Evolution of Historical Urban Landscape with Computer Vision and Machine Learning: A Case Study of Berlin

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Abstract: Previous studies of historical urban landscape usually focused on the qualitative analysis of city planning and development with the social, economic, and political context, but overlooked quantitative analysis from human perceptions. In this study, we objectively measured the seemingly subjective qualities of the eye-level urban landscape perceptions with computer vision and machine learning technologies. We then explored correlations between the measured perceptual qualities and characteristics from the historical context. We chose Berlin as a research object because it is a capital city that owns a rich history of division and reunification, as well as a variety of residential zones built at different periods. We extracted 30 street features from the 150,000 Google Street View Imagery (SVI) dataset with a computer vision algorithm and evaluated eight perceptual qualities including typology, order, ecology, enclosure, aesthetics, richness, accessibility and scale with a machine learning method. Then we defined seven residential districts in Berlin, according to their spatial distributions and construction periods. Through a systematic comparison of perceptual qualities of the seven residential districts, we find perceptual qualities of ecology and enclosure have been improved a lot over a hundred years in Berlin. The housing policies and design codes in different social, economic and political contexts evolved to end overcrowding living conditions, create more open spaces, and develop a better ecological environment. This study enriches our understanding and application of subjective measures of human-centred built environment perception to the evolution of the historical urban landscape. The proposed quantitative framework of subjective human perception measures provides great testimony to evaluate the effects of the implementation of housing and other urban planning policies. Such an automated, multisource, high-throughput and scalable framework can be applied to other cities to determine the personality of the city and assess the impact of urban design and planning policies in streetscape improvement.

Keywords: Computer vision, machine learning, Google street view image, perceptual qualities

1 Introduction

Inspecting the development of urban landscape and investigating influence factors has long been a vital topic in the study of urban history. A variety of methods and data sources have been adopted to analyze the urban historical environment in urban studies. For example, historical maps have been scanned and digitized for long-term spatial change studies (TUCCI et al. 2010, LLOYD et al. 2012, KIM et al. 2018). Modeling software has enabled comparisons of built environments in three-dimensional space (ARNOLD & LAFRENIERE 2018). Satellite images have been utilized for examining the historical development of urban landscape structures and their dynamic changes (GUO et al. 2020, TANG et al. 2008, WENG & LU 2009).

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However, previous studies have almost exclusively focused on qualitatively describing historical changes in cities from a macro perspective, but overlooked nuanced and subjective perspectives on the human experience of place.

Previous studies of subjective perception of the built environment relied on traditional methods such as visual collages, interviews, field surveys, and virtual audits (LAAKSONEN et al. 2006, OGUZ 2000, SÁENZ DE TEJADA GRANADOS & VAN DER HORST 2020) to collect people's overall perceptions. These measurements have problems in consistency, reliability of the operation and limited application to larger geographic contexts. With multi-source, open data especially the Street View Imagery (SVI) and advanced technologies of artificial intelligence, it becomes possible to quantify how cities are perceived by their inhabitants with more human-centered and eye-level experiences and on a large scale. New analytical frameworks show great advantages in efficiency and accuracy over traditional methods. For example, NAIK et al. (2014) used Place Pulse data to train a computer vision algorithm called Streetscore that accurately predicts human-derived ratings for the perception of a streetscape's safety. Some authors have driven further development of crowdsourcing and computer vision methods to calculate the green view index of the streetscape. LI et al. (2015) explored Google Street View (GSV) images as an urban greenery assessment tool on street-level and modified the Green View Index (GVI) formula. LI et al. (2019) further utilized panorama images to predict the occurrence of sun glare from street-level. DOERSCH et al. (2014) analyzed street view images and attempted to extract characteristic features, such as windows, balconies, and street signs, that are most distinctive for a certain geospatial area. TANG and LONG (2019) measured the characteristics of Hutongs, typically representative of historical streets in Beijing, from the perspectives of greenery, openness, enclosure, street wall continuity, cross-sectional proportion, and stay willingness. This also allows them to analyze differences between physical and perceived qualities and evaluate the level of urban renewal in Hutong during recent years. Another study identified important indicators from both human-centered street scores as well as the more objective street feature measures with positive or adverse effects on property values based on a hedonic modelling method (QIU et al. 2020). The above-mentioned studies show that the SVI dataset has unique advantages in human-scale street perception measurement, quantitative urban landscape studies, and urban renewal performance assessment, which can compensate for the limitations of past historical landscape studies. However, the application of new data source and new analytical tools in the historical urban landscape contexts has not been addressed adequately. Few studies have systematically investigated and evaluated how and to what extent the citizen's human perception of the built environment changed as a result of various planning policies.

Against the backdrops of the existing literature, this study aimed to incorporate human perception in historical urban landscapes by utilizing computer vision and machine learning technologies. Berlin, a capital divided and governed by Capitalist and Socialist ideologies historically, was chosen as a research object. Its uniqueness not only represents different aesthetic preferences and morphological characteristics between East and West Berlin, but also reflects their changes during a long history of division and reunification. With computer vision and machine learning technologies, we extracted more than 30 street view features and estimated 8 perceptual qualities scores from 150,000 Google SVI images. We examined the spatial formation, landscape elements composition, and landscape perception through data mining and visualization of the SVI image dataset. We further compared human perception in different historical districts to find correlations between perceptual qualities and historical context. This study achieved three key contributions: (1) it offered a test of how these digital technologies can be used to quantify physical features and perceptual qualities; (2) it quantified the differences in human perceptions of the built environment under the impact of major historical events; (3) it revealed the correlations between perceptual qualities and historical context and interpreted it from the perspective of Berlin's planning policy. This study will help urban designers and planners understand the historical development of urban landscapes from a human perspective, as well as the influencing factors and driving mechanisms, which sheds light on future urban policies and urban design of an integrated city.

The rest of the paper is organized as follows. In section 2, we provide the definition of perception qualities and introduce the proposed methodology. Section 3 presents the result of the perceptual qualities score and discusses its correlations with historic context and planning policies. The conclusions and future work are given in Section 4.

2 Methodology

2.1 Definition of Perceptual Qualities

Perceptual qualities, affected by physical features, urban design qualities and individual reactions to the built environment, can be assessed objectively by observers. EWING and CLEMENTE (2013) used traditional research methods, such as observing, counting, and manually rating, to establish relationships among physical features, urban design qualities and perceptual qualities. In our research, we added an individual reaction process – 300 training samples derived from a random survey with 50 people – to predict the perceptual qualities of the rest SVI dataset with a machine learning algorithm.

We set up eight perceptual qualities for further study based on a review of classic landscape architecture and urban design. They are typology, order, ecology, enclosure, aesthetics, accessibility, richness, and scale. (1) Typology is the arrangement of physical elements which evoke people's impressions of land use and urban characters. They cover five common types: residential, office, commercial, suburban, and rural. (2) Order refers to the geometrical, sameness or presence of repetitions observed in an urban area. (3) Ecology indicates the detection of living organisms, including animals, plants and humans, and the physical environment around them. (4) Enclosure refers to "the degree to which streets and other public spaces are visually defined by buildings, walls, trees, and other vertical elements." (EWING & CLEMENTE 2013) It is strengthened by continuous building fronts of rough height, while being eroded by breaks in the vertical elements. (5) Aesthetics presents the overall visual quality of a street being comfortable and distinct (EWING et al. 2006). (6) Accessibility is about people's ability to reach geographically dispersed activities, attractions, and amenities (SOLÁ et al. 2018). (7) Richness (or complexity) refers to the complexity of a place depending on the variety of the physical environment, such as the numbers and kinds of buildings, landscape elements, street furniture, signage, and human activity (EWING & HANDY 2009). (8) Scale refers to human scale here, which means "physical elements to match the size and proportions of humans" (EWING & CLEMENTE 2013). It is an innovative method to quantify ecology and aesthetics with machine learning since they are closely related to the landscape architecture field but have been neglected in previous urban studies. The rest of the six perceptual qualities are also important in the literature of urban design as well as the landscape architecture field.

2.2 Methodology

The proposed methodology includes four processes: SVI sampling, SVI perception data acquisition, street features extraction and ML model training. We also zoned historic residential districts for comparative studies. The whole framework of the methodology is shown in Figure 1.

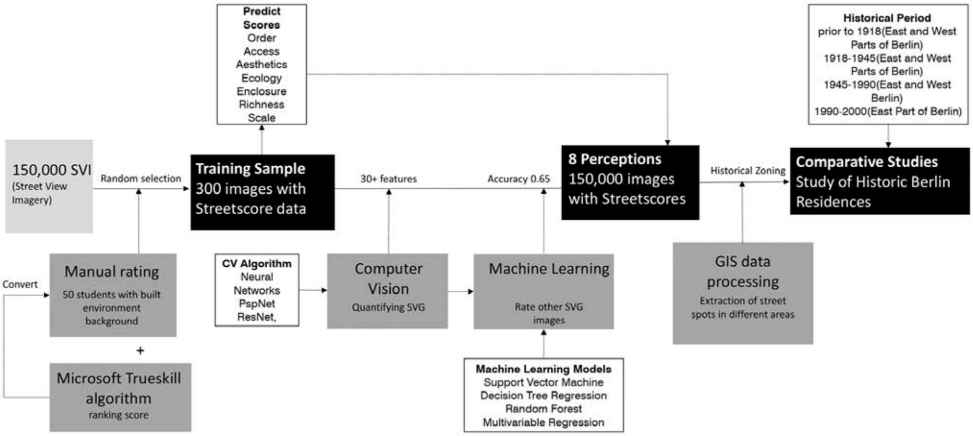


Fig. 1: Workflow of technology

2.2.1 Street View Image Sampling

Street View Imagery (SVI) provides a horizontal view of the street environment that is closer to the perception of pedestrians, making it an ideal data source for measuring a streetscape environment. Most Google Street View (GSV) images are taken by GSV cars along streets with 15 cameras that snap 360-degree views at a height of 8.2 feet (RICHARD 2012). It is considered as an accurate and efficient dataset by a great number of studies focused on the streetscape, for instance, GONG et al. (2018) verified the accuracy of the GSV-based method by comparing sky, tree and building view factors measured by GSV with field surveys. We sampled points every 50 meters along public streets in Berlin and downloaded 150,000 pictures of Berlin streetscape from Google Street View API. We set up angles as heading forward, pitch (0°), horizontal field of view (120°) and size (900 by 600 pixels) to ensure the consistent perspective. 300 SVIs were selected randomly for perception scoring as a training dataset (Fig. 2).

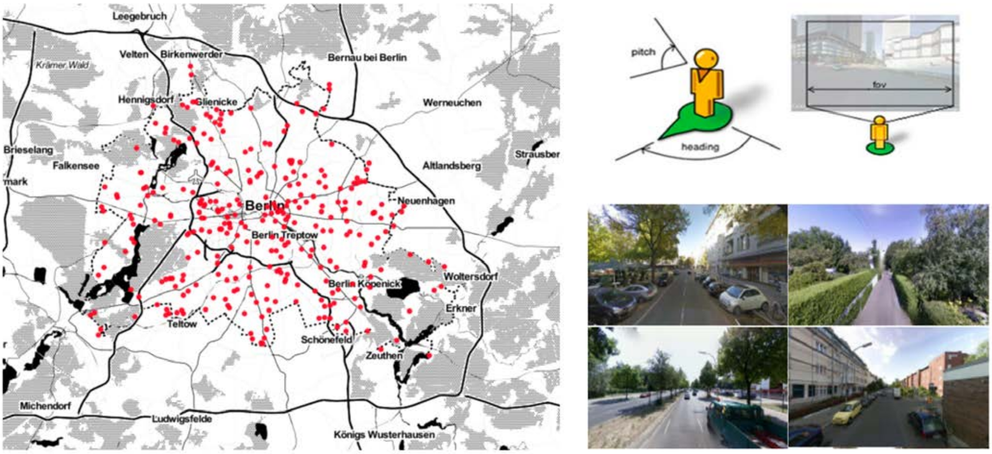


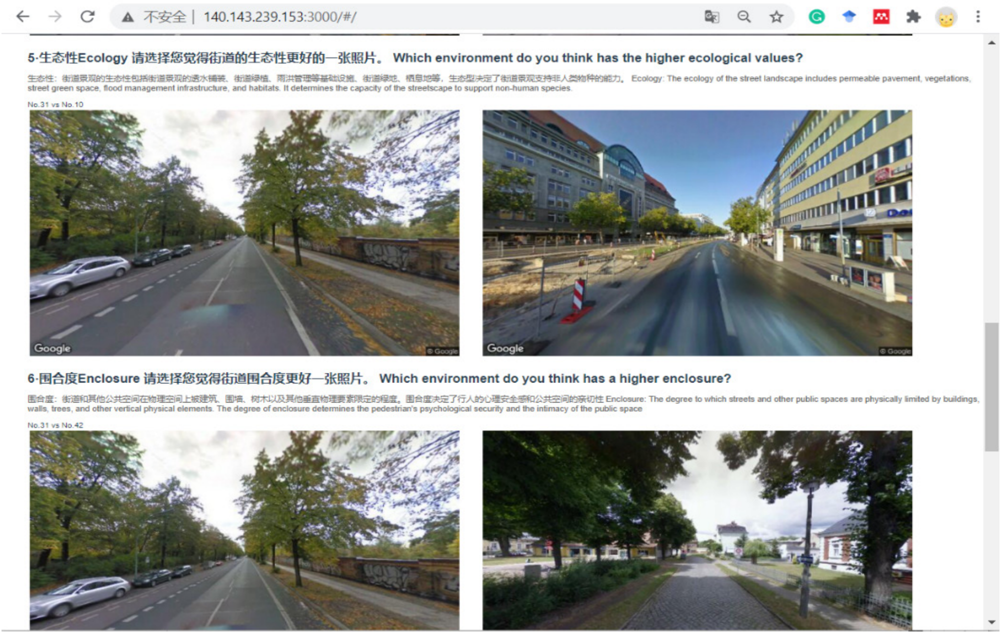
Fig. 2: A random sample of 300 street view image points across Berlin as the training dataset; Downloaded street view images from Google Street View API

2.2.2 Street View Perception Data Acquisition

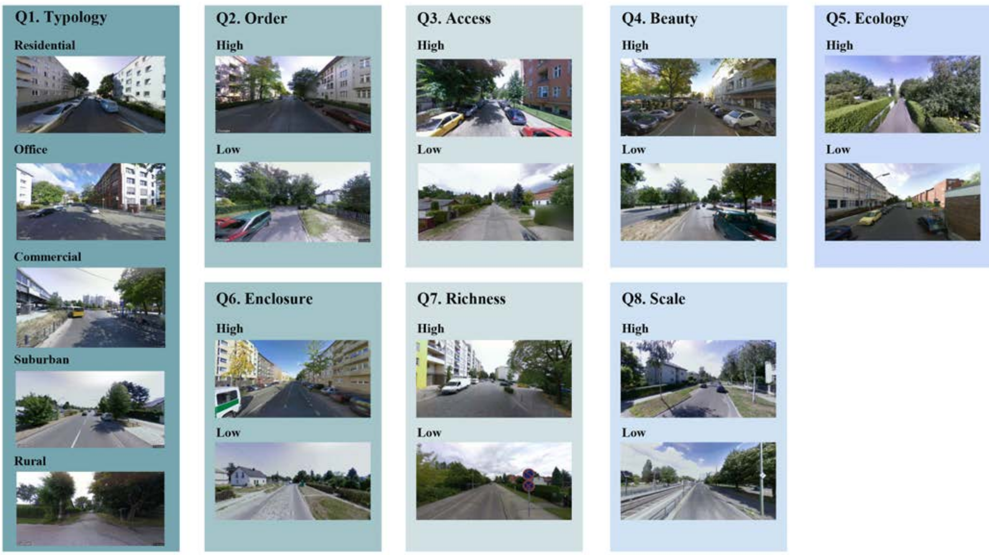
To obtain training data on people's streetscape preferences from SVIs, we used a high-throughput approach developed in emerging research (NAIK et al. 2014, SALESSES et al. 2013). Specifically, we developed an online survey platform where participants were presented with two images randomly selected from the Berlin SVI dataset. Participants were asked to click on their preferred SVI to answer eight evaluative questions about eight perceived street qualities (Figure 3). For example, a short definition of “ecology” was given. Then, we asked the participants the question “Which place do you think has a higher visual ecology?” Notably, to ensure that the training images covered a variety of street scenes from the city center to the suburbs to the outskirts, these preferences were converted into a ranking score (range 0-10) for each image by the Microsoft Trueskill algorithm (NAIK et al. 2014).

2.2.3 Street Features Extraction

After acquiring the perception scores, we quantified the proportion or number of pixels of 30 street features using a pre-trained Computer Vision model. Pyramid scene parsing network (PSPNet) is one of the most well-recognized image segmentation algorithms as it won ImageNet Scene Parsing Challenge 2016 and its research study is highly cited by the computer vision community (ZHAO et al. 2016). Through training on the PSPNet network, we performed image segmentation and element detection on 150,000 streetscapes, and ultimately extracted a proportion of more than 30 streetscape features as evaluation indicators, including building, sky, tree and so on (Figure 4). Instance segmentation with Mask R-CNN algorithm (Figure 5) can generate a segmentation map for each detected instance of an object and accommodate multiple classes and overlapping objects (HE et al. 2017).



(a) Online survey system asking participants to click on one of a pair of SVIs in response to evaluative questions



(b) Evaluation examples of 8 perception factors

Fig. 3: Online survey system and perception factor

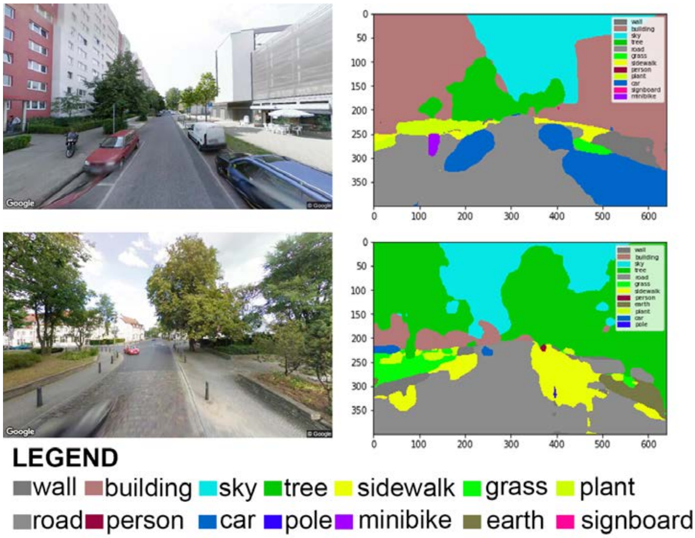


Fig. 4: Semantic segmentation example of physical features

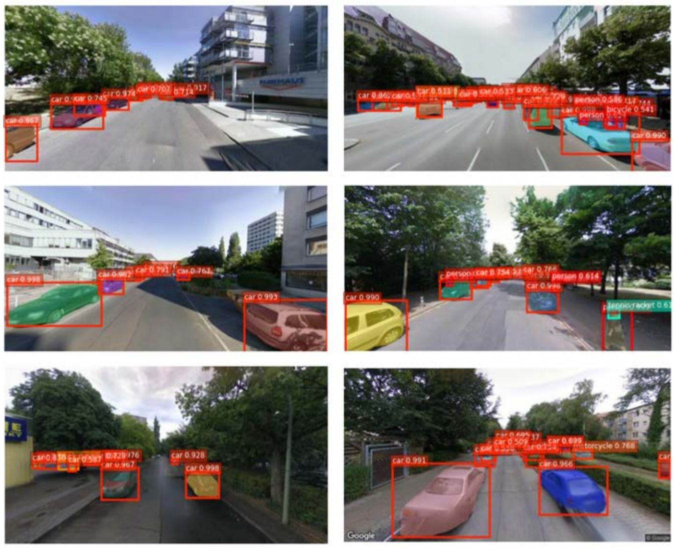


Fig. 5: Instance segmentation example of counting the number of cars

2.2.4 Machine Learning Models Training and Perceived Scores Estimation

We trained ML models including K-nearest neighbors (KNN), support vector machine (SVM), random forest (RF), decision tree, and gradient boost (GB) to estimate eight perceived scores from the 30 features extracted from SVI. The 300 labelled images from the online survey were split into a training set and a testing set. The input of the ML model is 30 street view features, and the output of the ML model is the eight perceived scores. To choose the optimal model, we compared model performances regarding the R-square, the Root Means Square Error (RMSE) and the Mean Absolute Error (MAE). RF performed best in predicting all the scores (Table 1). Then, using the random optimization method (LIU & SUN

2019, SMITH 2010), we further improve the RF model by optimizing the two parameters, the number of branches in the forest structure and the maximum number of levels in each decision tree. RF accuracy reached 0.65 after improvement and the accuracy of ML model was considered acceptable, limited by the small training dataset. Therefore, we considered the obtained street-perception data to be accurate. The final improved RF model was applied to estimate the perceived scores of the rest of the 150,000 SVI of Berlin streetscapes.

Table 1: Comparing the accuracy of different ML algorithms

ML Models	Q1_Type	Q2_Order	Q3_Access	Q4_Aesth	Q5_Eco	Q6_Enclo	Q7_Rich	Q8_Scale
KNN	0.47	0.36	0.40	0.38	0.48	0.44	0.49	0.41
Random Forest	0.60	0.48	0.55	0.54	0.56	0.59	0.59	0.51
Decision Tree	0.59	0.49	0.50	0.54	0.52	0.56	0.53	0.49
Gaussian Process	0.58	0.44	0.51	0.52	0.55	0.53	0.58	0.45
GradientBoosting Regression	0.58	0.46	0.52	0.49	0.52	0.57	0.54	0.48
ADA	0.56	0.47	0.51	0.49	0.53	0.54	0.53	0.48

2.3 Historic Residential District Zoning

We divided the existing residential area into seven districts according to every national government based in Berlin (BODENSCHATZ 2010): Mass housing, Mietskasernen, was built in the east area (E1) and west area (W1) between the German Empire of 1871 and the Weimar Republic of 1918, though nothing was built during WW1 from 1914 -1918. The apartments of new modernism were built in the east area (E2) and west area (W2) from 1918 to the end of Nazi Germany (1945), with little estate development during WWII from 1939 to 1945. Later, reconstruction occurred in East Berlin (E3) and West Berlin (W3) during the 1945-1990 period as a divided city. And 1991-2000 was the redevelopment period (E4) after reunification in East Berlin.

According to the interactive map of residential districts built in different periods (Figure 7), we selected the streetscape data that is closest to chronological age through an image calibration operation in Geographic information system (GIS) and divided them into E1-4 and W1-3 sections. E1 and W1, built in the early age, take up the central area of Berlin, and E4 is mainly located in the eastern suburbs of Berlin, while all other periods are distributed surrounding the centre (Figure 8).

Fig. 6:
Distribution of residential areas in Berlin at different historical times (Source: Berliner Morgenpost, https://interaktiv.morgenpost.de/so-alt-wohnt-berlin/)

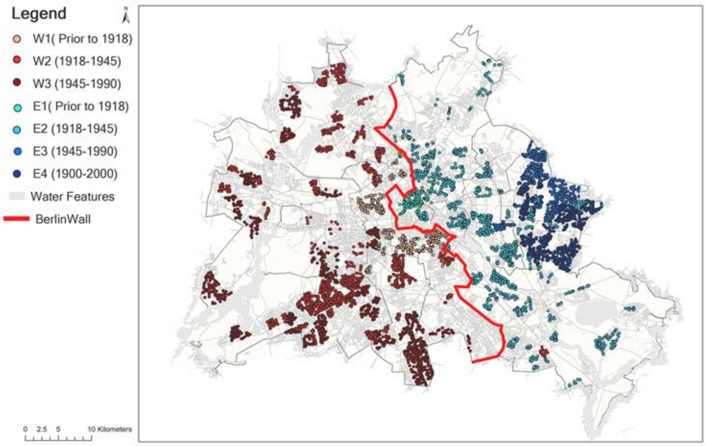


Fig. 7:
The distribution of observer spots in different periods extracted by GIS

3 Analysis and Discussion

3.1 Street View Perception Data Visualization

With the computer vision and machine learning technology introduced above, we extracted more than 30 streetscape features and acquired 8 perceptual qualities scores from 150,000 SVI images. The streetscape features provide quantitative support for predicting perception scores. For instance, there are four key streetscape features, namely sky, tree, building, and road taking significant fractions in a SVI image. Through visualization of data from GIS, we find that the building visibility is high in the center of Berlin, while high tree visibility is more distributed in the north and south outskirts, such as Frohnau and Lichtenrade and high sky visibility can be found in the east and west outskirts, such as Hellersdorf and Neustaaken. Correspondingly, the perception score of the enclosure is positively correlated to building visibility and tree visibility, but negatively correlated to sky visibility (Figure 9).

3.2 Analysis of Perceptual Qualities in Different Historical Districts

According to the seven historical periods in chronological order, we selected several representative clusters of residential districts of each period. By overlaying the histograms of predicted perceptual scores at seven historical periods, we found that the shapes of curves fell into three main categories. Firstly, data are moderately skewed at certain periods. Take the perceptual score of Ecology as an example, the E1 and W1 periods have a right-skewed distribution while the W3 and E4 periods have a left-skewed distribution. Secondly, the datasets are close to a normal distribution, such as the perceptual score of Aesthetics. Lastly, the data are evenly distributed with no clear pattern, such as the perceptual score of Enclosure (Figure 9). To compare the data more precisely, we selected the median score from each period and region to represent its score in the middle (Table 2). E1 and W1 districts share a lot in common in every perception evaluation: high score in access and order but low evaluation in perception score of ecology and aesthetics. E2 and W2, overlapping with each other at a high level, show relatively even performance in each perceptual score. W3 has a low evaluation of order though, better performance in the evaluation of scale and enclosure, compared to the buildings' low evaluation of enclosure in East Berlin (E3) during the same era. E3 also has a low evaluation of scale and enclosure, but a fair evaluation score of ecology. E4 district inherits a low evaluation of order and enclosure from the E3 district, but a better performance of ecology and aesthetics. Through comparison, we find ecology, enclosure and scale are the critical perceptual qualities to reflect the historical development of the urban landscape.

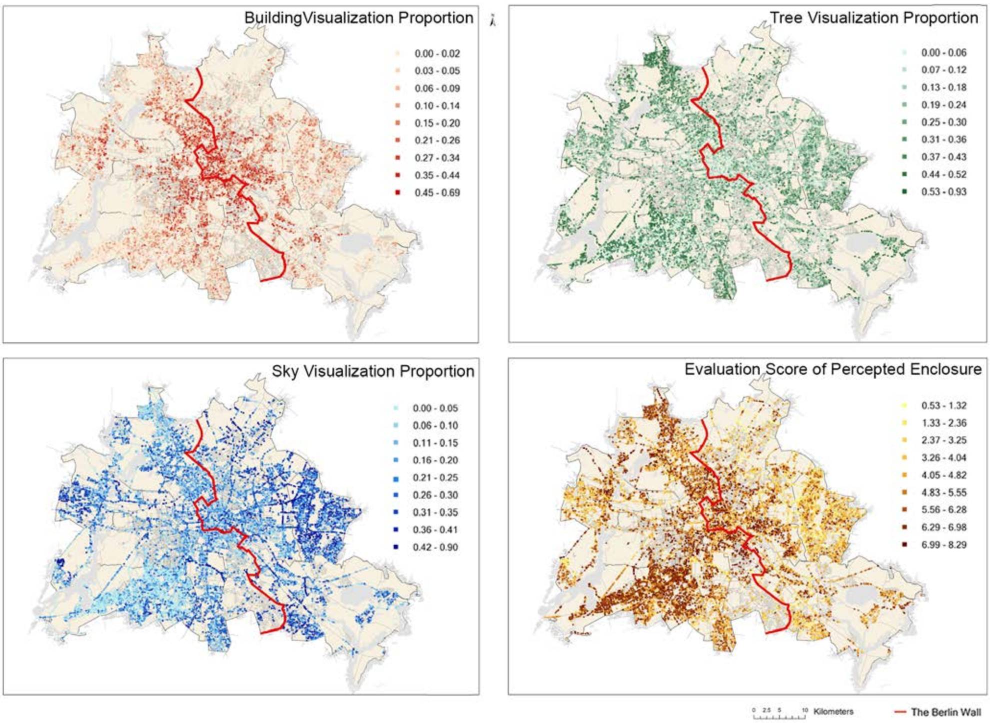


Fig. 8: Visibility of key streetscape features and perceptual qualities of enclosure

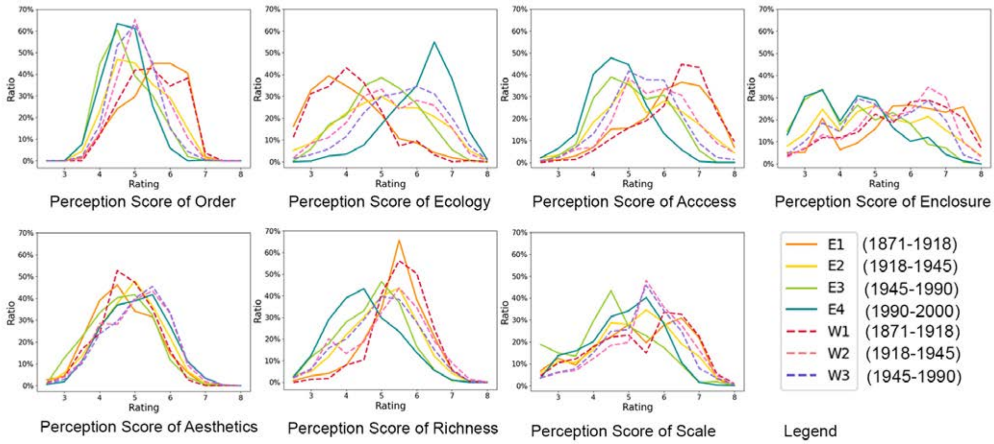


Fig. 9: Histograms of prediction perceptual score in 7 historical districts

Table 2: Comparing Prediction Perception Median Score in different periods and regions

Comparison of Perception Median Score							
Perception / Time	Order	Ecology	Access	Enclosure	Aesthetic	Richness	Scale
East1 (1871-1918)	5.61	3.92	6.32	5.87	4.64	5.49	5.32
East2 (1918-1945)	5.03	5.11	5.38	4.84	4.90	5.11	5.23
East3 (1945-1990)	4.62	5.02	5.04	3.74	4.65	4.82	4.46
East4 (1990-2000)	4.70	6.31	4.62	3.74	5.00	4.41	5.02
West1 (1871-1918)	5.46	4.02	6.51	5.89	4.76	5.59	5.59
West2 (1918-1945)	5.08	5.22	5.69	5.72	5.11	5.34	5.58
West3 (1945-1990)	4.95	5.68	5.38	5.06	5.17	5.11	5.44

3.3 Perceptual Qualities to Historical Context and Planning Policies

We attempted to explain these variances among the seven districts in Berlin from the perspective of historical contexts and planning policies. The analysis estimated the potential effects of individual policies on the perceptual qualities as below.

Berlin experienced rapid growth in population and economy in the mid-nineteenth century, with a perceived need for housing units for new immigrants (ARANDELOVIC & BOGUNOVICH 2013). Engineer James Hobrecht, appointed by the Prussian government, drew up a zoning plan (Hobrecht Plan), encompassing the existing city like a belt, for large residential districts in 1862. The Hobrecht Plan established limits between public spaces and private spaces and left the development to individual property owners since Hobrecht didn't think the aesthetic design was a task of planning (BERNET 2004). However, the loss of regulation within the blocks resulted in a high parcel density: these units were followed by a sequence of rear buildings where factories were located and most courtyards within buildings were used for industry instead of green space until the 1920s (BENTLIN 2018). This may explain why these planning policies had a negative effect on the perceived ecology and aesthetics of the built environment but are associated with a positive effect on the perceptual score of access and order in the E1 and W1 sections.

The Weimar Republic, declared in 1918, began a vibrant period of "Golden Twenties" in the history of Berlin. The 1925 Building Code put an end to the high density of buildings with rear blocks and limited accessibility only through the courtyards (BENTLIN 2018). In the building reform movement for improving housing and living conditions, Martin Wagner as the city planner with Bruno Taut and Walter Gropius as leading architects, set the style for social housing with spacious green areas and openings to light and air. The housing estates reflect the highest degree of quality, the combination of urbanism, architecture, garden design and aesthetic research of early 20th century modernism, as well as the application of new hygienic and social standards (URBAN 2018). Six representative "Berlin Modernism Housing Estates" were listed as UNESCO World Heritage Sites (PUGH 2014). The high quality of the housing standard might provide theoretical support for no apparent shortage among each perceptual score in the E2 and W2 sections. Few constructions, especially housing estates were preserved from the Nazi Germany era (1933-1945), so we did not evaluate the influence of the megalomaniac planning in that period.

Berlin suffered enormous destruction during World War II. In 1949, two German governments were constituted and separated the country into East and West over the next forty years. The influence of Soviet urban planning was evident in East Berlin, such as Karl-Marx-Allee, with wide boulevards and grandiose plazas to praise its social system. 'Plattenbau' (prefabricated concrete slab building) as a typical style of a residential building, was built to curb the country's severe housing shortage in East Berlin since the 1970s. However, 'Plattenbau' are often not desirable, due in part to their rapid deterioration caused by cheap and quick construction methods (PENSLEY 1995). A 1975 report to the top leader Gerhard Trölitzsch's office pointed out that the low aesthetic quality of East German housing blocks seriously endangered the citizens' identification with the socialist state (BAUWESEN 1975). Such planning policies and design standards represent a negative effect on the perceived scale, enclosure, and aesthetics of the built environment in the E3 section. But its grand scale of public space leaves potential for green areas, which contributes to the perceptual score of ecology.

To respond to construction projects in East Berlin, Hansaviertel residential complex (Hansa District) was the showcase of German design in West Berlin at the Interbau 1957 International Building Exhibition, which is an important testimony to the modern architecture and urban planning of the 1950s. The "star architects" as well as urban planners, engineers, public transport experts, sociologists and economists built this "City of Tomorrow" in West Berlin (WAGNER-CONZELMANN 2018). The Hansaviertel residential complex improved the dwelling conditions to a level that was unprecedented in history and set the design standard for later housing estate development. The planner Edgar Salin and the sociologist Hans Paul Bahrdt promoted the new urban planning paradigm Urbanität durch Dichte (urbanity-through-density) in West Berlin's large estates around 1960. Märkisches Viertel, Gropiusstadt and Falkenhagener Feld, which aimed at urbanity in this sense, were modelled after the principles of the Athens Charter such as functional separation, separation of traffic flows and predominance of light and air (URBAN 2018). Such planning policies probably have positive effects on perceived scores of Ecology, Scale, Richness and Aesthetics in the W3 section, relatively low performance in score of access and enclosure. Generally, the W3 section inherited good performance of perceptual qualities from the W2 section (Figure 10).

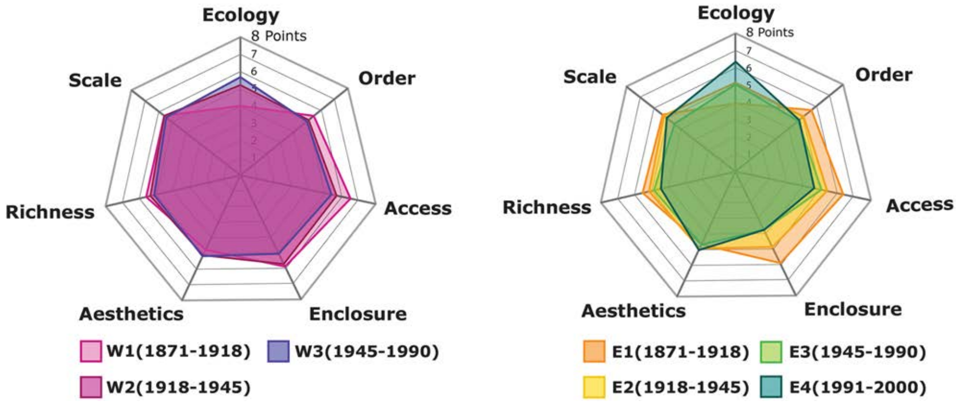


Fig. 10: Median score chronological change in 7 historical districts

After unification into the Federal Republic of Germany in 1990, the government attempted to integrate the urban streetscape of East Berlin to West Berlin in three ways: (1) visually change Plattenbau facades to a more Western face; (2) reconstruct the central city according to existing urban fabric (COBBERS 2011); (3) develop single-family houses and smaller apartment buildings in previously undeveloped areas. We took a cluster of residential developments, which are mainly single-family houses in Kaulsdorf, as an example to evaluate perceptual qualities. A low perceptual evaluation of order and enclosure, but a better performance of ecology and aesthetic prediction might be associated with the planning policies for the suburban new developments.

4 Conclusion

This study introduced a scalable, automated and high-throughput framework to apply machine learning and computer vision methods to publicly available SVI. The framework objectively measured eight perceptual qualities of the urban streetscape, and applied the result to comparative research of seven residential districts in Berlin. We compared the results from two perspectives: by chronological order and by geographic locations. First, in the chronological order perspective, we found perceptual qualities of ecology and enclosure have got significant improvement from the German Empire, the Weimar Republic, the divided city of West and East Berlin to a reunified Germany. The increase of ecology and enclosure evaluation evaluations represents housing policies and design codes have improved overcrowding densities, created more open spaces, and developed a better ecological environment since the post-war period. Second, the evaluation of perceptual qualities in the west part of Berlin showed consistent results with the east part at the same period until Berlin was divided into West and East Berlin in 1945. The housing estates built in the East Berlin period (E3) represents a low evaluation of enclosure, aesthetics, richness and scale. Though the Federal Republic of Germany government attempted to integrate the urban landscape of East Berlin to West Berlin after the reunification, people's perceptions can still tell the difference of the urban features which respond to their construction characters and historical contexts. The quantitative analysis of human perceptions provides great testimony to evaluate the effects of the implementation of planning policies and design codes.

This study presented a novel approach to interpret people's perceptions of the urban built environment, then date it back to the context of previous policy, society and economy. For a city with a long and rich history like Berlin, it explains the context of historical events and planning policy's impacts on the urban streetscape in a quantitative way. This digital city model technology can calculate various metrics to describe and quantify diversity or similarity of urban landscape from a human perception. It can help the local government to determine the personality of the city and assess the impact of policies in streetscape improvement.

Several limitations should be noted. First, with limited data acquisition and time, the small sample of 300 SVIs for the training set might bring bias to the machine learning model. Second, the training model is built based on evaluations from students with a built environment background. To a certain extent, it does not represent the public's perception. Lastly, the points we selected come from certain representative residence clusters. In other words, they do not cover all the areas built in that historical period. Future work includes zooming in specific residential districts of Berlin and analyzing their perceptual qualities more precisely.

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