceived environmental features and pedestrian perception between human FOV and PP2 view during a five-minute walk.

In our case study of Spadolini Street in Milan, we found that in the PP2 view, pedestrians perceive more physical features on the horizon, such as buildings, trees, and grass, but fewer features above and below the horizon, like sky and road, compared to the human FOV. Regarding design qualities, the PP2 view shows decreased openness and complexity but increased imageability, greenness, and enclosure. Human FOV scores higher for beauty, liveliness, and wealth perceptions, while the PP2 view scores higher for safety. The PP2 view has fewer high scores for beauty and liveliness, fewer low scores for safety, and higher scores for wealth compared to human FOV. Perceptions vary significantly between PP2 view and human FOV, with some changes in the relationship between the environment and perceptions. The results indicate differing correlations between the PP2 view and Human FOV in both directions. In the Human FOV, the noticeable amount of sidewalk reduces the sense of wealth, and the noticeable amount of minibikes reduces the sense of boredom, but these correlations are not present in the PP2 view. Conversely, the noticeable amount of plants reduces the sense of wealth in the PP2 view, but there is no such correlation in the Human FOV.

In summary, comparing the results of SVIs in PP2 FOV and human FOV in the same location and viewpoint yields difference in human urban perceptions, perceived physical features, and design qualities of urban environments. This finding highlights the importance of consider-ing representation from a human perspective in urban studies by gathering multi-source data such as PP2 or SVIs, including simulating an appropriate field of view. Accurate representation is crucial for gaining insights into improving the person-environment relationship and en-hancing urban design with a focus on public well-being. Furthermore, while the PP2 dataset is based on SVIs, recent studies have identified differences in people's reactions to urban views between street view images or videos and real urban environments [Feng et al. 2021, pp. 740–748; Fitch and Handy 2018, pp. 116–124]. Additionally, methods for measuring perceivable qualities in street environments through ma-chine learning need refinement, current pixel ratio-based approaches oversimplify human perception as global visual pattern auditing of street scenes is essential to capture the overall structural information of the environment comprehensively [Z. Zhang et al. 2021, pp. 18] . These findings suggest the need for further investigation to validate the PP2 dataset, despite its application in various urban studies.

Ackowledgements

The authors' contributions are as follows, according to CRediT (Con-tributor Roles Taxonomy). Shangyu L.: conceptualization, methodology, software, formal analysis, investigation, resources, data curation, writing-original draft preparation, visualization; Stancato G.: visualization, formal analysis, software, resources, writing-review and editing; Boffi M.: conceptualization, formal analysis, resources; Nicola R.: conceptu-alization, resources; Ceravolo P.: formal analysis, software, resources; Piga B.E.A.: conceptualization, methodology, writing-review and edit-ing, visualization, supervision, project administration, funding acquisition. All authors have read and agreed to the manuscript version for publication.

Credits

This research was developed through two EU-funded projects – NextGenerationEU (National Recovery and Resilience Plan), Mission 4 Education and research – Component 2 From research to business":
- MUSA – Multilayered Urban Sustainability Action – Spoke 1 "Urban Regeneration" – Investment Line 1.5.
- MED4PED: Mobility Experience Decision support system for pre-assessing PEDedestrian walkability through on-site and off-site simula-tion project. D.D. 104 of 02/02/2022 (call PRIN 2022), – Investment Line 1.1.
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To cite this chapter: Shangyu Lou, Gabriele Stancato, Marco Boffi, Nicola Rainisio, Paolo Ceravolo, Barbara E. A. Piga (2024). Evaluating Urban Perception: Comparing Place Pulse 2.0 Dataset Results with Images of Varied Field of View. In Bergamo F., Calandriello A., Ciammaichella M., Friso I., Gay F., Liva G., Monteleone C. (Eds.). *Misura / Dismisura. Atti del 45° Convegno Internazionale dei Docenti delle Discipline della Rappresentazione/ Measure / Out of Measure. Transitions. Proceedings of the 45th International Conference of Representation Disciplines Teachers*. Milano: FrancoAngeli, pp. 471-482.

 Isbn 9788835166948